The Effects Of Age And Distraction On Interlimb Synchronization Of The Center Of Pressure

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Abstract

Older adults experience falls more frequently than young adults. Older adults also experience increased distractibility and cognitive decline, which contribute to fall risk. One of the mechanisms that may contribute to or mitigate fall risk is the coordination of balance control mechanisms between limbs. This thesis probes the effects of cognitive distractions on interlimb synchronization and balance, focusing on two groups: young adults, and older adults. The primary research question is: how do cognitive distractions impact interlimb synchronization and balance among these groups, and what implications might this have for understanding fall risk? To answer this question, participants performed quiet standing (QS) trials with each foot on separate force plates. Participants stood with the eyes open or closed, with or without distraction (counting backwards by 7's). Interlimb synchrony was measured by identifying the peak of the cross-correlation function (CCF) of the center of pressure (COP) under each foot in both the anteroposterior (AP) and mediolateral (ML) directions. Other parameters measured were root means square (RMS) of COP and mean sway velocity (MSV) of the COP movements. It was hypothesized that cognitive distractions will result in lower synchrony values, with greater impact observed in older populations, especially those with a history of falls. The results indicated no significant differences in CCF and RMS between groups or conditions. However, MSV showed significant differences across conditions but not between groups. These findings suggest that while cognitive distractions influence postural control velocity, they do not significantly affect CCF or RMS at this degree of cognitive distraction. This research contributes to our understanding of balance and cognitive function interactions, setting the stage for exploring how technological ubiquity and increasing cognitive demands may impact this interplay between balance and cognitive function, especially in the aging population.

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List of Abbreviations and Definitions

- AP (Anteroposterior): Refers to movements or measurements that occur in the sagittal plane, from front to back of the body.
- BOS (Base of Support): The area beneath an individual that includes every point of contact that the person makes with the supporting surface. This is crucial for maintaining balance as it determines the stability limits.
- CCF (Cross-Correlation Function): A measure used to examine the relationship between two signals or data sets, often used to assess the synchronization between the movements of the limbs.
- CCR (Cross-Correlation): A statistical tool used to quantify the degree to which two signals are correlated at various time lags, providing insight into the timing relationships between them.
- CNS (Central Nervous System): The part of the nervous system consisting of the brain and spinal cord, responsible for processing sensorimotor information and coordinating bodily functions.
- CO (Counting Ones): The condition in which participants count upwards by increments of one.
- COM (Center of Mass): The point at which the total average of body mass segments is considered to be positioned, and around which the body's mass is evenly distributed.
- COP (Center of Pressure): The point of application of the ground reaction force vector, representing the average location of the forces exerted by the ground on the limb making contact with the ground during standing or movement.
- COP_{net} (Net Center of Pressure): The summation of all center of pressures.

- DT (Dual-Task): A paradigm in which individuals are asked to perform two tasks simultaneously, typically one cognitive and one motor task, to study the impact of cognitive load on motor performance.
- DTC (Dual-Task Cost): The decrement in performance on one or both tasks when they are performed together compared to when they are performed separately.
- DTI (Dual-Task Interference): The phenomenon where performing two tasks simultaneously leads to a decrease in performance on one or both tasks due to competition for cognitive resources.
- EC (Eyes Closed): A condition in balance studies where participants keep their eyes closed to remove visual input and increase reliance on other sensory systems.
- EO (Eyes Open): A condition in balance studies where participants keep their eyes open, allowing them to use visual input for maintaining balance.
- LOG (Line of Gravity): An imaginary vertical line that passes through the center of mass, and, ideally, falling within the base of support to maintain balance.
- ML (Mediolateral): Refers to movements or measurements that occur in the frontal/coronal plane, from side to side of the body.
- MSV (Mean Sway Velocity): The average speed of movement of the center of pressure, providing a measure of the dynamism of postural control, typically measured in millimetres per second (mm/s).
- ND (No Distraction): A condition in which participants perform a task, typically quiet standing, without any additional cognitive load or distractions.

- QS (Quiet Standing): A condition where participants stand still without any intentional movements, used to study basic postural control mechanisms.
- RMS (Root Mean Square): A statistical measure of the magnitude of a varying quantity. In the context of COP, it represents the average magnitude of sway and provides an indication of postural stability, measured in millimetres (mm) for assessing sway.
- SD (Standard Deviation): A measure of the amount of variation or dispersion in a set of values.
- ST (Single Task): A condition in which participants perform only one task, used as a control or baseline measure in dual-task studies.
- TL (Time Lag): A quantitative measure representing the temporal offset in synchronization of the center of pressure (COP) signals between the limbs (measured in milliseconds, ms).
- WD (With Distraction): A condition in which participants perform a task while being subjected to an additional cognitive load or distraction.

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Chapter 1. Introduction

In an era marked by rapid technological advancements, the escalating cognitive demands of a digitally saturated environment intersect critically with the challenges faced by Canada's aging population. Canada's population is aging rapidly; in 2011, an estimated 5 million Canadians, or 15% of the population, were 65 years of age or older, a number expected to double by 2036 (*Seniors' Falls in Canada. Second Report*, 2014). This demographic shift has significant implications for public health, as falls among older adults remain a leading cause of injury-related hospitalizations (*Seniors' Falls in Canada. Second Report*, 2014). Approximately 20% to 30% of seniors fall each year, leading to serious injuries, including fractures and hospitalizations (*Seniors' Falls in Canada. Second Report*, 2014). Falls among older adults, a significant public health concern, result in substantial social and healthcare costs. In 2004, fall-related injuries cost the Canadian healthcare system approximately $2.0 billion, a figure projected to rise to around $4.4 billion by 2031 (Scott et al., 2010). Falls are a leading cause of injury among older adults over the age of 65, a demographic particularly vulnerable due to age-related changes in sensory, motor, and cognitive functions essential for maintaining balance (Scott et al., 2010). Effective balance control involves complex coordination of sensory inputs and motor outputs (Shumway-Cook & Woollacott, 2017), and the decline in this ability with age (Richer & Lajoie, 2020) may lead to a greater risk of falls and related injuries (Shumway-Cook et al., 1997). Cognitive distractions can further exacerbate balance problems. When individuals are distracted, their ability to automatically maintain balance is compromised, leading to increased postural sway and instability (Woollacott & Shumway-Cook, 2002). This phenomenon is particularly concerning for older adults, who already face challenges in allocating attentional resources efficiently

(Huxhold et al., 2006).

Interlimb coordination, defined as the control scheme that governs the coordinated movement between limbs, is essential for maintaining balance, particularly during complex motor tasks (Shumway-Cook & Woollacott, 2017). This coordination involves the precise timing and activation of muscles across different limbs to ensure smooth and coordinated movements, which are crucial for postural control and stability (Shumway-Cook & Woollacott, 2017). According to Shumway-Cook and Woollacott (2017), interlimb coordination is achieved through both passive and active mechanisms, regulated at the brainstem and cortical levels. Disruptions in this coordination, often due to age-related changes or neurological impairments, may lead to significant balance issues, increasing the risk of falls.

What remains unknown is whether distraction alters functional coordination between limbs in terms of COP synchronization, though age-related differences in synchronization are well-documented (Rakhra & Singer, 2022). This is particularly relevant because interlimb coordination and synchronization are vital for activities such as walking and maintaining balance while standing. Disruptions in this synchronization due to cognitive load could exacerbate balance issues, particularly in older adults. Given the aging population's increased susceptibility to both cognitive decline and balance impairments, it is essential to explore how cognitive distractions might impact these critical coordination mechanisms. Understanding and enhancing both interlimb coordination and synchronization are therefore crucial for developing strategies to prevent falls and improve balance in aging populations. By investigating these mechanisms, this study aims to fill a significant gap in our understanding of the interaction between cognitive load and balance control.

As individuals age, their ability to respond to postural disturbances diminishes, leading to increased reliance on reactive control mechanisms, such as high-frequency synchronization and less adaptable balance strategies (Rakhra & Singer, 2022). This investigation delves into these mechanisms, aiming to elucidate the impact of cognitive distractions on interlimb synchronization and overall balance control among both young and older adults. The primary objective of this thesis is to enhance our understanding of how cognitive distractions influence postural control and interlimb synchronization, with a specific focus on the aging population.

The complex interplay between aging, cognitive load, and balance highlights the need for targeted interventions designed to improve postural stability and reduce the risk of falls in older adults (Fernie et al., 1982). This study is framed within a detailed exploration of postural control, dual-task (DT) paradigms, automatic postural control, aging, and the descending control of quiet standing (QS). By investigating these domains, the research aims to provide a comprehensive understanding of the interactions between cognitive load and balance, ultimately contributing to a better understanding of the impact of distraction on balance control in older adults.

In this study, it was hypothesized that cognitive distractions would negatively impact interlimb synchronization, with a more significant effect observed in older adults. Interlimb synchronization was assessed using CCR in both the AP and ML directions. It was expected that, especially under cognitive distraction, older adults would exhibit greater reductions in CCR compared to younger adults, reflecting impaired coordination between limbs. This thesis aims to determine whether cognitive distractions significantly alter COP synchronization and interlimb coordination during quiet standing and dynamic tasks. Chapter 1 introduces the key concepts and provides a comprehensive literature review, covering balance and posture, cognitive distractions, and aging. Chapter 2 details the methodologies employed in this study, including participant recruitment, data collection, and analysis procedures. Chapter 3 presents the findings of this study, organized according to the research questions and hypotheses. Finally, Chapter 4 discusses the results in the context of existing literature, explores their implications, and suggests directions for future research.

1.1 Literature Review

This literature review will delve into key areas: balance and posture, cognitive distractions, aging and its impacts on balance when distracted, and a synthesis of these concepts to formulate the rationale and conceptual model for the study. This structured approach will ensure a comprehensive exploration of the intricate relationships between balance, cognitive load, and interlimb synchronization, setting the stage for the exploration of the effects of cognitive distractions on balance control in young and older adults.

1.1.1 Balance and Posture

Balance control becomes increasingly crucial when considering the susceptibility of different age groups to fall risks. Studies have highlighted a significant correlation between increased postural sway and the frequency of falls in the elderly (Fernie et al., 1982). Research has revealed that individuals with greater mean sway speed are more prone to falling, irrespective of sex or age, underscoring the importance of understanding balance impairments associated with aging (Fernie et al., 1982).

Age-related changes in balance control include reduced sensory input from the visual, vestibular, and somatosensory systems, decreased muscle strength, and impaired coordination (Shumway-Cook & Woollacott, 2017). These changes lead to increased postural sway and a higher risk of falls (Shumway-Cook & Woollacott, 2017). Recent studies have also emphasized that cognitive decline, common in older adults, further exacerbates balance problems by diminishing the ability to process and integrate sensory information effectively (Hernandez et al., 2010). Functional stability limits, which refer to how far an individual can lean or reach without losing balance, also decline with age, contributing to increased fall risk (Thompson & Medley, 2007).

Cognitive distractions, such as counting backwards or solving mathematical problems, impose a dual-task scenario where attention is divided between maintaining balance and performing a cognitive task. This competition for attentional resources can lead to increased postural sway and instability (Woollacott & Shumway-Cook, 2002), particularly in older adults, who often have diminished capacity to efficiently manage such tasks (Huxhold et al., 2006; Richer & Lajoie, 2020). The dual-task interference (DTI) theory supports this, suggesting that cognitive and motor tasks draw from a shared pool of neural resources (Pashler, 1994), potentially reducing the efficiency of interlimb synchronization. Effective interlimb synchronization remains crucial in this context, as it helps maintain stability by coordinating the actions of both limbs, ensuring that the center of pressure (COP) remains well-regulated (Richer & Lajoie, 2020; Winter, 2009).

1.1.1.1 Concepts and Definitions

Balance is a complex motor skill involving the integration of sensory inputs from the visual, vestibular, and somatosensory systems to maintain the body's stability and posture. Effective balance control is achieved by coordinating sensory inputs to maintain the center of mass (COM) within the base of support (BOS), ensuring the body remains upright and stable during both static and dynamic activities. This coordination of sensory inputs and motor outputs is crucial for responding to perturbations and maintaining postural stability in various environments. It is defined as the ability to maintain the center of mass (COM) within the base of support (BOS) (Shumway-Cook & Woollacott, 2017). The COM is the point where the body's average total mass, measured by calculating each body segment's mass, is considered to be located, and it shifts depending on the body segment's position and movement (Shumway-Cook & Woollacott, 2017). The BOS refers to the area beneath an individual that includes every point of contact the person makes with the supporting surface, which is crucial for maintaining stability limits (Shumway-Cook & Woollacott, 2017).

Stability refers to the ability to maintain or return the body's COM within the BOS during both static (standing still) and dynamic (moving) conditions (Shumway-Cook & Woollacott, 2017). Effective stability requires precise coordination between different parts of the body, which involves both anticipatory and reactive adjustments to maintain balance (Shumway-Cook & Woollacott, 2017). Posture is the alignment and positioning of the body in space (Shumway-Cook & Woollacott, 2017). It is maintained through the coordinated action of the musculoskeletal and nervous systems. Postural control is essential for performing daily activities and involves maintaining an upright stance, adjusting the body position, and responding to perturbations.

The central nervous system (CNS) processes sensory inputs from the visual, vestibular, and somatosensory systems to produce coordinated motor outputs that keep the body upright and stable (Winter et al., 1996). Center of Pressure (COP) is a key concept in balance control, representing the point of application of the ground reaction force and providing a measure of postural control (Winter, 2009; Winter et al., 1993). The COP is determined by the forces exerted by the ground on the feet during standing or movement, and its movements reflect the body's efforts to control the position of the centre of mass.

As previously mentioned, effective balance control requires precise coordination between different parts of the body, and interlimb synchronization, or the coordinated movement between limbs to maintain the COP within the BOS, is essential for maintaining balance during QS and dynamic activities, such as but not limited to, walking, running, or navigating uneven surfaces. This coordination involves the simultaneous and well-timed activation of muscles in both limbs to maintain stability during static or dynamic activities. However, in the context of balance tasks, synchronization of the COP between limbs is crucial for stabilizing the body's COM (Habib-Perez et al., 2016). As people age, there is often a decline in the efficiency of these neural mechanisms (Thompson & Medley, 2007), leading to increased postural sway (Fernie et al., 1982) and a higher risk of falls (Scott et al., 2010).

1.1.1.2 Synchrony in Balance of the Centre of Pressure

Interlimb synchrony plays a crucial role in maintaining postural stability, especially during challenging tasks. Studies have shown that effective synchronization between limbs helps reduce postural sway and improves balance (Mansfield et al., 2011). This coordination between limbs is vital for the dynamic adjustments required to maintain balance during QS and in response to external perturbations (Winter et al., 1996). Disruptions in interlimb synchrony can lead to impaired balance (Habib-Perez et al., 2016). Impaired balance, in turn, is associated with a higher risk of falls, particularly in older adults and individuals with neurological impairments (Davis et al., 2009; Mansfield et al., 2011).

Research by Mochizuki et al. (2005) examined the synchronization of motor units in the soleus muscle during quiet standing and found that significant synchronization between bilateral motor units was relatively uncommon. Despite this, the study reported strong correlations in AP sway between legs, indicating that the legs function in a highly coordinated manner during quiet standing. This suggests that while motor unit synchronization between limbs is rare during QS, the overall postural control mechanism still relies on a high degree of coordination at the level of COP adjustments. The findings highlight the need to distinguish between different levels of motor control—specifically, between the synchronization of motor units within a muscle and the broader coordination of movements across the entire body, as reflected in COP synchronization. Mochizuki et al. (2005) found that only a small percentage of bilateral soleus motor unit pairs exhibited significant synchronization during standing with eyes open (EO) (4/39 pairs) and eyes closed (EC) (3/36 pairs). Despite this low incidence, they observed a high correlation in AP sway between legs ($\rho = 0.80$ with EO and $\rho = 0.83$ with EC), suggesting that the legs work together to control sway. In contrast, a higher incidence of synchronization was found within the same leg, indicating stronger intralimb coordination. Therefore, these results suggest that balance control during QS may rely more on intralimb coordination within a single muscle group, while interlimb coordination appears less common. This finding implies that, under stable conditions, the body's balance mechanisms are primarily dependent on localized muscle control rather than coordination between limbs.

While the role of interlimb synchronization may appear less critical during quiet standing or under stable conditions, it becomes increasingly important under postural challenges. Habib-Perez et al. (2016) demonstrated that interlimb synchronization plays a significant role when individuals anticipate postural instability, showing that the degree of synchronization between the limbs is modulated by the predictability of the perturbation. Specifically, their research indicated that higher synchronization occurs when the magnitude of the perturbation is predictable, suggesting that the central nervous system adjusts interlimb coordination to optimize balance control in these scenarios.

Although Habib-Perez et al. (2016) did not directly study older adults or fall risk, their findings imply that enhancing interlimb synchronization could be beneficial for maintaining balance under challenging conditions. This insight is particularly relevant for populations at higher risk of falls, such as older adults, where targeted interventions could focus on improving synchronization to reduce fall risk. Although Mansfield et al. (2011) did not directly study older adults or fall risk, their findings imply that enhancing interlimb synchronization could be beneficial for maintaining balance under challenging conditions. Structural alterations to the brain, such as those observed in stroke survivors, have been shown to cause a decrease in interlimb synchronization, leading to increased postural sway and instability (Mansfield et al., 2011). This underscores the importance of not only addressing these structural changes but also exploring functional alterations, such as cognitive distractions, which may similarly impact synchronization. By probing the effects of functional alterations on interlimb synchronization, this study aims to deepen our understanding of how cognitive load influences balance control, particularly in populations that may not yet exhibit overt structural impairments.

Singer and Mochizuki (2015) investigated the relationship between interlimb synchronization of the center of pressure (COP) and postural stability in stroke survivors with and without lower limb spasticity. The study found that individuals with lower limb spasticity exhibited altered synchronization patterns compared to those without spasticity, particularly in the mediolateral direction. These changes were associated with increased postural sway, indicating that reduced synchronization may contribute to balance control challenges in this population. However, the study did not conclude that reduced synchronization was the sole cause of increased instability. Instead, the findings suggest that the altered synchronization observed in stroke survivors with spasticity may reflect compensatory strategies or adaptations due to impaired balance control. This highlights the importance of exploring how functional alterations, such as cognitive distractions, might similarly disrupt synchronization in populations that do not have overt structural impairments. By understanding these functional impacts, we can better assess and address the subtler factors that influence balance control and fall risk.

Given that falls are a leading cause of injury-related hospitalizations among seniors, understanding the mechanisms of balance control is crucial for developing effective fall prevention strategies (*Seniors' Falls in Canada. Second Report*, 2014). This research aims to investigate how cognitive distractions impact interlimb synchronization and balance, as cognitive load can significantly affect postural control. By exploring the interaction between cognitive distractions and interlimb coordination, this study seeks to provide insights that can inform interventions to improve balance and reduce fall risk in aging populations. Specifically, understanding how distractions impact balance and interlimb synchronization can lead to better strategies for preventing falls, which are a significant concern for older adults due to age-related declines in sensory, motor, and cognitive functions.

1.1.2 Distraction Models and Definitions

Distraction in the context of balance control refers to the cognitive load imposed by secondary tasks that divert attention from maintaining stability. Various models explain how distraction impacts postural control, with Dual-task Interference (DTI) theory being one of the most prominent. DTI theory suggests that performing a cognitive task while maintaining balance competes for attentional resources, potentially compromising postural control (Pashler, 1994). This competition for cognitive resources can lead to increased postural sway and instability, particularly in older adults who may already have diminished attentional capacities (Huxhold et al., 2006). As cognitive tasks demand more attention, the resources available for maintaining balance are reduced. This reduction is especially critical for older adults because they often experience a natural decline in cognitive function, including slower processing speeds and reduced working memory capacity (Huxhold et al., 2006). These age-related cognitive changes make it more challenging for older adults to multitask effectively, exacerbating the risk of falls (Stinchcombe et al., 2014). The increased postural sway and instability observed during cognitive distractions can lead to a higher incidence of falls, which are a major cause of injury and loss of independence in the elderly population (Balasubramaniam et al., 2000; Scott et al., 2010). Understanding this interaction is crucial for developing targeted interventions that can help older adults maintain balance and prevent falls, thereby improving their overall quality of life and reducing healthcare costs associated with fall-related injuries.

1.1.2.1 Resource Allocation Model

The resource allocation model posits that cognitive and motor tasks draw from a common pool of attentional resources. When a secondary task is introduced, it competes with the primary task (e.g., maintaining balance) for these limited resources. The efficiency of postural control decreases as more resources are diverted to the cognitive task, leading to increased postural sway (Huxhold et al., 2006). This model suggests that individuals have a finite capacity for attention, and performing multiple tasks simultaneously can exceed this capacity, resulting in degraded performance in one or both tasks.

For example, when an individual is asked to solve a complex arithmetic problem while maintaining balance, the cognitive task demands attention that would otherwise be used for postural control. As a result, the individual may experience increased postural sway and reduced stability. This effect is more pronounced in older adults, who generally have a reduced overall capacity for attention and cognitive processing (Huxhold et al., 2006). The competition for attentional resources can lead to significant decrements in balance performance, increasing the risk of falls.

1.1.2.2 Bottleneck Model

According to the bottleneck model, there is a processing bottleneck when multiple tasks require the same cognitive processes simultaneously. This model suggests that cognitive and postural tasks are processed in a serial manner rather than in parallel, leading to delays and increased errors in one or both tasks (Pashler, 1994). For example, performing a mental arithmetic task while trying to maintain balance may cause delays in postural adjustments, increasing the risk of instability (Pashler, 1994).

The bottleneck model highlights the limitations of the human brain in processing multiple streams of information at the same time. When two tasks require similar cognitive resources, such as attention or working memory, they must be processed sequentially, creating a bottleneck (Pashler, 1994). This can lead to delays in task performance and increased cognitive load, which can impair balance control. For instance, if an individual is asked to react to an unexpected perturbation while simultaneously performing a cognitive task, the delay in processing the postural response can result in a loss of balance.

1.1.2.3 Crosstalk Model

The crosstalk model explains DTI by proposing that concurrent tasks may interfere with each other through crosstalk, where the neural signals for one task interfere with the neural processing of another (Koch, 2009). This interference can disrupt motor control processes, leading to impaired balance. Cognitive tasks that require similar neural pathways as those used for balance control, such as visuospatial tasks, may cause more significant interference and greater postural sway (Koch, 2009).

Research has shown that when tasks share response codes, performance deteriorates due to the increased potential for interference (Koch, 2009). In studies where participants performed a visual task and an auditory-manual reaction time task simultaneously, the degree of crosstalk was manipulated by varying the instructions given to participants (Koch, 2009). Findings revealed that strong crosstalk, where there was explicit overlap in response codes between tasks, led to significantly worse performance compared to weak crosstalk (Koch, 2009). This detrimental effect highlights how response-code interference can impair DT performance.

These findings underscore the importance of understanding how crosstalk affects DT performance, particularly in contexts where cognitive resources are shared. The insights gained from this research can inform strategies to mitigate interference and enhance performance in multitasking environments.

1.1.2.4 Central Capacity Sharing Model

The central capacity sharing model suggests that the brain has a central processing capacity that can be flexibly allocated to various tasks. When a cognitive task is added, the available capacity for postural control is reduced, leading to compromised balance (Bristow et al., 2016). The model highlights that the allocation of resources is dynamic and can vary depending on task demands and individual differences, such as age or cognitive ability (Bristow et al., 2016).

In this model, the brain acts like a central processing unit that allocates resources to different tasks based on their priority and complexity (Bristow et al., 2016). When a secondary task, such as a cognitive distraction, is introduced, the brain reallocates resources from the primary task of maintaining balance to the cognitive task (Bristow et al., 2016). This reallocation can lead to reduced efficiency in postural control and increased postural sway. The central capacity sharing model also suggests that the allocation of resources can be influenced by individual factors, such as cognitive reserve and prior experience with multitasking (Bristow et al., 2016).

1.1.2.5 Constrained Action Hypothesis

The constrained action hypothesis suggests that conscious attention to the control of movements can interfere with automatic control processes, leading to less efficient performance (Wulf, 2013). When individuals focus on a specific aspect of their movement, it can disrupt the smooth execution of automatic motor skills. In the context of balance, directing attention to maintaining posture can reduce the efficiency of automatic postural control mechanisms, leading to increased postural sway (Wulf, 2013).

This hypothesis proposes that focusing on the mechanics of movement can constrain the natural flow of motor control processes. For example, if an individual consciously thinks about the placement of their feet or the alignment of their body while trying to maintain balance, this conscious control can disrupt the automatic processes that typically manage postural stability (Wulf, 2013). This can lead to less effective balance control and increased postural sway. The constrained action hypothesis is supported by research showing that external focus of attention (e.g., focusing on the environment or the effect of the movement) results in better motor performance and balance control compared to an internal focus of attention (e.g., focusing on body movements) (Wulf, 2013).

1.1.2.6 Compensation-Related Utilization of Neural Circuits Hypothesis (CRUNCH)

The Compensation-Related Utilization of Neural Circuits Hypothesis (CRUNCH) posits that older adults engage additional neural resources at lower cognitive loads compared to younger adults (Reuter-Lorenz & Cappell, 2008). This compensatory mechanism helps maintain performance levels but can lead to earlier depletion of cognitive resources, making older adults more susceptible to interference from dual-tasking and other cognitive distractions (Reuter-Lorenz & Cappell, 2008). The CRUNCH hypothesis is supported by neuroimaging data showing greater brain activation in older adults compared to younger adults for similar levels of task difficulty (Reuter-Lorenz & Cappell, 2008).

Schneider-Garces et al. (2010) provide compelling evidence for the CRUNCH hypothesis by demonstrating that older adults exhibit greater and more widespread brain activation than younger adults during working memory tasks. Their study found that older adults show increased activation in prefrontal and parietal regions even at low memory loads, indicating that they recruit additional neural circuits to compensate for age-related declines in cognitive function. This over-recruitment at lower loads results in a ceiling effect where older adults reach their maximum cognitive capacity more quickly than younger adults, leading to performance decrements at higher loads (Schneider-Garces et al., 2010).

In the context of balance control, CRUNCH suggests that older adults may show increased brain activity when maintaining posture, especially under DT conditions where cognitive and motor tasks compete for limited resources. This increased neural activity reflects an attempt to compensate for reduced sensory and motor function, but it also means that older adults have fewer resources available for handling additional cognitive loads, making them more vulnerable to balance disturbances when distracted (Schneider-Garces et al., 2010).

Studies have shown that cognitive distractions, such as counting backwards or solving arithmetic problems, can significantly impact balance by increasing postural sway and reducing the effectiveness of automatic postural control mechanisms (Woollacott & Shumway-Cook, 2002). This impact may be more pronounced in older adults, who may struggle to allocate sufficient cognitive resources to both tasks. For example, dual-tasking studies have demonstrated that older adults exhibit greater postural sway and instability when performing concurrent cognitive tasks, such as arithmetic or memory-based challenges, compared to younger adults (Huxhold et al., 2006). These findings align with the notion that aging reduces cognitive capacity and the ability to simultaneously manage motor and cognitive tasks efficiently, thereby compromising balance in multitasking scenarios (Shumway-Cook et al., 1997).

1.1.3 Impacts of Aging and Distraction on Balance

Aging significantly impacts balance control through sensory degradation, motor decline, and cognitive deterioration, all of which contribute to an increased risk of falls among older adults. Sensory inputs, particularly from the visual, vestibular, and somatosensory systems, decline with age (Shaffer & Harrison, 2007; Shumway-Cook & Woollacott, 2017). This includes reduced visual acuity, contrast sensitivity, and depth perception, which impair obstacle detection and safe navigation (Lord & Menz, 2000). The vestibular system, essential for spatial orientation and balance, also deteriorates, with a reduction in vestibular hair cells and nerve fibers, leading to decreased sensitivity to head movements and a greater risk of falls (Baloh et al., 1993; Shumway-Cook & Woollacott, 2017).

Motor functions decline as well, with sarcopenia - loss of muscle strength and mass - affecting the ability to make quick adjustments, thus increasing instability (Larsson et al., 2019). Joint flexibility diminishes due to changes in connective tissues, resulting in reduced range of motion and a decreased ability to recover from perturbations (Larsson et al., 2019). Additionally, motor coordination becomes less precise and slower, impairing the ability to perform complex motor tasks and further elevating fall risk (Seidler et al., 2010).

Cognitive aging is marked by a decline in attentional resources, processing speed, and working memory capacity, making it more challenging for older adults to maintain balance while performing cognitive tasks (Salthouse, 1996; Baddeley, 2000). Executive functions, such as planning, problem-solving, and multitasking, also deteriorate, affecting the ability to adapt to new or complex situations requiring quick and efficient responses to maintain stability (Verhaeghen & Cerella, 2002). Cognitive distractions exacerbate these issues, as older adults' reduced cognitive capacity makes it more difficult to manage dual-task scenarios, leading to greater balance disturbances (Huxhold et al., 2006; Laatar et al., 2017).

The combined effects of sensory, motor, and cognitive declines lead to increased postural sway and instability, underscoring the need for targeted interventions to enhance postural stability and reduce fall risks in older adults (Fernie et al., 1982). One promising approach is external focus training, which emphasizes directing attention to environmental cues rather than internal body movements (Wulf, 2013). This strategy has been shown to improve postural stability by enhancing automaticity in balance control, particularly in older adults (Wulf, 2013).

By investigating the impact of cognitive distractions on interlimb synchronization and balance, this research aims to provide insights that can inform interventions to improve balance and reduce fall risk in aging populations. Understanding the interaction between cognitive load, interlimb synchronization, and balance is crucial for developing strategies that address the specific challenges faced by older adults.

1.1.4 Conscious Postural Control

The control of posture can be categorized into automatic and conscious processes. Conscious postural control involves the deliberate attention to maintaining balance and stability, which can interfere with the automatic control processes usually responsible for postural adjustments. This interference can lead to less efficient balance control and increased postural sway. As aforementioned, the constrained action hypothesis suggests that directing conscious attention to movement mechanics can disrupt the natural flow of motor control processes, resulting in degraded performance (Wulf, 2013).

As individuals age, there is often a greater reliance on conscious control due to the decline in automatic postural control mechanisms. This shift can be attributed to age-related changes in sensory, motor, and cognitive functions. Older adults tend to exhibit increased prefrontal cortex activity during balance tasks, indicating greater cognitive involvement (Schneider-Garces et al., 2010). This compensatory mechanism, known as CRUNCH, posits that older adults recruit additional neural circuits to maintain performance, but this over-recruitment can lead to cognitive resource depletion and increased susceptibility to DTI (Reuter-Lorenz & Cappell, 2008).

Research has demonstrated that cognitive distractions, such as counting backwards or solving arithmetic problems, significantly impact balance by increasing postural sway and reducing the effectiveness of automatic postural control mechanisms (Laatar et al., 2017). This impact is more pronounced in older adults, who may struggle to allocate sufficient cognitive resources to both tasks (Laatar et al., 2017). Consequently, understanding how conscious postural control affects balance in the presence of cognitive distractions is crucial for developing effective interventions.

Studies have shown that interventions focusing on enhancing automaticity in postural control can improve balance and reduce fall risk (Wulf, 2013). For instance, training programs that emphasize external focus of attention have been found to enhance motor performance and postural stability compared to an internal focus of attention (Wulf, 2013). Such interventions could be particularly beneficial for older adults who are more prone to balance disturbances when distracted.

1.2 Rationale

Understanding the interaction between cognitive load, interlimb synchronization, and balance is crucial for developing effective fall prevention strategies. Given the fact that aging is associated with a decline in sensory, motor, and cognitive functions, one would assume that these declines contribute significantly to the increased fall risk observed in older adults. Furthermore, in consideration of the view that cognitive distractions can impact balance, it stands to reason that these distractions might specifically affect interlimb synchronization, a critical component of maintaining balance.

Much is known about the general effects of cognitive distractions on balance. Cognitive tasks that demand attention, such as counting backwards or solving mathematical problems (Bristow et al., 2016), have been shown to increase postural sway and instability, particularly in older adults who have diminished attentional capacities (Huxhold et al., 2006). This competition for cognitive resources can lead to instability, highlighting the significant impact of cognitive load on postural control in this population. Research has shown that older adults are more susceptible to balance disturbances when distracted (Huxhold et al., 2006), underscoring the need for targeted interventions to improve postural stability and reduce fall risks in aging populations.

What remains unknown is how these distractions specifically impact interlimb synchronization and how this varies with age. This research study aims to fill that gap by investigating the effects of cognitive distractions on interlimb synchronization and balance control in young and older adults.

The rationale for focusing on interlimb synchronization stems from its critical role in maintaining balance. Interlimb synchronization, defined as the coordinated movement between limbs, involves the precise timing and activation of muscles across different limbs to ensure smooth and coordinated movements, even during static postures such as standing. Disruptions in synchronization can lead to significant stability issues, particularly in older adults who are already at a higher risk of falls. Research by Mochizuki et al. (2005) demonstrated that synchronization of motor units within the same muscle (intralimb coordination) was more common than between homologous muscles in both legs (interlimb coordination) during quiet standing (QS). Specifically, only a small percentage of bilateral soleus motor unit pairs exhibited significant synchronization during QS, despite a high correlation in anteroposterior sway between legs. Further research, such as that by Habib-Perez et al. (2016), indicates that interlimb synchronization can vary depending on the context, with increased synchronization observed prior to predictable postural perturbations. This highlights the importance of understanding synchronization patterns in different conditions to improve balance interventions.

Given these findings, it stands to reason that understanding how cognitive distractions impact interlimb synchronization could provide valuable insights for developing targeted interventions to improve balance and reduce fall risks in aging populations. Effective interlimb synchronization ensures that actions are performed efficiently, thereby maintaining stability (Winter, 2009). Disruptions in this synchronization, often due to age-related changes or neurological impairments, may lead to significant balance issues, increasing the risk of falls (Lord et al., 2021). By examining how cognitive distractions impact this synchronization, the study seeks to provide insights that could inform the development of interventions to enhance balance and reduce fall risks in older adults.

Overall, the proposed research aims to explore the intricate relationship between cognitive load, interlimb synchronization, and balance control across different age groups. By addressing this gap in knowledge, the study intended to contribute to the understanding of the scientific community in understanding the connection between cognitive load and interlimb synchronization in hopes that future research may develop more effective fall prevention strategies, ultimately improving the quality of life for older adults.

1.3 Conceptual Model

The conceptual model that frames the main components of this thesis illustrates the hypothesized relationships between fall risk, cognitive distractions, aging, and interlimb synchronization. It suggests that cognitive distractions negatively affect interlimb synchronization, with more pronounced effects in older adults due to their reduced cognitive capacity and higher susceptibility to balance disturbances. In understanding these dynamics, it is crucial to recognize the relationship between various factors that influence postural control. The flowchart below (Figure 1) illustrates the interconnected elements of the conceptual model of this study, emphasizing how cognitive distractions, conscious control, and balance interact to influence interlimb synchronization, particularly within the aging population. The model highlights that cognitive distractions can impair balance by diverting attentional resources, which in turn may affect the synchronization between limbs. Additionally, the flowchart incorporates the role of conscious control mechanisms, which are essential for maintaining postural stability, especially when automatic balance responses are insufficient. Together, these elements underscore the complexity of balance control in aging adults, where the interplay between cognitive load, conscious control, and interlimb synchronization is critical in determining balance outcomes and fall risk.

This conceptual model captures the complexity of interactions between fall risk, distraction, aging, and interlimb synchronization. It highlights the critical areas where cognitive load can disrupt balance, underscoring the need for targeted strategies to mitigate fall risks in older adults. By delving into these relationships, this research aims to provide valuable insights that will inform future interventions designed to enhance balance and stability among the elderly.

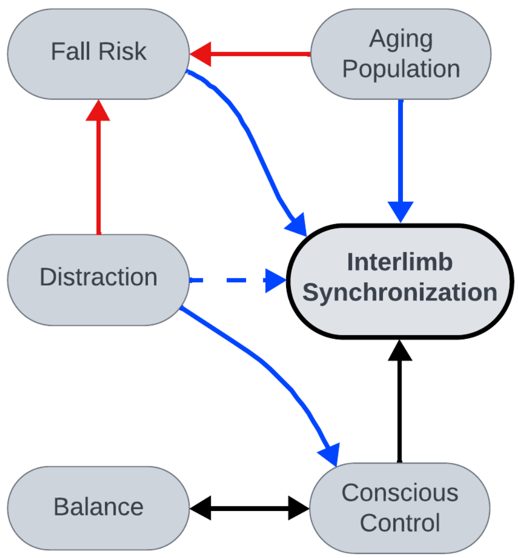

Figure 1. Conceptual model illustrating the impact of distraction on interlimb synchronization in older adults. This model delineates the hypothesized relationships between fall risk, aging, distraction, and their combined effects on interlimb synchronization and balance. It illustrates that with increasing age, the risk of falls rises, and cognitive distractions are postulated to negatively affect synchronization, which is crucial for maintaining balance. The model also suggests a bidirectional relationship between balance and conscious control, which may influence overall stability. The red arrows show a positive effect in the direction of the arrow, whereas the blue arrows show a negative effect in the direction of the arrow. The black arrows represent a neutral relationship where the influence may be positive or negative. The dotted arrow shows where the gap in literature lies and how this study hypothesizes that distraction impacts interlimb synchronization negatively (blue).

Chapter 2. Methods

2.1 Participants

Participants were recruited through community engagement and advertisement. Announcements were made at local community centers during gatherings, inviting older adults to participate. Recruitment flyers and posters were also distributed and displayed across the university to target young adults. These strategies ensured representation across the desired age groups. Additionally, participants were informed about the purpose of this study and provided with an opportunity to ask questions before enrollment. Interested individuals underwent a pre-screening process to confirm eligibility based on inclusion and exclusion criteria, ensuring safety and data reliability.

This study involved a total of 39 participants, divided into two age groups: young healthy adults (aged 18 to 35 years) and older adults (aged 55 years and above). The young adult group consisted of 22 participants (11 males and 11 females), and the older adult group consisted of 17 participants (11 females and 8 males). Participants were required to meet several criteria to be included in the study: the ability to stand unassisted for at least one minute, no history of neurological or musculoskeletal disorders that could affect balance, and normal or corrected-to-normal vision. Inclusion criteria required participants to have no current musculoskeletal injury, such as a sprain or fracture of the lower limb, the ability to understand English and perform simple arithmetic tasks, and willingness to engage in simple questionnaires and cognitive tasks. Participants were excluded if they reported recent use of alcohol, caffeine, cannabis, or other drugs within 4 hours prior to the study, or if they had any neurological or musculoskeletal disorders that could affect balance.

To further assess participants' balance and confidence in performing various activities, the Berg Balance Scale (BBS) and the Activities-specific Balance Confidence (ABC) Scale were utilized. The BBS is a 14-item assessment used as a functional balance assessment to identify fall risk, where participants are scored on their ability to perform daily life activities with balance challenges (Berg et al., 1989). A score of 40/56 or below on the BBS is an indicator of elevated fall risk in older adults (Berg et al., 1989). The ABC Scale is a 16-item questionnaire that asks participants to rate their level of confidence in performing a number of daily tasks from 0-100% confidence (Powell & Myers, 1995). The cut-off scores for high, moderate, and low functioning older adults are >80%, 50-80%, and <50%, respectively (Powell & Myers, 1995). The ABC scale demonstrates high internal consistency (Cronbach's $\alpha = 0.96$) and test-retest (ICC = 0.92) (Powell & Myers, 1995). It is a robust tool for assessing balance confidence across a wide spectrum of activities, from simple tasks like walking indoors to more challenging situations like walking on icy sidewalks. The BBS, similarly, exhibits excellent inter-rater and intra-rater reliability (ICC = 0.98) and strong construct validity, correlating well with laboratory measures of postural sway and functional independence (Berg et al., 1992). These characteristics make both scales suitable for assessing balance in diverse populations, including the elderly. The reliability and validity of the ABC and BBS scales strengthen the confidence in the baseline comparisons. Their established psychometric properties ensure that group differences in other measures are not confounded by inaccuracies in balance assessment tools. This study employed a cross-sectional design, comparing younger and older adults to evaluate the effects of cognitive distraction on balance measures. This study was approved by the Research Ethics Board at York University (Certificate e2020-056). All participants provided informed consent prior to participation.

2.1.1 Assumptions for Sample Size Calculation

To determine the appropriate sample size for this study, G*Power 3.1.9.4 was used on Microsoft Windows (Faul et al., 2007). The effect size value was chosen based on the expected magnitude of the difference between the groups, which was informed specifically by the Rakhra & Singer (2022) study. The study provided data on High Frequency Temporal Synchrony ($R_{xy}(0)$) from the ML direction (which is impacted more during distracting tasking when compared to AP), which was used to estimate the expected differences and variability in the COP measurements between groups. This study was selected because it provided relevant and detailed statistical data on the synchronization metrics that are central to this thesis. By using their reported means and standard deviations, a realistic and evidence-based estimate of the expected variability and mean differences in the data was achieved.

The significance level was set to 0.05. This means there is a 5% risk of concluding that there is an effect when there is none (Type I error). The power of the study was set to 0.8, which corresponds to an 80% chance of detecting an effect if there is one (20% risk of Type II error). The type of statistical test used was “Means: differences between two independent means (two groups).” This test is appropriate for comparing the means of two independent groups. An a priori power analysis was conducted, which computes the required sample size given the alpha level, power, and effect size.

During the pilot trials of this study, there was 1 individual that dropped out, resulting in an approximate dropout rate of 11%. After accounting for this 11% dropout rate, the number of participants required to maintain sufficient power was adjusted. Initially, 19 participants were required to achieve the desired power. After accounting for potential dropouts, a total of 22 participants per group were deemed necessary.

2.2 Data Collection

The study required participants to stand with each foot on adjacent AMTI-OR6-1000 force plates (AMTI, Watertown, USA) to measure the ground reaction forces and calculate the COP under each foot. The force plates were spaced 1 mm apart with the y-axes in parallel. The forceplates were embedded in a wood frame that extended 30 cm beyond the front, back and sides of the plates. The top of the platform was flush with the top of the forceplates. Foot placement during quiet stance was standardized based on the preferred placement identified by McIlroy and Maki (1997). Participants were instructed to place their heels 17 cm apart and to angle their toes outwards at 14° from the median line. This standardized placement ensures consistent positioning across participants and trials, facilitating reliable measurement of balance parameters.

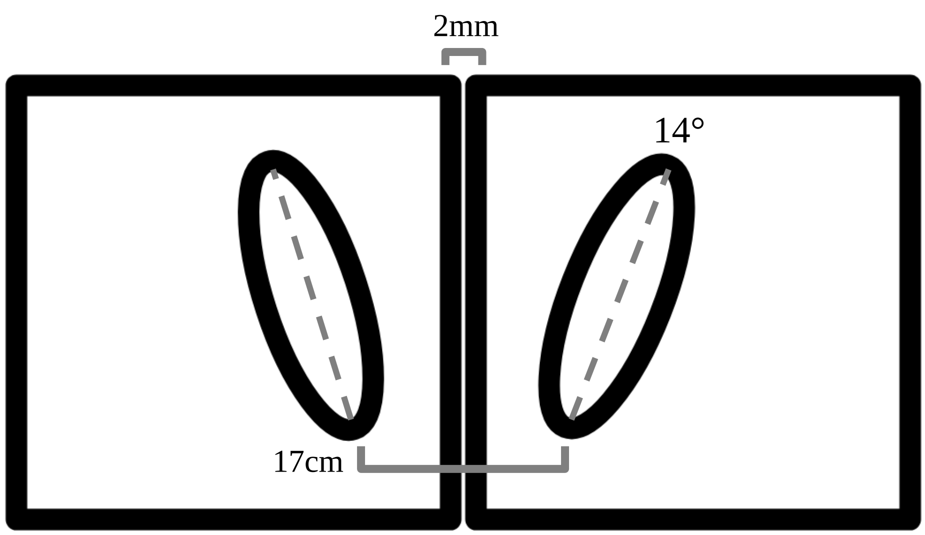

Figure 2. Experimental setup of force plates and foot placement of participants, with force plates placed 2mm apart from one another, and feet placed with heels 17cm apart and 14° away from the center line.

Forces and moments (force x (F_x), force y (F_y), force z (F_z), moment x (M_x), moment y (M_y), and moment z (M_z)) for each forceplate were amplified and collected using Spike2 v10 (Cambridge Electronic Design, Cambridge, UK). The amplifier for the left force plate was amplified at 1000 times gain, whereas the amplifier for the right force plate was amplified at 2000 times gain. The gain for the right force plate amplifier was not changed to 1000 because this amplifier was shared among different lab members and groups, necessitating consistency in its configuration. The amplified forces and moments were analog-to-digital converted using the Power1401 MK IIIA (Cambridge Electronic Design, Cambridge UK) with a sampling rate of 1024 Hz. Prior to analysis, signals were low-pass filtered at 10 Hz using a fourth-order Butterworth filter.

Participants were instructed to perform a series of trials under six different conditions: (1) no distraction, eyes open (NDEO); (2) no distraction, eyes closed (NDEC); (3) counting by ones, eyes open (COEO); (4) counting by ones, eyes closed (COEC); (5) with distraction, eyes open (WDEO); (6) with distraction, eyes closed (WDEC). Each condition was randomized across participants to minimize order effects. During the distraction conditions, participants were asked to count backwards by sevens from a randomly chosen three-digit number aloud (Bristow et al., 2016). Each trial lasted for 90 seconds, and participants were given a one-minute rest period between trials to minimize fatigue. The first 15 seconds and last 15 seconds of the trials were removed, leaving 60s of data for the analysis.

Before the trials, the Berg Balance Scale (BBS) and the Activities-specific Balance Confidence (ABC) Scale were administered to further assess participants' balance and confidence in performing various activities.

2.3 Data Analysis

Data were analyzed using Python code on PyCharm version PC-232.9559.58. COP data were derived from the forces and moments for both the AP and ML directions. The COP was calculated using the following formulas:

$$COP_{AP} = \frac{M_x}{F_z}$$

$$COP_{ML} = \frac{-M_y}{F_z}$$

The primary outcome measures were the peak of the cross-correlation function (CCF) of the COP signals between the left and right feet and the lag at which this peak occurred, all of which were used to assess interlimb synchronization. The cross-correlation (CCR) analysis was crucial to this study as it allowed us to quantify the degree of synchronization between the movements of the two feet, providing insights into balance control mechanisms. Secondary measures included the Time Lag (TL), RMS sway and MSV of the COP movements in both directions. TL represents the temporal delay between mediolateral (ML) or anteroposterior (AP) center of pressure (COP) signals of the two limbs, derived from the cross-correlation analysis. TL is measured in milliseconds and corresponds to the time shift from 0 ms at which the maximum correlation coefficient (ρ) occurs. In this study, a positive TL value indicates that the COP signal of the right foot leads the left foot, whereas a negative TL value indicates that the left foot leads the right foot. This directional information provides insight into the timing dynamics of interlimb synchronization. To illustrate the cross-correlation function calculation, an example of the CCF for one of the participants is presented below, in Figure 3. This figure shows the AP and ML COP displacements over time for the left and right feet, along with the corresponding cross-correlation functions. The peak value of the CCF within a time lag window of ±200 milliseconds was used as the measure of interlimb synchronization.

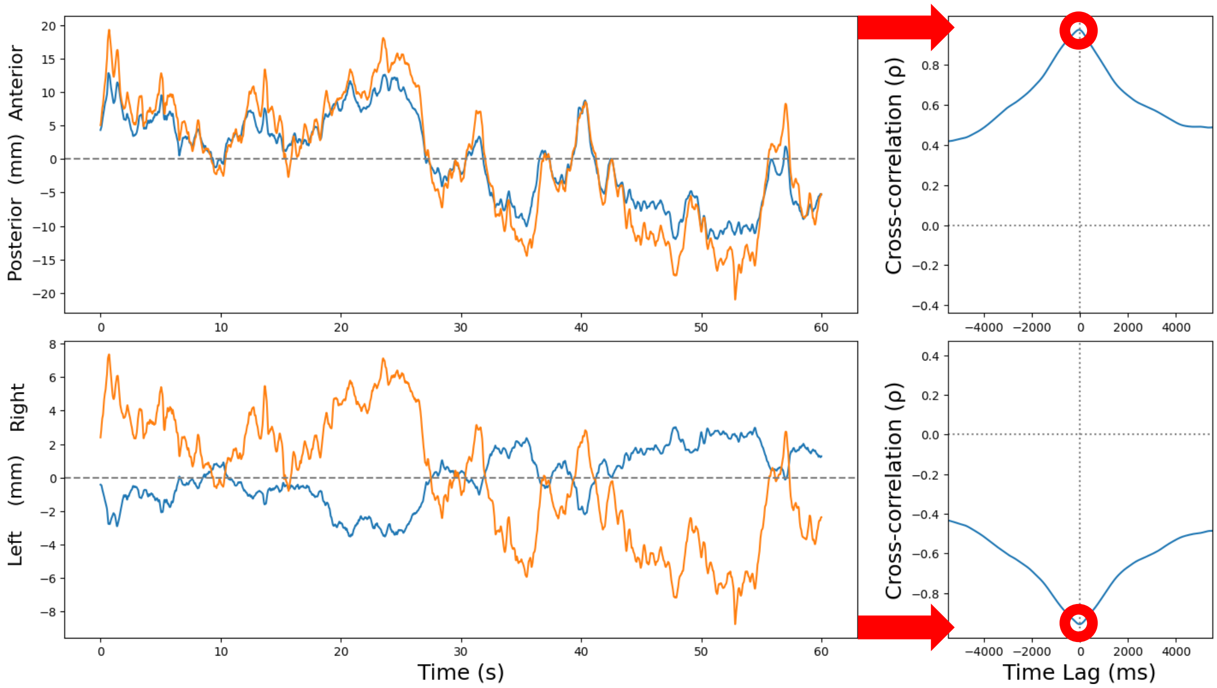

Figure 3. Exemplar COP traces and their corresponding cross-correlation function. The top panel shows AP COP displacements over time for the left (blue) and right feet (orange), highlighting anterior and posterior changes in COP and its respective CCF for AP COP on the right, indicating the interlimb synchronization between feet movements. The bottom panel shows ML COP displacements over time, illustrating lateral changes in COP and its respective CCF for ML COP on the right, showing interlimb synchrony between the feet.

2.3.1 Assumptions and Data Transformations

In this study, potential outliers were identified during the initial data screening process. According to Field (2013), there are several methods for handling outliers, including:

1. **Trimming the data**, where extreme values are removed based on a predefined criterion (e.g., ±2 or ±3 standard deviations).
2. **Winsorizing the data**, which involves replacing extreme values with the next highest or lowest non-outlier value.

3. **Using robust methods**, such as statistical tests designed to handle outliers without their removal.
4. **Transforming the data**, which applies mathematical functions (e.g., logarithmic, square root) to reduce the impact of outliers.

In this study, log transformations were applied to the variables CCR, TL, RMS, and MSV to reduce skewness and normalize distributions, thereby mitigating the effects of potential outliers. The transformations included shifting data points to avoid negative values where necessary.

Blanca et al. (2017) provide further support for this approach, highlighting that ANOVA is robust to violations of normality and the presence of outliers, particularly when sample sizes are equal across groups and variances are homogeneous. Their findings demonstrate that ANOVA maintains acceptable Type I error rates under conditions of moderate or severe non-normality. Thus, the decision to retain outliers post-transformation was justified based on these conclusions, ensuring the validity of the statistical analyses while preserving the integrity of the dataset.

Preliminary inspection of the data identified the presence of outliers, which contributed to non-normal distributions of the data. Outliers were identified using a threshold of ±2 standard deviations (Field, 2013). Logarithmic transformations were then applied to CCR, TL, RMS, and MSV measures to address non-normality and outliers. For TL data, values were shifted by +250.00 ms to eliminate negative values prior to transformation. Similarly, ML CCR data points were shifted by +1.00 units to ensure all values were positive. These adjustments align with best practices for stabilizing variance and normalizing distributions (Field, 2013). After the logarithmic transformations were conducted, a re-assessment of normality and outliers was conducted again. Distributions for the following measures were still not normalized after applying the log-transformation: CCR: AP COEC older adults, AP COEO both groups, AP NDEC older adults, AP NDEO older adults, AP WDEC both groups, AP WDEO older adults, ML NDEC young adults; TL: AP COEC both groups, AP COEO young adults, AP NDEO older adults, AP WDEC young adults, AP WDEO older adults, ML COEC both groups, ML COEO both groups, ML NDEC both groups, ML NDEO older adults, ML WDEO young adults; RMS: AP COEC older adults, AP WDEO young adults, ML COEC older adults; MSV: AP COEO young adults, AP WDEC older adults, AP WDEO both groups. However, ANOVA was conducted with outliers included, given the robustness of the test against violations of the normality assumption (Blanca et al., 2017). The assumption of sphericity was assessed using Mauchly’s test. When the assumption of sphericity was violated, the Greenhouse-Geisser correction was applied to adjust the degrees of freedom for the F-tests.

2.3.2 Cross-Correlation Calculation

The CCF is a statistical tool used to measure the similarity between two signals as a function of the time-lag applied to one of them (Fritsch et al., 1988). In this study, the COP data for both the AP and ML directions were used to calculate the CCF. The COP signals from the left and right force plates were first subject to mean removal to ensure that the analysis focused on the dynamic components of the signals.

The cross-correlation between two signals, $x(t)$ and $y(t)$, is defined as:

$$R_{xy}(\tau) = \frac{1}{T}\sum_{t=0}^{T-1} x(t)y(t+\tau)$$

Where $R_{xy}(\tau)$ is the cross-correlation function, τ is the time lag, T is the total number of data points, $x(t)$ is the signal from the left COP, and $y(t + \tau)$ is the signal from the right COP shifted by τ time units (milliseconds, ms). In Python, the cross-correlation function was calculated using the `'numpy'` library. The signals were first subject to mean removal, and then the `'numpy.correlate'` function was used to compute the cross-correlation for a range of time lags. The peak value of the CCF within a time lag window of ±200 milliseconds was used as the measure of interlimb synchronization.

2.3.3 Mathematical Explanation of Cross-Correlation

By following these following steps, the degree of synchronization was quantified between the COP movements of the left and right feet, providing a critical measure for assessing balance control. This CCR analysis played a pivotal role in understanding the impact of cognitive distractions on interlimb synchronization and balance in both young and older adults.

1. **Mean Removal of the Signals:**

Mean removal involved removing the mean (average) value from each signal. This is done to eliminate any constant bias in the data, allowing the analysis to focus on fluctuations around the mean rather than the mean value itself.

$$x'(t) = x(t) - \bar{x}$$

$$y'(t) = y(t) - \bar{y}$$

Here, $x'(t)$ and $y'(t)$ are the signals with their respective means removed for the left and right COP, respectively, and where $\bar{x}$ and $\bar{y}$ are the means of the left and right COP signals, respectively.

2. **Normalizing the Cross-Correlation:**

Normalization ensures that the CCR values are comparable across different signals. Each mean removed signal was normalized by dividing by its standard deviation. This process scales the signals, making them comparable.

$$\hat{x}(t) = \frac{x'(t)}{\sigma_x}$$

$$\hat{y}(t) = \frac{y'(t)}{\sigma_y}$$

3. **Computing Cross-Correlation**

CCR measures the similarity between two signals at different time lags. It helps to determine how one signal is related to another over time. The formula for CCR between two signals $x(t)$ and $y(t)$ is:

$$R_{xy}(\tau) = \frac{1}{T}\sum_{t=0}^{T-1} x'(t)y'(t+\tau)$$

Here, $R_{xy}(\tau)$ is the CCF, τ is the time lag, T is the total number of data points, $x'(t)$ is the mean removed left COP signal, and $y'(t+\tau)$ is the mean removed right COP signal shifted by τ time units.

4. **Finding the Peak Values**

The peak value of the normalized cross-correlation function within a time lag window of ±200 milliseconds was identified as the measure of synchronization. This peak value indicates the maximum similarity (in magnitude) between the two signals within the given time lag range. The positive peak value indicates the maximum value of the CCF in the AP direction, whereas the negative peak value indicates the minimum value of the CCF in the ML direction.

2.3.4 Mathematical Explanation of Root Means Square of Center of Pressure

Root Mean Square (RMS) of the COP is a statistical measure of the variability in the center of pressure signal, reflecting the fluctuations in postural stability (Winter, 2009). In the context of COP data, RMS is used to quantify the average magnitude of sway, providing an indication of postural stability (Winter, 2009). The RMS value represents the square root of the average of the squares of the values. The RMS calculation was performed separately for the AP and ML components of the COP data.

The RMS for a given dataset x consisting of n values is calculated using the following formula:

$$\text{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$$

Where x_i represents each data point in the dataset, n is the total number of data points, and i is the data point of interest.

In this study, the COP data were collected from force plates for both the left and right feet. The data for the AP and ML directions were processed separately. The RMS values were calculated for each participant and each condition, as follows:

1. **Data Loading:** The COP data for the left and right feet in both AP and ML directions were loaded.
2. **Combining Data:** The left and right foot data were combined for each direction.
3. **RMS Calculation:** The RMS for the combined data in each direction was calculated using the formula above and then converted to millimeters (mm).

The left and right COP data were merged to calculate the resultant COP ($COP_{net(t)}$) using the equation described by Termoz et al. (2008). This method involves computing the weighted sum of the time-varying COP positions under each foot, scaled by the respective vertical ground reaction forces ($F_{z,l(t)}$ and $F_{z,r(t)}$). Specifically:

$$COP_{net}(t) = \left[COP_l(t) \times \frac{F_{z,l}(t)}{F_{z,l}(t) + F_{z,r}(t)}\right] + \left[COP_r(t) \times \frac{F_{z,r}(t)}{F_{z,l}(t) + F_{z,r}(t)}\right]$$

Where $COP_{r(t)}$ and $COP_{l(t)}$ are the COP signals under the right and left feet, respectively. This approach ensured an accurate representation of the overall COP by accounting for the contribution of each foot based on its supporting force. The Python code used for calculating RMS can be found in the Appendix.

2.3.5 Mathematical Explanation of Total Excursion

Total excursion is a measure used to quantify the total distance traveled by the COP during a specific period (Prieto et al., 1996). It represents the cumulative sum of the absolute differences between consecutive data points of the COP trajectory, reflecting the overall movement and activity level of the COP (Prieto et al., 1996). This measure is particularly useful in balance and postural control studies as it provides an indication of the amount of sway experienced by an individual. The total excursion for a given dataset x is calculated using the following formula:

$$\text{Total Excursion} = \sum_{i=1}^{n-1} |x_{i+1} - x_i|$$

Where x_i represents each data point in the dataset, n is the total number of data points, and i is data point of interest. In the context of this study, total excursion was calculated separately for the AP and ML directions. This allows for a detailed analysis of COP movements in both directions, providing insights into the stability and control of balance.

2.3.6 Mathematical Explanation of Mean Sway Velocity

Mean Sway Velocity (MSV) is a measure of the average speed of movement of the center of pressure (COP), providing an indication of the dynamism of postural control. It is calculated as the total excursion of the COP divided by the duration of the measurement. Similar to RMS, the MSV calculation was performed separately for the AP and ML components of the COP data.

The mean sway velocity for a given dataset x with a sampling rate f_s is calculated using the following formula:

$$\text{MSV} = \frac{\sum_{i=1}^{n-1} |x_{i+1} - x_i|}{T}$$

Where x_i represents each data point in the dataset, T is the total duration of the measurement, calculated as $T = \frac{n}{f_s}$, and i is the data point of interest.

In this study, the COP data were collected from force plates for both the left and right feet. The data for the AP and ML directions were processed separately. The MSV was calculated for each participant and each condition, as follows:

1. **Data Loading:** The COP data for the left and right feet in both AP and ML directions were loaded.
2. **Combining Data:** The left and right foot data were combined for each direction.
3. **Mean Sway Velocity Calculation:** The total excursion was calculated as the sum of the absolute differences between consecutive data points. The mean sway velocity was then calculated by dividing the total excursion by the duration of the measurement and converting to millimeters per second (mm/s).

The Python code used for calculating MSV can be found in the Appendix.

2.4 Statistical Analysis

Statistical analyses were performed using SPSS Statistics version 27.0.1.0 (IBM, Armonk, USA). A mixed model analysis of variance (Mixed Model ANOVA) was conducted separately for each visual condition (eyes open and eyes closed) to examine the effects of age group (young vs. older adults) as the between-groups factor and distraction condition (no distraction vs. distraction, including the specific task of counting) as the within-groups factor on the CCF, RMS sway, and MSV. Post-hoc analyses using the Bonferroni correction were conducted following significant main effects and interactions. These analyses compared all pairs of conditions within each visual and distraction category to determine specific differences between the groups and conditions. Independent samples t-tests were conducted to compare the total responses, the number of correct responses, and the percentage of correct responses between younger and older adults under the WDEO and WDEC conditions. The total responses were measured by counting the number of responses participants provided during each condition. The number of correct responses was calculated by counting the instances where participants accurately subtracted by 7 from the given starting number. Finally, the percentage of correct responses was determined by dividing the number of correct responses by the total responses and multiplying by 100 to obtain a percentage. Independent samples t-tests were also performed between groups for ABC and BBS scores. These analyses aimed to determine whether significant differences existed between the age groups in their performance under these distraction conditions. The significance level was set at $p < 0.05$ for all tests.

2.4.1 G*Power Calculation

The specific inputs for G*Power were as follows:

- **Effect Size (Cohen's d):** 0.15
- **Alpha Level (α):** 0.05
- **Power (1 - β):** 0.8
- **Statistical Test:** Means: Differences between two independent means (two groups)
- **Type of Power Analysis:** A priori: Compute required sample size

These inputs generated the required sample size, ensuring the study would have adequate power to detect meaningful differences between the groups. By using detailed parameters and referencing the Rakhra & Singer (2022) study for empirical data, the sample size calculation was robust and reliable, providing a strong foundation for the statistical analysis of this study.

Chapter 3. Results

The analyses focused on three primary outcome measures: the peak of the cross-correlation function (CCF) of the COP signals between the left and right feet and the lag at which this peak occurred. In addition, RMS sway and the mean sway velocity (MSV) of COP movements were compared. A combination of descriptive statistics, Mixed Model ANOVA, and Bonferroni post-hoc tests were employed to explore differences between the groups and conditions. The findings from these analyses are organized and presented in the following sections.

3.1.1 Participants

This study involved a total of 39 participants, divided into two age groups: young adults (aged 18-35) and older adults (aged 55+). The young adult group consisted of 22 participants (11 males and 11 females), while the older adult group consisted of 17 participants (11 females and 6 males). Demographic information is presented in Table 1, below.

Table 1. Participant Demographics and Assessment Outcomes.

Participant ID	Group	Age	Gender	Fall History	Height (m)	Mass (kg)	BBS (/56)	ABC (%)
11	Young	26	F	N	1.65	55.85	56	97.5
12	Young	25	M	N	1.68	69.31	56	100.0
13	Young	19	M	N	1.75	120.31	56	81.9
14	Young	23	F	Y	1.65	61.51	56	100.0
15	Young	23	M	N	1.83	94.45	56	99.4
16	Young	31	M	N	1.88	132.84	56	100.0
18	Young	31	M	N	1.83	135.65	56	99.4
20	Young	20	M	N	1.83	82.96	56	96.3
21	Young	31	F	N	1.60	55.92	56	99.4
22	Young	23	M	N	1.78	73.96	56	100.0
23	Young	33	M	N	1.74	87.18	56	94.4
24	Young	22	M	N	1.64	60.79	56	93.1
25	Young	34	F	N	1.65	78.36	56	90.0
26	Young	18	F	N	1.57	53.12	56	100.0
27	Young	18	F	N	1.57	49.23	56	100.0
28	Young	18	M	N	1.93	112.74	56	89.4
30	Young	22	F	N	1.68	55.02	56	95.6
31	Young	24	F	N	1.61	53.58	56	99.4
34	Young	26	F	N	1.58	57.74	56	97.1
41	Young	19	F	N	1.55	59.20	56	98.8
44	Young	29	F	N	1.62	58.89	56	98.1
46	Young	25	M	N	1.68	71.21	56	96.9
19	Old	60	F	Y	1.70	82.54	56	98.8
29	Old	59	F	N	1.50	56.93	56	93.8
32	Old	58	F	N	1.50	84.95	56	95.6
33	Old	59	F	N	1.70	70.19	56	96.9
37	Old	66	F	Y	1.58	69.40	56	50.6
38	Old	81	M	N	1.60	58.44	56	94.4
39	Old	56	M	Y	1.89	104.25	43	55.3
40	Old	70	M	N	1.75	80.07	56	100.0
42	Old	59	F	N	1.60	77.19	56	79.4
43	Old	57	F	N	1.67	74.53	56	92.5
45	Old	70	M	N	1.72	62.44	53	98.8
47	Old	63	M	N	1.78	87.88	56	100.0
48	Old	62	M	N	1.65	62.02	56	98.1
49	Old	58	F	N	1.52	64.28	56	98.1
50	Old	60	M	Y	1.67	86.23	56	96.9
51	Old	59	M	N	1.78	74.71	56	100.0
52	Old	55	F	N	1.68	74.09	56	100.0

This table summarizes the demographic and assessment outcomes for each participant in the study. It includes participant ID, group (young or older adult), age (years), gender, fall history, height (m), mass (kg), Berg Balance Scale (BBS) score out of 56, and Activities-specific Balance Confidence (ABC) score as a percentage.

3.2 Primary Outcome: Cross-Correlation (ρ)

Table 2 displays the means and standard deviations (SD) of the CCR (ρ) for the AP and ML directions across various conditions for young healthy adults and older adults. These descriptive statistics provide an overview of the synchronization between the movements of the left and right feet under different cognitive distraction conditions.

Table 2. CCR (ρ) in AP and ML Directions.

Condition	Group	Mean AP (SD)	Mean ML (SD)
COEO	Young	0.78 (0.14)	-0.74 (0.17)
	Old	0.78 (0.17)	-0.76 (0.17)
NDEO	Young	0.81 (0.11)	-0.80 (0.16)
	Old	0.81 (0.17)	-0.79 (0.22)
WDEO	Young	0.76 (0.12)	-0.77 (0.13)
	Old	0.80 (0.19)	-0.76 (0.20)
COEC	Young	0.82 (0.09)	-0.79 (0.11)
	Old	0.80 (0.14)	-0.78 (0.11)
NDEC	Young	0.84 (0.10)	-0.81 (0.12)
	Old	0.82 (0.12)	-0.79 (0.19)
WDEC	Young	0.82 (0.11)	-0.79 (0.17)
	Old	0.78 (0.18)	-0.77 (0.19)

Note: CO (counting), EO (eyes open), EC (eyes closed), ND (no distraction), and WD (with distraction). Values are presented as Mean (SD).

3.2.1 Cross-Correlation Analysis

The results, summarized in Table 3 and shown in Figure 4, revealed no significant differences in CCR between the conditions or groups. Specifically, no main effects of condition or group, and no significant interactions between condition and group were observed in either the AP or ML directions. This indicates that interlimb synchronization, as measured by CCR, remained consistent across different conditions and age groups, suggesting that cognitive distractions did not significantly disrupt synchronization in this study.

Table 3. Mixed Model ANOVA Results for CCR values (ρ) on log-transformed data comparing corresponding conditions and groups. The ML comparisons were shifted by +1.00 units before being log-transformed.

Comparison	Source	SS	DF1	DF2	MS	F	p-unc	ηp^2	ε
AP COEO AP NDEO AP WDEO	Group	3.610E-5	1	37	3.610E-5	0.002	0.961	<0.001	
	Condition	0.011	2	74	0.006	0.892	0.414	0.024	0.889
	Interaction	0.002	2	74	0.001	0.125	0.882	0.003	0.889
ML COEO ML NDEO ML WDEO	Group	0.170	1	37	0.170	0.803	0.376	0.021	
	Condition	0.052	2	74	0.230	2.642	0.078	0.067	0.905
	Interaction	0.016	2	74	0.002	0.026	0.974	0.001	0.905
AP COEC AP NDEC AP WDEC	Group	0.013	1	37	0.013	1.093	0.303	0.029	
	Condition	0.009	2	74	0.004	0.987	0.378	0.026	0.887
	Interaction	0.003	2	74	0.002	0.392	0.677	0.010	0.887
ML COEC ML NDEC ML WDEC	Group	0.030	1	37	0.030	0.146	0.705	0.004	
	Condition	0.009	1.630	60.325	0.139	1.579	0.217	0.009	0.815
	Interaction	0.001	1.630	60.325	0.003	0.037	0.940	<0.001	0.815

Note: SS = Sum of Squares, DF1 = Degrees of Freedom (between-group), DF2 = Degrees of Freedom (within-group), MS = Mean Squares, F = F-value, p-unc = uncorrected p-value, ηp^2 = Partial eta squared, ε = epsilon.

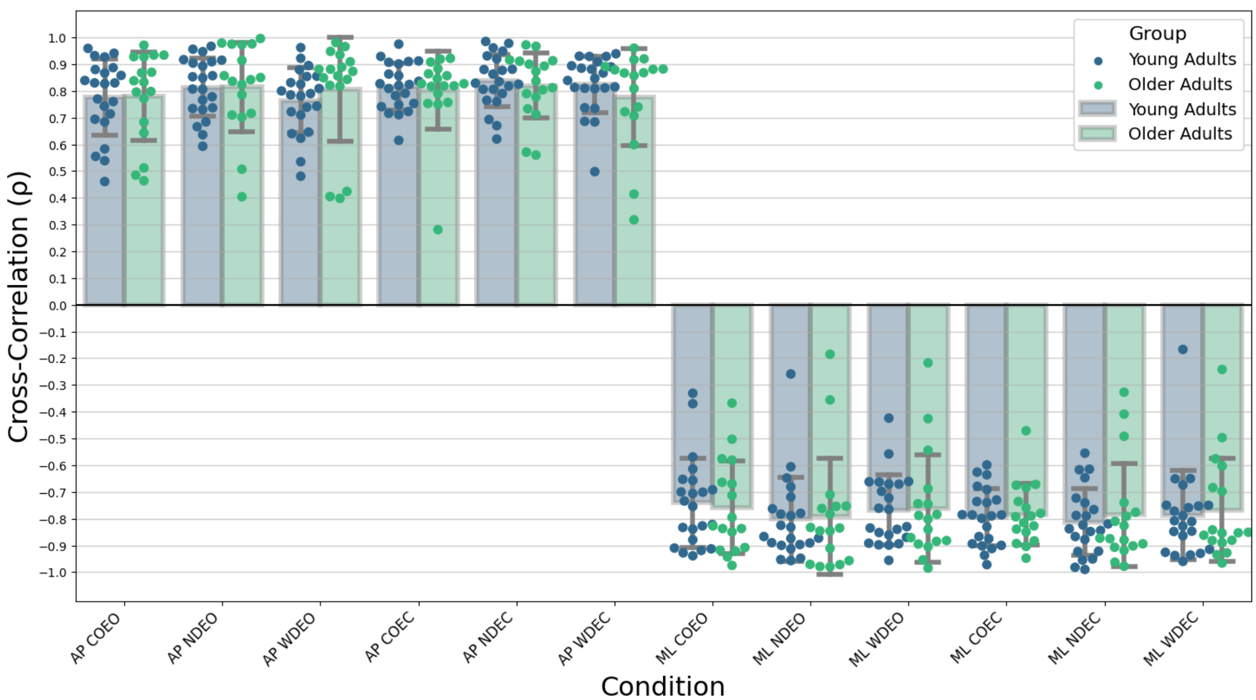

Figure 4. Cross-Correlation (ρ) for Young Adults (blue) and Older Adults (green) across various conditions in the AP and ML direction. The beeswarm plots show individual data points superimposed on bar plots representing group means (with SD bars). The conditions are coded as: CO (counting), EO (eyes open), EC (eyes closed), ND (no distraction), and WD (with distraction).

3.3 Secondary Outcomes: Time Lag, Root Mean Square Sway, Mean Sway Velocity, Correct Responses, ABC and BBS

The analysis revealed that Time Lag (TL) did not show significant differences across conditions or between young and older adults, as shown in Tables 6 and Figures 4. This indicates that TL was not significantly affected by the presence of cognitive distractions, nor did it differ between age groups. A significant interaction effect was observed, however, between group and condition for ML RMS sway across COEC, NDEC, and WDEC conditions ($F(2,74) = 3.292$, $p = 0.043$). However, no significant main effects for group or condition were detected, and no post-hoc comparisons were performed.

Furthermore, significant differences were observed in the Mean Sway Velocity (MSV) of the Center of Pressure (COP) movements between conditions but not between groups, as shown in Table 8 and Figure 6. Specifically, MSV showed a significant increase when comparing the no distraction, eyes open (NDEO) condition against both the counting, eyes open (COEO) and with distraction, eyes open (WDEO) conditions, in both AP and ML directions. A similar pattern was observed in the eyes closed conditions, however, there was no significance found in the ML comparison between NDEC and WDEC. For instance, during the eyes-open with distraction condition, the mean sway velocity in the anteroposterior (AP) direction increased significantly for both young and older adults, suggesting that cognitive distractions impact postural stability.

The analysis revealed significant differences between conditions in MSV across age groups, suggesting that cognitive distractions primarily influenced postural sway velocity, while no significant effects were observed for CCF or RMS metrics. The Bonferroni post hoc test revealed significant increases in MSV in the following comparisons:

- Eyes Open (EO) Conditions:

- AP NDEO vs. AP COEO: MSV increased significantly ($p < 0.001$)
- AP NDEO vs. AP WDEO: MSV increased significantly ($p < 0.001$)
- ML NDEO vs. ML COEO: MSV increased significantly ($p < 0.001$)
- ML NDEO vs. ML WDEO: MSV increased significantly ($p < 0.001$)

- Eyes Closed (EC) Conditions:
    - AP NDEC vs. AP COEC: MSV increased significantly ($p = 0.014$)
    - AP NDEC vs. AP WDEC: MSV did not increase significantly ($p = 0.750$)
    - ML NDEC vs. ML COEC: MSV increased significantly ($p < 0.001$)
    - ML NDEC vs. ML WDEC: MSV increased significantly ($p = 0.005$)

No significant differences were found between the young and older adults' RMS sway values, indicating that while cognitive distractions significantly altered sway velocity, they did not affect the overall magnitude of sway across age groups. This suggests that the impact of cognitive distractions on postural control is more condition-dependent than group-dependent, highlighting that distractions influence the velocity of sway rather than its magnitude.
Post-hoc analyses with Bonferroni correction further supported these findings, showing significant increases in MSV in the AP direction for conditions such as NDEO vs. COEO and WDEO, and in the mediolateral (ML) direction for NDEO vs. COEO. In the eyes-closed conditions, similar increases were noted, except for AP NDEC vs. WDEC, which did not reach significance. These findings indicate that cognitive distractions significantly impact the speed of postural adjustments rather than the overall sway magnitude, regardless of the distraction type or age group.

After performing independent sample t-tests, significant differences were observed in the total number of responses and correct responses between groups during the WDEC condition, as shown in Table 5. Older adults demonstrated a lower total response ($t = 2.168$, $df = 37$, $p = 0.037$) and correct response ($t = 2.339$, $df = 37$, $p = 0.025$) count compared to younger adults. This finding highlights the increased cognitive load experienced by older adults when performing dual tasks, consistent with age-related declines in executive functioning.

Lastly, baseline measures from the ABC Scale and the BBS did not differ significantly between groups, as confirmed by independent samples t-tests (BBS: $t = 1.024$, $df = 16.996$, $p = 0.320$; ABC: $t = 1.452$, $df = 18.247$, $p = 0.163$). Log transformations were not performed on the ABC and BBS scores due to the presence of a ceiling effect, which arose from the relatively healthy status of the participants. This homogeneity in the sample resulted in scores clustering near the upper limit of the scales, thereby reducing variability and diminishing the potential impact of non-normality on the statistical analyses. This lack of baseline difference suggests that the absence of significant differences in primary summary measures (e.g., cross-correlation and RMS sway) may not be attributable to pre-existing disparities in self-perceived balance confidence or functional balance abilities. Instead, it reflects comparable baseline postural stability between younger and older adults.

Table 4. Time Lag, RMS Sway, and MSV.

Condition	Group	AP TL (ms)	ML TL (ms)	AP RMS (mm)	ML RMS (mm)	AP MSV (mm/s)	ML MSV (mm/s)
COEO	Young	5.23 (31.62)	8.59 (33.52)	4.60 (2.75)	1.96 (1.27)	8.12 (4.55)	4.79 (2.64)
	Old	-7.76 (32.66)	-1.76 (26.84)	4.40 (1.61)	1.80 (0.83)	8.64 (4.17)	3.53 (1.24)
NDEO	Young	1.64 (18.94)	2.82 (17.02)	4.22 (1.80)	1.71 (0.90)	5.42 (1.65)	3.18 (1.56)
	Old	-8.24 (40.32)	-5.24 (56.00)	5.00 (2.42)	1.68 (0.74)	7.49 (3.54)	2.83 (0.91)
WDEO	Young	6.73 (31.55)	3.28 (32.73)	5.14 (4.82)	1.95 (1.02)	8.98 (8.44)	4.40 (2.30)
	Old	-13.35 (60.90)	19.00 (57.90)	5.09 (2.96)	2.14 (1.19)	9.87 (7.35)	3.76 (1.55)
COEC	Young	0.91 (21.44)	3.41 (25.69)	4.54 (1.80)	1.76 (0.79)	9.08 (3.85)	4.25 (1.92)
	Old	-15.53 (35.54)	-6.24 (42.35)	5.10 (3.06)	2.33 (1.73)	11.10 (4.52)	4.16 (1.61)
NDEC	Young	1.45 (41.40)	4.00 (40.49)	5.41 (2.45)	1.90 (0.89)	8.10 (3.69)	3.65 (1.59)
	Old	-11.29 (26.38)	2.41 (19.22)	4.70 (1.85)	1.86 (1.41)	9.98 (4.91)	3.26 (1.25)
WDEC	Young	-1.73 (23.17)	2.41 (23.06)	5.04 (2.87)	2.15 (1.49)	9.99 (5.44)	4.49 (2.30)
	Old	-4.06 (30.62)	7.65 (36.90)	4.80 (1.74)	1.79 (0.82)	10.64 (5.13)	4.20 (1.99)

Note: CO (counting), EO (eyes open), EC (eyes closed), ND (no distraction), and WD (with distraction). Values are presented as Mean (SD).

Table 5. Total Responses, Correct Responses, and Correct Responses Percentage.

Condition	Group	Number of Responses (number)	Correct Responses (%)	Number of Correct Responses (number)
WDEO	Young	19.4 (9.4)	86.1% (12.3%)	17.1 (9.9)
	Old	17.0 (6.9)	76.6% (21.4%)	12.9 (7.2)
WDEC	Young	20.4 (9.1)†	84.7% (16.9%)	17.9 (10.2)†
	Old	14.9 (5.4)†	73.3% (24.6%)	11.2 (6.6)†

Note: The superscripts (†) shows significant differences after performing independent sample t-test. Values are presented as Mean (SD).

Table 6. Mixed Model ANOVA Results for Time Lags (ms) that have been log transformed comparing corresponding conditions and groups. The TL comparisons were shifted by +250.00 units before being log transformed.

Comparison	Source	SS	DF1	DF2	MS	F	p-unc	ηp^2	ε
AP COEO AP NDEO AP WDEO	Group	0.035	1	37	0.035	2.789	0.103	0.070	
	Condition	0.004	1.524	56.399	0.003	0.387	0.624	0.010	0.762
	Interaction	0.007	1.524	56.399	0.005	0.684	0.471	0.018	0.762
ML COEO ML NDEO ML WDEO	Group	0.003	1	37	0.003	0.275	0.603	0.007	
	Condition	0.014	2	74	0.007	1.267	0.288	0.033	0.889
	Interaction	0.017	2	74	0.008	1.506	0.229	0.039	0.889
AP COEC AP NDEC AP WDEC	Group	0.011	1	37	0.011	2.163	0.150	0.055	
	Condition	0.002	2	74	0.001	0.325	0.724	0.009	0.924
	Interaction	0.004	2	74	0.002	0.743	0.479	0.020	0.924
ML COEC ML NDEC ML WDEC	Group	0.001	1	37	0.001	0.108	0.744	0.003	
	Condition	0.004	2	74	0.002	0.769	0.467	0.020	0.999
	Interaction	0.005	2	74	0.002	0.983	0.2379	0.026	0.999

Note: SS = Sum of Squares, DF1 = Degrees of Freedom (between-group), DF2 = Degrees of Freedom (within-group), MS = Mean Squares, F = F-value, p-unc = uncorrected p-value, ηp^2 = partial eta squared, ε = epsilon.

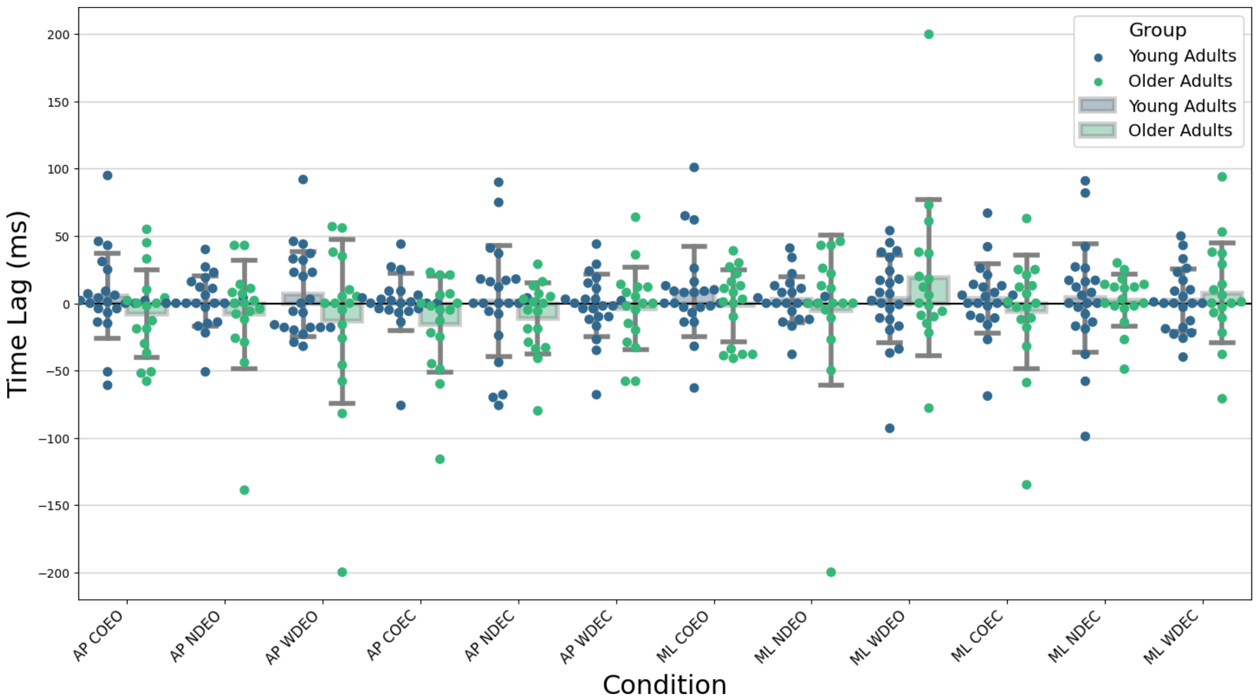

Figure 5. Time Lags (ms) for Young Adults (blue) and Older Adults (green) across various conditions in the AP and ML direction. The beeswarm plots show individual data points superimposed on bar plots representing group means (with SD bars). The conditions are coded as: CO (counting), EO (eyes open), EC (eyes closed), ND (no distraction), and WD (with distraction).

Table 7. Mixed Model ANOVA Results for RMS values (mm) that have been log transformed comparing corresponding conditions and groups.

Comparison	Source	SS	DF1	DF2	MS	F	p-unc	ηp^2	ε
AP COEO AP NDEO AP WDEO	Group	0.043	1	37	0.043	0.437	0.513	0.012	
	Condition	0.013	2	74	0.007	0.384	0.683	0.010	0.902
	Interaction	0.016	2	74	0.008	0.462	0.632	0.012	0.902
ML COEO ML NDEO ML WDEO	Group	0.006	1	37	0.006	0.069	0.794	0.002	
	Condition	0.062	2	74	0.33	1.113	0.334	0.029	0.946
	Interaction	0.010	2	74	0.005	0.188	0.829	0.005	0.946
AP COEC AP NDEC AP WDEC	Group	<0.001	1	37	<0.001	0.005	0.944	<0.001	
	Condition	0.012	2	74	0.006	0.543	0.583	0.014	0.914
	Interaction	0.029	2	74	0.015	1.348	0.266	0.035	0.914
ML COEC ML NDEC ML WDEC	Group	<0.001	1	37	<0.001	0.002	0.969	<0.001	
	Condition	0.025	2	74	0.013	0.757	0.473	0.020	0.976
	Interaction*	0.108	2	74	0.054	3.292	0.043*	0.082	0.976

Note: SS = Sum of Squares, DF1 = Degrees of Freedom (between-group), DF2 = Degrees of Freedom (within-group), MS = Mean Squares, F = F-value, p-unc = uncorrected p-value, ηp^2 = partial eta squared, ε = epsilon. Significant difference is shown using an asterisk (*).

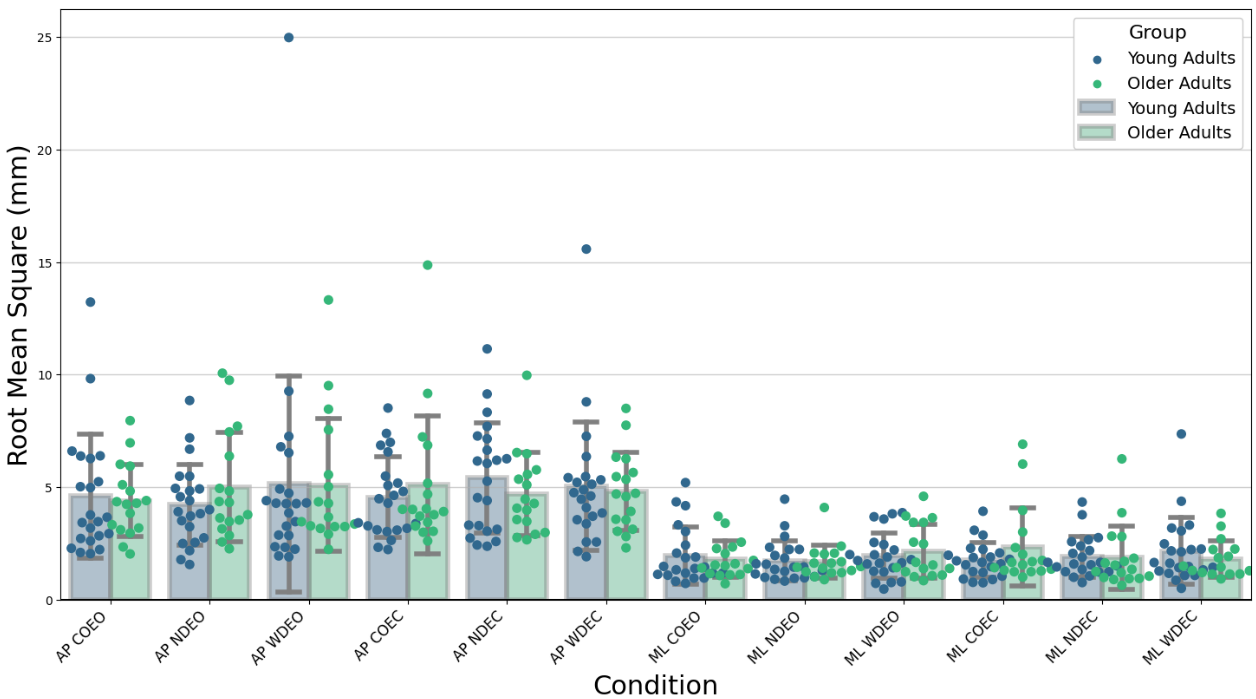

Figure 6. Root Means Square (mm) for Young Adults (blue) and Older Adults (green) across various conditions in the AP and ML direction. The beeswarm plots show individual data points superimposed on bar plots representing group means (with SD bars). The conditions are coded as: CO (counting), EO (eyes open), EC (eyes closed), ND (no distraction), and WD (with distraction). * = statistically significant interaction (p = 0.043).

Table 8. Mixed Model ANOVA Results for MSV values (mm/s) that have been log transformed comparing corresponding conditions and groups.

Comparison	Source	SS	DF1	DF2	MS	F	p-unc	ηp²	ε
AP COEO† **AP NDEO†,‡** **AP WDEO‡**	Group	0.135	1	37	0.135	1.635	0.209	0.042	
	Condition†,‡	0.348	1.723	63.739	0.202	17.657	<0.001†,‡	0.323	0.861
	Interaction	0.046	1.723	63.739	0.027	2.340	0.135	0.059	0.861
ML COEO† **ML NDEO†,‡** **ML WDEO‡**	Group	0.113	1	37	0.113	1.512	0.227	0.039	
	Condition†,‡	0.394	2	74	0.197	17.263	<0.001†,‡	0.318	0.984
	Interaction	0.021	2	74	0.010	0.911	0.407	0.024	0.984
AP COEC† **AP NDEC†** **AP WDEC**	Group	0.097	1	37	0.097	1.029	0.317	0.027	
	Condition	0.056	1.466	54.227	0.038	1.919	0.014†	0.049	0.733
	Interaction	0.042	1.466	54.227	0.028	1.429	0.246	0.037	0.733
ML COEC† **ML NDEC†,‡** **ML WDEC‡**	Group	0.017	1	37	0.017	0.218	0.643	0.006	
	Condition†,‡	0.205	1.699	62.868	0.121	9.799	<0.001†,‡	0.209	0.850
	Interaction	0.007	1.699	62.868	0.004	0.342	0.677	0.009	0.850

Note: SS = Sum of Squares, DF1 = Degrees of Freedom (between-group), DF2 = Degrees of Freedom (within-group), MS = Mean Squares, F = F-value, p-unc = uncorrected p-value, ηp2 = partial eta squared, ε = epsilon. The superscripts (†,‡) indicate significant differences between specific conditions as determined by the Bonferroni post-hoc test. † corresponds to the comparison made between the following pairs: NDEO and COEO or NDEC and COEC, in both AP and ML. ‡ corresponds to the comparison made between the following pairs: NDEO and WDEO or NDEC and WDEC, in both AP and ML directions.

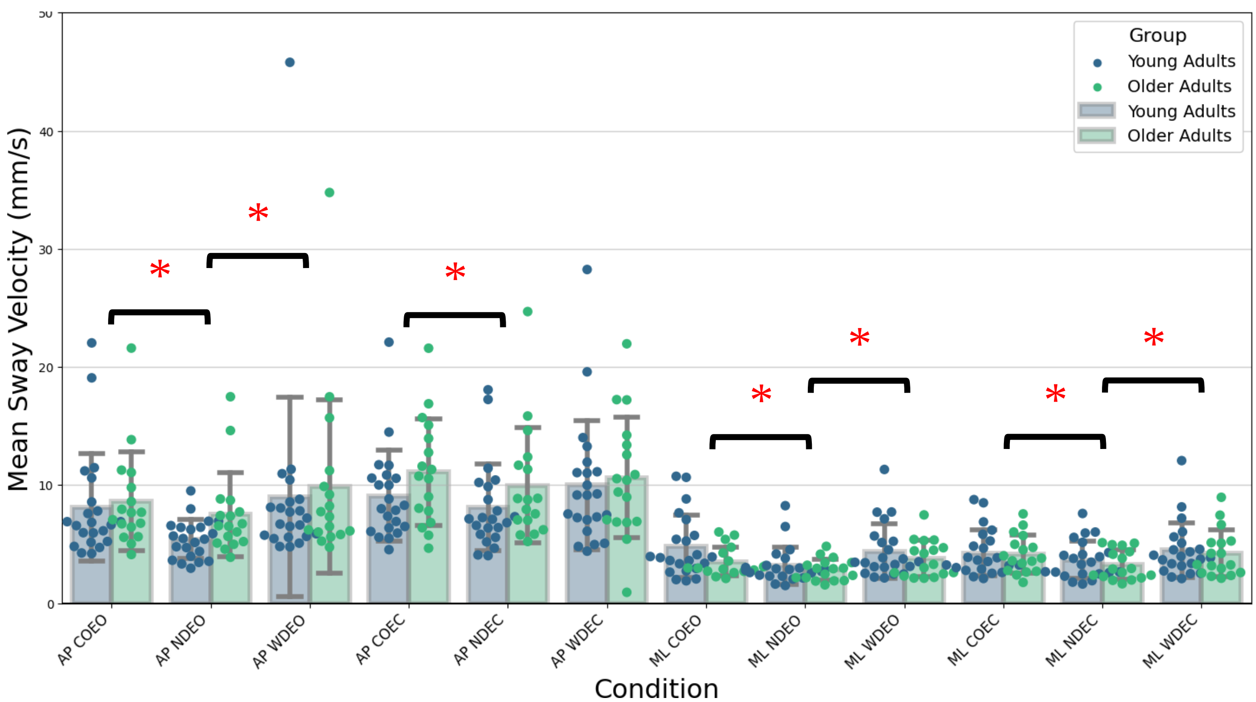

Figure 7. Mean Sway Velocity (mm/s) for Young Adults (blue) and Older Adults (green) across various conditions in the AP and ML direction. The beeswarm plots show individual data points superimposed on bar plots representing group means (with SD bars). The conditions are coded as: CO (counting), EO (eyes open), EC (eyes closed), ND (no distraction), and WD (with distraction). * = statistically significant difference between conditions (p < 0.05).

Chapter 4. Discussion

This chapter provides a comprehensive analysis and interpretation of the findings of this study on the effects of cognitive distractions on interlimb synchronization and balance in young and older adults. The discussion synthesizes the results in the context of existing literature, elucidates the practical implications for fall prevention, acknowledges the limitations of the study, and proposes directions for future research. By examining the impacts of cognitive distractions on different aspects of postural control, this chapter aims to deepen the understanding of cognitive-motor interactions and their implications for balance and stability, particularly in aging populations.

4.1 Summary of Findings

This study investigated the effects of cognitive distractions on interlimb synchronization and balance in young and older adults. The primary research question focused on how cognitive distractions impact interlimb synchronization and balance among these groups, with an emphasis on understanding the potential implications for balance control, particularly in aging populations. The analysis did not reveal significant differences in the CCF values of the COP between the young and older adult groups across different conditions. This suggests that interlimb synchronization, as measured by the CCF, was not substantially affected by either age or cognitive distraction in the sample studied. Similarly, there were no significant differences in RMS sway between the groups or conditions. RMS sway, which reflects the variability of postural sway as measured by the standard deviation of the COP time series, showed no significant differences regardless of the presence of cognitive distractions or the age of the participants.

Unlike the CCF and RMS measures, MSV showed significant differences across conditions but not between groups. This indicates that while the mean sway velocity of COP was influenced by cognitive distractions, this effect was similar for both young and older adults. Specifically, tasks involving cognitive distractions resulted in increased MSV, suggesting that participants exhibited more dynamic and variable postural adjustments when distracted.

The absence of significant differences in CCF and RMS sway between groups and conditions suggests that interlimb synchronization and the magnitude of postural sway are robust to the levels of cognitive distraction applied in this study. This finding implies that both young and older adults are able to maintain stable interlimb coordination and overall postural stability even when subjected to cognitive tasks such as counting backwards.

However, the significant differences in MSV across conditions indicate that cognitive distractions do affect the dynamics of postural control. Increased MSV in the presence of cognitive distractions suggests that both young and older adults experience more variable and potentially less controlled postural movements when their attention is divided. This finding aligns with previous research, such as the studies by Woollacott and Shumway-Cook (2002), which indicated that cognitive load could impact the automaticity of postural control mechanisms, leading to more frequent and pronounced postural adjustments. Furthermore, it was also shown to align with Rakhra & Singer (2022), who observed that older adults exhibit increased high-frequency COP_{net} oscillations, indicating a reliance on reactive stability mechanisms under challenging conditions. Similarly, Huxhold et al. (2006) found that older adults, in particular, experience greater postural instability when engaged in DT scenarios. However, this increase in instability does not necessarily translate into greater MSV or variability in RMS sway in all contexts. The lack of significant age-related differences in MSV under cognitive distractions in our study suggests that while older adults may exhibit greater instability in some DT scenarios, the specific nature of the distraction and the task demands may play a critical role in determining the extent of these effects.

Overall, these findings contribute to the understanding of how cognitive distractions influence balance and interlimb synchronization, highlighting their effects on different aspects of postural control. While interlimb synchronization and the magnitude of sway appear resilient, the increased variability in sway velocity under distraction emphasizes the importance of considering cognitive load in balance assessments and interventions, particularly in aging populations.

4.2 Interpretation of Results and Comparison with Existing Literature

The findings of this study provide valuable insights into the interactions between cognitive load, interlimb synchronization, and balance control in both young and older adults. The lack of significant differences in the Cross-Correlation Function (CCF) and Root Mean Square (RMS) sway between groups and conditions suggests a resilience in interlimb synchronization and postural sway magnitude, respectively, to the levels of cognitive distraction applied. This resilience indicates that the basic mechanisms of balance control remain intact across age groups, even under cognitive load. The stability in CCF values, regardless of the presence of cognitive distractions, highlights the robustness of the neural and motor systems involved in coordinating limb movements. This finding aligns with research by Habib-Perez et al. (2016), which suggested that effective synchronization between limbs prior to postural instability significantly reduces instability.

The resilience observed in CCF values supports the notion that interlimb coordination plays a critical role during quiet standing. Despite the low incidence of motor unit synchronization between limbs, as noted by Mochizuki et al. (2005), the high correlation coefficients between the COP movements of the left and right feet suggest that the limbs work together to maintain balance. This coordination may explain the stable CCF values, indicating that established interlimb coordination mechanisms are robust enough to withstand the cognitive distractions tested in this study.

The lack of baseline differences in ABC and BBS scores may have contributed to the absence of differences in the balance outcomes between groups. These results suggest that both younger and older adults began the tasks with similar levels of self-reported balance confidence and functional balance capacity. On the one hand, these similarities serve as a verification and control that individuals from both groups were comparable in these balance-related domains. Thus, any differences observed between groups should have been attributable to the effect of age on interlimb synchronization, ruling out pre-existing disparities in baseline stability as a confounding factor. Previous research has shown that self-reported confidence and functional balance assessments are strong predictors of postural performance (Powell & Myers, 1995; Berg et al., 1992). However, the absence of age effects on synchronization and sway indicate that the ABC and BBS were representative of more precise measures of balance as derived from the forceplates. Future studies could investigate whether more nuanced or ecologically valid baseline assessments might reveal subtle pre-existing disparities or selectively probe whether individuals with more varied scores on these tests demonstrate more varied levels of interlimb synchrony, regardless of age.

In contrast to the stable CCF, TL and RMS values, MSV and responses varied significantly across conditions, highlighting the impact of cognitive distractions on the dynamics of postural adjustments, as well as the cognitive aspects of balance. The increase in MSV suggests that cognitive distractions lead to more frequent and potentially less controlled postural corrections, regardless of age. This finding is consistent with the Constrained Action Hypothesis proposed by Wulf (2013), which posits that directing attention to a specific aspect of movement can interfere with automatic control processes, leading to less efficient performance. In addition, the significantly lower number of total and correct responses in the older adult group in comparison to their younger counterparts indicates a prioritization of the balancing task over the cognitive task, which aligns with previous research (Doumas et al., 2009).

Moreover, the finding that there is a significant difference between young and old cohorts' responses (as discussed in section 3.3) underscores the well-documented challenges older adults face when managing cognitive and motor tasks simultaneously. Age-related declines in executive functioning, such as reduced working memory and slower processing speeds, make it more difficult for older adults to allocate sufficient cognitive resources to dual-task scenarios (Huxhold et al., 2006). The increased cognitive load in tasks like WDEC likely exacerbates this limitation, leading to greater postural instability and poorer performance. This aligns with the CRUNCH hypothesis, which posits that older adults over-recruit neural resources at lower levels of task difficulty, leaving fewer reserves for more challenging conditions (Reuter-Lorenz & Cappell, 2008). These findings suggest that interventions targeting cognitive resource allocation, such as dual-task training or attentional focus strategies, could help mitigate the dual-task cost and improve balance performance in older adults.

Cognitive decline plays a significant role in balance impairment, particularly as older adults may have difficulty processing and integrating sensory information, leading to delayed or inappropriate postural adjustments (Woollacott & Shumway-Cook, 2002). Cognitive aging, characterized by a decline in attentional resources and processing speed (Salthouse, 1996), along with a decrease in working memory capacity (Baddeley, 2000) and executive functions such as planning and multitasking (Verhaeghen & Cerella, 2002), further complicates the ability to maintain postural stability under cognitive load.

The results also align with Tworzyanski's (2023) findings, which indicated that any form of distraction significantly alters balance performance. Both studies demonstrate that cognitive distractions universally impact balance, reinforcing the notion that cognitive load competes with the attentional resources needed for maintaining postural stability. However, the absence of significant group differences in CCF and RMS sway, as well as in MSV between young and older adults, suggests that both age groups managed to maintain similar levels of postural stability under cognitive load. This finding contrasts with earlier studies, such as those by Huxhold et al. (2006), which reported greater instability in older adults during dual-task scenarios. The discrepancy could be attributed to the cognitive tasks used in this study not being sufficiently demanding to reveal age-related differences or the relatively high levels of physical and cognitive function in the older adult sample.

Motor decline, including reduced muscle strength and flexibility, known as sarcopenia (Larsson et al., 2019), along with decreased joint flexibility due to changes in connective tissues (Seidler et al., 2010), may contribute to less efficient postural corrections. However, the older adults in this study may have maintained relatively high motor function, which could explain the lack of significant group differences.

The significant increase in MSV under cognitive distraction conditions supports the Central Capacity Sharing Model (Bristow et al., 2016), which proposes that the brain allocates processing resources dynamically between tasks based on their demands. In this study, when participants were required to perform a cognitive task while maintaining balance, the increased cognitive demands likely diverted attentional resources away from postural control. This resulted in less efficient coordination, as it was reflected by the increased sway velocity. This shift underscores the importance of considering cognitive load in balance assessments, particularly for tasks requiring multitasking.

This dynamic resource allocation mechanism highlights the inherent trade-offs between cognitive and motor tasks during DT. For example, research has shown that postural control, although often automatic, requires attentional input, especially under conditions of reduced sensory input or increased task complexity (Woollacott & Shumway-Cook, 2002). The increased MSV observed in the ML direction under distraction conditions may reflect the prioritization of cognitive task performance over postural stability. This is consistent with findings by Huxhold et al. (2006), who observed greater dual-task costs in older adults during cognitively demanding tasks, indicating a reduction in their ability to distribute attentional resources effectively.

Moreover, these findings have broader implications for understanding the interaction between cognitive load and postural control in daily activities. For instance, real-world tasks such as walking while talking or navigating busy environments often require individuals to manage multiple streams of information simultaneously. The increase in MSV under distraction conditions observed here suggests that such DT scenarios may disproportionately challenge postural stability, particularly in populations with reduced cognitive capacity, such as older adults or individuals with neurological impairments.

The significant increases in MSV observed in multiple conditions highlight the sensitivity of postural sway velocity to cognitive distractions. The results of this study revealed consistent increases in both AP and ML MSV under cognitive distraction in EO conditions, whereas the EC conditions presented a slightly different pattern. For instance, under EC conditions, significant increases in AP MSV were observed between NDEC and COEC but not between NDEC and WDEC, suggesting that the addition of visual restriction may diminish the effect of cognitive distractions on AP stability. In contrast, ML MSV remained significantly elevated between NDEC and both COEC and WDEC conditions, emphasizing the vulnerability of lateral stability even in the absence of visual input.

These findings provide key insights into the directional specificity of sway responses under cognitive load. The consistent increases in ML MSV across distraction conditions, regardless of visual input, align with research suggesting that ML stability is more sensitive to balance challenges due to the critical role of lateral sway in preventing falls (Winter et al., 1993). Both AP and ML sway rely on the dynamic integration of sensory inputs and motor coordination to maintain postural stability. While AP sway involves forward-backward adjustments supported by the BOS through ankle plantar- and dorsi-flexor activity, ML sway primarily relies on hip abductor/adductor muscles (Winter, 2009). Cognitive distractions can influence sway in both directions, but ML sway may show greater sensitivity in populations at higher fall risk due to sarcopenia and age-related neuromuscular degeneration. Sarcopenia, characterized by the preferential loss of type II muscle fibers essential for rapid and forceful lateral adjustments, may have a more significant impact on hip abductors and adductors given their higher proportion of type II muscle fibers (Doherty, 2003; Larsson et al., 2019). In contrast, distal muscles at the ankle, which control AP sway, have a higher proportion of type I fibers, and may thus be partially spared from the effects of sarcopenia (Van De Casteele et al., 2024). These changes highlight the unique challenges faced by older adults in maintaining lateral stability, especially during DT conditions. This directional vulnerability underscores the need for targeted interventions to improve ML stability, particularly during DT conditions that replicate real-world challenges such as navigating crowded environments or multitasking while walking.

These results highlight the importance of incorporating DT paradigms into balance training and assessment protocols. Interventions aimed at improving ML stability, such as lateral weight-shifting exercises or DT training programs, could address this directional vulnerability and reduce fall risk, particularly in older adults or populations with impaired balance. Additionally, future studies should explore the neural and sensory mechanisms underlying these directional differences in MSV responses to cognitive distractions, as well as their implications for dynamic tasks such as walking or obstacle negotiation.

Overall, this study builds on existing literature by providing a detailed analysis of how cognitive distractions affect various aspects of postural control. The findings underscore the need for a comprehensive approach to balance control that accounts for the effects of cognitive load, particularly in aging populations where attentional resources are already compromised. The universal effect of cognitive distractions on MSV highlights the necessity of developing interventions to help older adults manage distractions effectively, thereby maintaining postural stability and reducing fall risk (Sibley et al., 2021).

4.3 Revisiting the Conceptual Model

In the introduction, the conceptual model proposed that cognitive distractions would differentially affect interlimb synchronization and postural control, potentially leading to increased fall risk in aging populations. Based on the findings of this study, the overall structure of the conceptual model remains the same and maintains the same unknown parameters. The lack of significant changes in interlimb synchronization across conditions suggests that the neural mechanisms underlying synchronization are robust, even under cognitive load, which aligns with the model's prediction of a resilient balance control system in stable conditions and may suggest that future research probes this by having a varying gradient of task difficulties.

However, the observed significant differences in MSV between conditions indicate that the dynamics of postural adjustments are more sensitive to cognitive distractions than previously anticipated. This finding suggests that while the basic synchronization mechanisms may remain stable, the rate at which postural adjustments occur can be influenced by cognitive load, particularly in more challenging tasks or environments.

Given these insights, the conceptual model could be expanded to include the role of task difficulty and environmental distractors as moderating factors that influence the relationship between cognitive load and postural control. These elements could help explain why significant changes in MSV were observed without corresponding changes in synchronization. The model (Figure 8) would benefit from incorporating these additional variables to better predict and understand balance outcomes under different conditions.

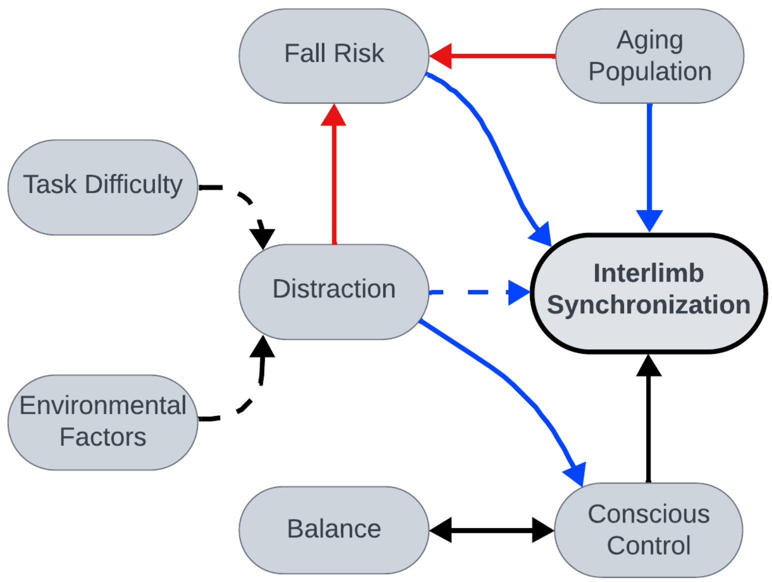

Figure 8. New Conceptual Model Illustrating the Impact of Distraction on Interlimb Synchronization in the Aging Population. This model delineates the new hypothesized relationships between fall risk, aging, distraction, task difficulty, environmental factors and their combined effects on interlimb synchronization and balance. It illustrates that with increasing age, the risk of falls rises, and cognitive distractions, which may be further influenced by task difficulty and environmental factors, are postulated to negatively affect synchronization, which is crucial for maintaining balance. The model also suggests a bidirectional relationship between balance and conscious control, which may influence overall stability. The red arrows show a positive effect in the direction of the arrow, whereas the blue arrows show a negative effect in the direction of the arrow. The black arrows represent a neutral relationship where the influence may be positive or negative. The dotted arrow shows where the gap in literature lies and how this study hypothesizes that distraction impacts interlimb synchronization negatively (blue).

4.4 Limitations

Despite the valuable insights gained from this study, several limitations must be acknowledged. These limitations pertain to sample size, demographic constraints, methodological aspects, and the generalizability of the findings.

Firstly, the sample size of 39 participants, divided into 22 young adults and 17 older adults, may not be large enough to detect more subtle effects of cognitive distractions on balance. A larger sample size could provide a more robust analysis and help uncover smaller differences that might exist between age groups or within the various conditions tested.

Secondly, the demographic characteristics of the sample may limit the generalizability of the findings. The study included healthy young adults aged 18-35 and older adults aged 55 and above, all of whom were relatively physically and cognitively fit. However, classifying individuals aged 55-64 as ‘older adults’ may have influenced the results, potentially masking age-related differences that are typically observed in older populations. According to Lord et al. (1993), significant age-related declines in balance and increased fall risk are more commonly observed in adults aged 65 and above. By including participants in their late 50s and early 60s—an age range often considered late middle age—the study may have included individuals who do not yet exhibit the pronounced physiological and cognitive changes associated with older age. This broader age categorization might explain the lack of significant differences between the groups in this study. Future research should consider using more precise age categorizations, such as distinguishing between middle-aged adults and those aged 65 and above, to better understand the impact of cognitive distractions on balance across the lifespan. Methodological limitations also need to be considered. The cognitive tasks used in this study, while representative of common distractions, might not fully capture the range of cognitive loads encountered in daily life. For instance, real-world distractions can vary in complexity and duration, and future research should incorporate a wider variety of cognitive tasks to better simulate everyday scenarios. Netz et al. (2018) explored the link between postural control and posture-unrelated attention control in older adults, highlighting the differential impacts of various cognitive tasks. In their study, Netz et al. (2018) included a range of tasks such as simple arithmetic calculations, memory tasks, and those involving visual and auditory distractors to assess their effects on postural control. They found that different types of cognitive tasks, particularly those with auditory distractors, had varied impacts on postural sway. Specifically, tasks with auditory distractions led to greater postural sway compared to tasks without distractions, indicating that the nature of the cognitive task significantly influences balance control. This suggests the importance of incorporating a diverse set of cognitive tasks in future research to better understand how different types of distractions affect balance. Additionally, this current study primarily used force plates to measure postural sway, which, while accurate, may not capture all aspects of balance and postural control. Incorporating other measurement tools, such as wearable sensors or motion capture systems, could provide a more comprehensive assessment of balance.

Furthermore, the cross-sectional design of this study limits the ability to draw causal conclusions about the effects of cognitive distractions on balance over time. Longitudinal studies are needed to examine how cognitive load impacts balance and fall risk across different stages of aging and to explore the long-term effects of cognitive training on balance control.

Lastly, the findings of this study are context-specific and may not generalize to all environments. The controlled laboratory setting provides a high degree of internal validity but might not reflect the complexity of real-world environments where multiple and varied distractions occur simultaneously. Future research should aim to replicate these findings in more ecologically valid settings to enhance the external validity of the results.

In conclusion, while this study provides important insights into the effects of cognitive distractions on balance, these limitations highlight the need for further research with larger, more diverse samples, a broader range of cognitive tasks, and more comprehensive measurement tools. Addressing these limitations will help to deepen our understanding of cognitive-motor interactions and improve strategies for maintaining balance and preventing falls in various populations.

4.5 Directions for Future Research

The findings of this study open several avenues for future research that can further elucidate the relationship between cognitive load, interlimb synchronization, and balance control. Addressing the limitations highlighted in this study will be crucial in advancing our understanding and developing more effective interventions.

Firstly, future research should aim to include larger and more diverse samples to increase the robustness and generalizability of the findings. Including participants with varying levels of physical and cognitive health, especially within older adult populations, will provide a more comprehensive understanding of how cognitive distractions impact balance across different demographics. Additionally, examining different age ranges, including middle-aged adults, could help identify critical periods where cognitive load begins to significantly affect postural control.

Secondly, it is important to incorporate a wider range of cognitive tasks that better represent the complexity and variety of real-world distractions. This could include tasks of varying difficulty, duration, and type, such as multitasking scenarios that combine cognitive and motor demands. By simulating more realistic cognitive loads, future studies can better assess the practical implications of cognitive distractions on balance and fall risk.

Longitudinal studies are also needed to explore the long-term effects of cognitive load on balance. Such studies could track changes in postural control over time, providing insights into how cognitive-motor interactions evolve with aging and whether interventions can have lasting benefits. Investigating the efficacy of cognitive training programs aimed at enhancing attentional control and reducing the impact of distractions on balance would be particularly valuable. These programs could be tailored to different age groups and levels of cognitive function to determine their effectiveness in improving balance and reducing fall risk.

Future research should also consider using more comprehensive and advanced measurement tools to assess balance. Incorporating wearable sensors, motion capture systems, and other technologies can provide a more detailed analysis of postural control and the specific mechanisms affected by cognitive load. These tools can capture dynamic aspects of balance, such as anticipatory postural adjustments and compensatory movements, which are crucial for understanding how cognitive distractions influence stability.

Another important direction for future research is to replicate and extend the findings in more ecologically valid settings. Conducting studies in environments that closely resemble real-world conditions, where multiple and varied distractions occur simultaneously, can enhance the external validity of the results. This approach will help to better understand how cognitive load impacts balance in everyday life and inform the development of practical interventions and environmental modifications to reduce fall risk.

Finally, interdisciplinary research that combines insights from cognitive psychology, neuroscience, and biomechanics can provide a more holistic understanding of cognitive-motor interactions. Collaborations across these fields can lead to the development of innovative strategies to maintain and improve balance, particularly in aging populations. Exploring the neural mechanisms underlying the effects of cognitive load on postural control using techniques such as functional MRI or EEG could also provide valuable insights into the brain's role in balance regulation.

In brief, future research should focus on expanding sample diversity, incorporating a broader range of cognitive tasks, conducting longitudinal studies, utilizing advanced measurement tools, and enhancing ecological validity. Interdisciplinary approaches and investigations into the neural mechanisms of cognitive-motor interactions will further deepen our understanding and contribute to the development of effective interventions for maintaining balance and preventing falls in various populations.

4.6 Conclusion

This study contributes to the understanding of how cognitive load influences interlimb synchronization and postural control, particularly in aging populations. The primary findings indicate that while interlimb synchronization and the overall magnitude of postural sway remain resilient to cognitive distractions, the dynamics of postural adjustments, as indicated by MSV, are significantly affected by cognitive load.

The resilience observed in interlimb synchronization and RMS sway suggests that the fundamental mechanisms of balance control, involving muscle coordination and stability, are robust against typical cognitive distractions. This aligns with prior research indicating that the body's balance mechanisms can maintain coordination between limbs even when attentional resources are divided. However, the significant increase in MSV under cognitive distraction conditions underscores the impact of cognitive load on the efficiency of postural control. This finding supports models such as the Central Capacity Sharing Model, which suggests that the brain dynamically allocates processing resources between tasks based on their demands (Bristow et al., 2016).

The implications of this study for fall prevention strategies are significant, particularly for aging populations. Given that cognitive distractions can increase postural sway velocity, interventions aimed at improving balance should incorporate cognitive training to enhance multitasking abilities. Additionally, environments for older adults should be designed to minimize cognitive distractions or environmental changes to reduce the risk of falls.

Despite the valuable insights gained, several limitations must be acknowledged. The sample size and demographic characteristics may limit the generalizability of the findings, and the cognitive tasks used might not fully capture the range of real-world distractions. Future research should focus on larger and more diverse samples, incorporate a broader range of cognitive tasks, and utilize advanced measurement tools to provide a more comprehensive assessment of balance. Longitudinal studies are needed to explore the long-term effects of cognitive load on balance, and interdisciplinary research should combine insights from cognitive psychology, neuroscience, and biomechanics to develop innovative strategies for maintaining and improving balance, particularly in aging populations.

In conclusion, this study highlights the need for a comprehensive approach to balance assessment and fall prevention that considers both physical and cognitive factors. By expanding our understanding of cognitive-motor interactions, this research contributes to the development of effective interventions for maintaining balance and preventing falls in various populations.

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Appendix A: Python Code for COP traces, Stabilogram, and CCF

```
import pandas as pd
import numpy as np
from scipy.signal import butter, filtfilt, correlate
import matplotlib.pyplot as plt

# Correction coefficient calculation
R = 10  # Maximum voltage range in volts
L = 16  # Number of bits
GL = 1000  # Gain factor for left force plate
GR = 2000  # Gain factor for right force plate
E = 10  # Excitation voltage in volts
F = 10 ** (-6)

kL = GL * E * F
correction_coefficient_L = kL
kR = GR * E * F
correction_coefficient_R = kR

# Calculate time values based on the sampling rate and number of data points
sampling_rate = 1024
seconds = 60
start = 15
start_time = start * sampling_rate
num_data_points = sampling_rate * seconds
time = np.arange(0, num_data_points) / sampling_rate

# Importing the spreadsheet into python
file_path = r"C:\Users\arash\OneDrive\Documents\YorkU\Master's
Thesis\Research Data\Participants\052\AJDTI052 WDEO.txt"
df = pd.read_csv(file_path, sep='\t', header=None, skiprows=start_time+2,
nrows=num_data_points)

# Defining which columns to look at
left_columns = df.iloc[:, 1:7]  # Columns C to H
right_columns = df.iloc[:, 7:13]  # Columns I to N

# Flattening the matrices into a 1 by 6
left_calibration_matrix = np.diag([0.6715, 0.6770, 0.1713, 1.7002, 1.7003,
3.3547]).flatten()
right_calibration_matrix = np.diag([0.66724, 0.66679, 0.16944, 1.62101,
1.61812, 3.30440]).flatten() # For FP5236 or (0.67071, 0.66722, 0.17330,
1.69096, 1.68874, 3.31232) for FP5439

# Although the matrices were flattened, I didn't know how to return the
values of the flattened matrices to their respective values
FxR_cal = right_calibration_matrix[0]
FyR_cal = right_calibration_matrix[7]
FzR_cal = right_calibration_matrix[14]
MxR_cal = right_calibration_matrix[21]
MyR_cal = right_calibration_matrix[28]
MzR_cal = right_calibration_matrix[35]
FxL_cal = left_calibration_matrix[0]
FyL_cal = left_calibration_matrix[7]
```

```
FzL_cal = left_calibration_matrix[14]
MxL_cal = left_calibration_matrix[21]
MyL_cal = left_calibration_matrix[28]
MzL_cal = left_calibration_matrix[35]

# Accessing columns by numeric indices
FxL_column = df.iloc[:, 1]
FyL_column = df.iloc[:, 2]
FzL_column = df.iloc[:, 3]
MxL_column = df.iloc[:, 4]
MyL_column = df.iloc[:, 5]
MzL_column = df.iloc[:, 6]
FxR_column = df.iloc[:, 7]
FyR_column = df.iloc[:, 8]
FzR_column = df.iloc[:, 9]
MxR_column = df.iloc[:, 10]
MyR_column = df.iloc[:, 11]
MzR_column = df.iloc[:, 12]

# Calibrating the columns
cal_FxR_column = (FxR_column / correction_coefficient_R) / FxR_cal
cal_FyR_column = (FyR_column / correction_coefficient_R) / FyR_cal
cal_FzR_column = (FzR_column / correction_coefficient_R) / FzR_cal
cal_MxR_column = (MxR_column / correction_coefficient_R) / MxR_cal
cal_MyR_column = (MyR_column / correction_coefficient_R) / MyR_cal
cal_MzR_column = (MzR_column / correction_coefficient_R) / MzR_cal
cal_FxL_column = (FxL_column / correction_coefficient_L) / FxL_cal
cal_FyL_column = (FyL_column / correction_coefficient_L) / FyL_cal
cal_FzL_column = (FzL_column / correction_coefficient_L) / FzL_cal
cal_MxL_column = (MxL_column / correction_coefficient_L) / MxL_cal
cal_MyL_column = (MyL_column / correction_coefficient_L) / MyL_cal
cal_MzL_column = (MzL_column / correction_coefficient_L) / MzL_cal

# Define filter parameters
fs = sampling_rate  # Sampling frequency in Hz
cutoff_freq = 10  # Cutoff frequency in Hz
filter_order = 4  # Low-pass

# Apply Butterworth filter for each COP column
filtered_cal_FxR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_FxR_column)
filtered_cal_FyR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_FyR_column)
filtered_cal_FzR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_FzR_column)
filtered_cal_MxR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MxR_column)
filtered_cal_MyR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MyR_column)
filtered_cal_MzR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MzR_column)
filtered_cal_FxL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_FxL_column)
filtered_cal_FyL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_FyL_column)
```

```
filtered_cal_FzL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_FzL_column)
filtered_cal_MxL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MxL_column)
filtered_cal_MyL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MyL_column)
filtered_cal_MzL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MzL_column)

# Calculate COP for AP and ML based on the columns after both filters
COP_AP_L = filtered_cal_MxL_column / filtered_cal_FzL_column
COP_AP_R = filtered_cal_MxR_column / filtered_cal_FzR_column
COP_ML_L = filtered_cal_MyL_column / filtered_cal_FzL_column
COP_ML_R = filtered_cal_MyR_column / filtered_cal_FzR_column

# Pairing the data sets
LF_COP = list(zip(COP_ML_L, COP_AP_L))
RF_COP = list(zip(COP_ML_R, COP_AP_R))

# Define the folder path where you want to save the files
folder_path = r"C:\Users\arash\OneDrive\Documents\YorkU\Master's
Thesis\Coding\Results"

# Plotting the COP stabilogram for ML and AP of the left and right foot
plt.figure(figsize=(10, 5))

# Left Foot COP
plt.subplot(1, 2, 1)
plt.plot(COP_ML_L, COP_AP_L, label='Left Foot')
plt.xlabel('ML COP (m)')
plt.ylabel('AP COP (m)')
plt.title('COP Trace - Left Foot')
plt.gca().set_aspect('equal', adjustable='box')
plt.legend()

# Right Foot COP
plt.subplot(1, 2, 2)
plt.plot(COP_ML_R, COP_AP_R, label='Right Foot')
plt.xlabel('ML COP (m)')
plt.ylabel('AP COP (m)')
plt.title('COP Trace - Right Foot')
plt.gca().set_aspect('equal', adjustable='box')
plt.legend()

# Export datasets to text files in the specified folder
np.savetxt(folder_path + "\\left_foot_cop_traces.txt",
np.column_stack((COP_ML_L, COP_AP_L)), delimiter='\t',
           header="ML COP (m)\tAP COP (m)", comments='')
np.savetxt(folder_path + "\\right_foot_cop_traces.txt",
np.column_stack((COP_ML_R, COP_AP_R)), delimiter='\t',
           header="ML COP (m)\tAP COP (m)", comments='')

# Maximize the plot window
mng = plt.get_current_fig_manager()
```

```
# Calculate COP for AP and ML based on the columns
COP_AP_L = filtered_cal_MxL_column / filtered_cal_FzL_column
COP_AP_R = filtered_cal_MxR_column / filtered_cal_FzR_column
COP_ML_L = filtered_cal_MyL_column / filtered_cal_FzL_column
COP_ML_R = filtered_cal_MyR_column / filtered_cal_FzR_column

# Remove means from COP_AP_L, COP_AP_R, COP_ML_L, and COP_ML_R
nomean_COP_AP_L = COP_AP_L - np.mean(COP_AP_L)
nomean_COP_AP_R = COP_AP_R - np.mean(COP_AP_R)
nomean_COP_ML_L = COP_ML_L - np.mean(COP_ML_L)
nomean_COP_ML_R = COP_ML_R - np.mean(COP_ML_R)

# Plotting the superimposed COP time series traces for ML and AP of the left
and right foot
plt.figure(figsize=(15, 5))

# AP COP
plt.subplot(1, 2, 1)
plt.plot(time, nomean_COP_AP_L*1000, label='AP COP Left Foot')
plt.plot(time, nomean_COP_AP_R*1000, label='AP COP Right Foot')
plt.xlabel('Time (s)', fontsize=18)
plt.ylabel('AP COP (mm)', fontsize=18)
plt.title('AP COP of Left and Right Foot Time Trace', fontsize=18)
plt.legend()

# ML COP
plt.subplot(1, 2, 2)
plt.plot(time, nomean_COP_ML_L*1000, label='ML COP Left Foot')
plt.plot(time, nomean_COP_ML_R*1000, label='ML COP Right Foot')
plt.xlabel('Time (s)', fontsize=18)
plt.ylabel('ML COP (mm)', fontsize=18)
plt.title('ML COP of Left and Right Foot Time Trace', fontsize=18)
plt.legend()

# Save the COP traces for AP and ML of the left foot to text files in the
specified folder
np.savetxt(folder_path + "\\left_foot_COP_ML.txt", np.column_stack((time,
nomean_COP_ML_L)), delimiter='\t',
           header="Time (s)\tML COP (mm)", comments='')
np.savetxt(folder_path + "\\left_foot_COP_AP.txt", np.column_stack((time,
nomean_COP_AP_L)), delimiter='\t',
           header="Time (s)\tAP COP (mm)", comments='')

# Save the COP traces for AP and ML of the right foot to text files in the
specified folder
np.savetxt(folder_path + "\\right_foot_COP_ML.txt", np.column_stack((time,
nomean_COP_ML_R)), delimiter='\t',
           header="Time (s)\tML COP (mm)", comments='')
np.savetxt(folder_path + "\\right_foot_COP_AP.txt", np.column_stack((time,
nomean_COP_AP_R)), delimiter='\t',
           header="Time (s)\tAP COP (mm)", comments='')

# Adjusting the spacing between subplots
plt.tight_layout()
```

```
# Normalize the COP signals
normalized_COP_AP_L = (COP_AP_L - np.mean(COP_AP_L)) / np.std(COP_AP_L)
normalized_COP_AP_R = (COP_AP_R - np.mean(COP_AP_R)) / np.std(COP_AP_R)
normalized_COP_ML_L = (COP_ML_L - np.mean(COP_ML_L)) / np.std(COP_ML_L)
normalized_COP_ML_R = (COP_ML_R - np.mean(COP_ML_R)) / np.std(COP_ML_R)

# Calculate cross-correlation for AP COP
cross_corr_AP = (correlate(normalized_COP_AP_L, normalized_COP_AP_R,
mode='same')) / num_data_points

# Calculate cross-correlation for ML COP
cross_corr_ML = (correlate(normalized_COP_ML_L, normalized_COP_ML_R,
mode='same')) / num_data_points

# Determine the length of the shorter array
length = min(len(COP_AP_L), len(COP_AP_R))

# Calculate the time lag values for the cross-correlation
time_lags = np.arange(-length // 2, length // 2)

# Find the index of the time lag closest to 0 for AP and ML
zero_index = np.abs(time_lags).argmin()

# Define the range around zero time lag (in milliseconds)
lag_range = 200  # milliseconds

# Find the indices corresponding to the lag range (-200ms to +200ms)
lag_range_indices = np.where((time_lags >= -200) & (time_lags <= 200))[0]

# Get the peak value within the lag range for AP COP
peak_index_AP =
lag_range_indices[np.argmax(cross_corr_AP[lag_range_indices])]

# Get the minimum value within the lag range for ML COP
min_index_ML = lag_range_indices[np.argmin(cross_corr_ML[lag_range_indices])]

# Get the peak time lag and value for AP COP within the specified range
peak_time_lag_AP = time_lags[peak_index_AP]
peak_value_AP = cross_corr_AP[peak_index_AP]

# Get the minimum time lag and value for ML COP within the specified range
min_time_lag_ML = time_lags[min_index_ML]
min_value_ML = cross_corr_ML[min_index_ML]

# Create a DataFrame for the cross-correlation results within the specified
range
cross_corr_data_within_range = pd.DataFrame({
    'Time Lag (ms)': time_lags[lag_range_indices],
    'Cross-correlation AP (ro)': cross_corr_AP[lag_range_indices],
    'Cross-correlation ML (ro)': cross_corr_ML[lag_range_indices]
})

# Find the peak and time = 0 values for AP cross-correlation within the
specified range
peak_AP_data_within_range = cross_corr_data_within_range.loc[
```

```
    cross_corr_data_within_range['Cross-correlation AP (ro)'].idxmax()]
zero_time_AP_data_within_range =
cross_corr_data_within_range.loc[cross_corr_data_within_range['Time Lag
(ms)'] == 0]

# Find the minimum and time = 0 values for ML cross-correlation within the
specified range
min_ML_data_within_range = cross_corr_data_within_range.loc[
    cross_corr_data_within_range['Cross-correlation ML (ro)'].idxmin()]
zero_time_ML_data_within_range =
cross_corr_data_within_range.loc[cross_corr_data_within_range['Time Lag
(ms)'] == 0]

# Create a DataFrame for the peak and time = 0 values within the specified
range
result_data_within_range = pd.DataFrame({
    'Peak Time Lag AP (ms)': [peak_AP_data_within_range['Time Lag (ms)']],
    'Peak Value AP': [peak_AP_data_within_range['Cross-correlation AP
(ro)']],
    'Zero Time Lag AP (ms)': [zero_time_AP_data_within_range.iloc[0]['Cross-
correlation AP (ro)']],
    'Min Time Lag ML (ms)': [min_ML_data_within_range['Time Lag (ms)']],
    'Min Value ML': [min_ML_data_within_range['Cross-correlation ML (ro)']],
    'Zero Time Lag ML (ms)': [zero_time_ML_data_within_range.iloc[0]['Cross-
correlation ML (ro)']]
})

# Export the result_data DataFrame to a text file in the specified folder
result_data_within_range.to_csv(folder_path +
"\\cross_correlation_results.txt", sep='\t', index=False)

print("Cross-correlation results exported to:", folder_path +
"\\cross_correlation_results.txt")

# Plotting the cross-correlation results for AP and ML COP
plt.figure(figsize=(12, 6))

# Cross-correlation for AP COP
plt.subplot(1, 2, 1)
plt.plot(time_lags, cross_corr_AP)
plt.xlabel('Time (ms)', fontsize=18)
plt.ylabel('Cross-correlation (ro)', fontsize=18)  # Adjusted ylabel
plt.title('Cross-correlation of AP COP', fontsize=18)
plt.xlim(-500, 500)  # Set the X-axis limit to show from -500ms to +500ms

# Plot the peak value and its coordinates for AP COP (multiplied by 1000)
plt.plot(peak_time_lag_AP, peak_value_AP, 'ro', label=f'Peak:
({peak_time_lag_AP:.4f} ms, {peak_value_AP:.4f})')
plt.plot(time_lags[zero_index], cross_corr_AP[zero_index], 'go',
         label=f'At 0 ms: ({time_lags[zero_index]:.4f} ms,
{cross_corr_AP[zero_index]:.4f})')

plt.axhline(0, color='gray', linestyle='dotted')
plt.axvline(0, color='gray', linestyle='dotted')
plt.legend()
```

```
# Cross-correlation for ML COP
plt.subplot(1, 2, 2)
plt.plot(time_lags, cross_corr_ML)
plt.xlabel('Time (ms)', fontsize=18)
plt.ylabel('Cross-correlation (ro)', fontsize=18)  # Adjusted ylabel
plt.title('Cross-correlation of ML COP', fontsize=18)
plt.xlim(-500, 500)  # Set the X-axis limit to show from -500ms to +500ms

# Plot the minimum value and its coordinates for ML COP (multiplied by 1000)
plt.plot(min_time_lag_ML, min_value_ML, 'ro', label=f'Minimum:
({min_time_lag_ML:.4f} ms, {min_value_ML:.4f})')
plt.plot(time_lags[zero_index], cross_corr_ML[zero_index], 'go',
         label=f'At 0 ms: ({time_lags[zero_index]:.4f} ms,
{cross_corr_ML[zero_index]:.4f})')

plt.axhline(0, color='gray', linestyle='dotted')
plt.axvline(0, color='gray', linestyle='dotted')
plt.legend()

# Adjusting the spacing between subplots
plt.tight_layout()

# Save the cross-correlation plots to text files in the specified folder
np.savetxt(folder_path + "\\cross_corr_AP.txt", np.column_stack((time_lags,
cross_corr_AP)), delimiter='\t',
           header="Time Lag (ms)\tCross-correlation (ro)", comments='')
np.savetxt(folder_path + "\\cross_corr_ML.txt", np.column_stack((time_lags,
cross_corr_ML)), delimiter='\t',
           header="Time Lag (ms)\tCross-correlation (ro)", comments='')

# Show the plots
plt.show()
```

Appendix A: Python Code RMS and MSV

```
import pandas as pd
import numpy as np
from scipy.signal import butter, filtfilt, correlate
import matplotlib.pyplot as plt

# Correction coefficient calculation
R = 10  # Maximum voltage range in volts
L = 16  # Number of bits
GL = 1000  # Gain factor for left force plate
GR = 2000  # Gain factor for right force plate
E = 10  # Excitation voltage in volts
F = 10 ** (-6)

kL = GL * E * F
correction_coefficient_L = kL
kR = GR * E * F
correction_coefficient_R = kR

# Calculate time values based on the sampling rate and number of data points
sampling_rate = 1024
seconds = 60
start = 15
start_time = start * sampling_rate
num_data_points = sampling_rate * seconds
time = np.arange(0, num_data_points) / sampling_rate

# Importing the spreadsheet into python
file_path = r"C:\Users\arash\OneDrive\Documents\YorkU\Master's
Thesis\Research Data\Participants\011\AJDTI011 COEC.txt"
df = pd.read_csv(file_path, sep='\t', header=None, skiprows=start_time+2,
nrows=num_data_points)

# Defining which columns to look at
left_columns = df.iloc[:, 1:7]  # Columns C to H
right_columns = df.iloc[:, 7:13]  # Columns I to N

# Flattening the matrices into a 1 by 6
left_calibration_matrix = np.diag([0.6715, 0.6770, 0.1713, 1.7002, 1.7003,
3.3547]).flatten()
right_calibration_matrix = np.diag([0.67071, 0.66722, 0.17330, 1.69096,
1.68874, 3.31232]).flatten()

# Although the matrices were flattened, I didn't know how to return the
values of the flattened matrices to their respective values
FxR_cal = right_calibration_matrix[0]
FyR_cal = right_calibration_matrix[7]
FzR_cal = right_calibration_matrix[14]
MxR_cal = right_calibration_matrix[21]
MyR_cal = right_calibration_matrix[28]
MzR_cal = right_calibration_matrix[35]
FxL_cal = left_calibration_matrix[0]
FyL_cal = left_calibration_matrix[7]
FzL_cal = left_calibration_matrix[14]
```

```
MxL_cal = left_calibration_matrix[21]
MyL_cal = left_calibration_matrix[28]
MzL_cal = left_calibration_matrix[35]

# Accessing columns by numeric indices
FxL_column = df.iloc[:, 1]
FyL_column = df.iloc[:, 2]
FzL_column = df.iloc[:, 3]
MxL_column = df.iloc[:, 4]
MyL_column = df.iloc[:, 5]
MzL_column = df.iloc[:, 6]
FxR_column = df.iloc[:, 7]
FyR_column = df.iloc[:, 8]
FzR_column = df.iloc[:, 9]
MxR_column = df.iloc[:, 10]
MyR_column = df.iloc[:, 11]
MzR_column = df.iloc[:, 12]

# Calibrating the columns
cal_FxR_column = (FxR_column / correction_coefficient_R) / FxR_cal
cal_FyR_column = (FyR_column / correction_coefficient_R) / FyR_cal
cal_FzR_column = (FzR_column / correction_coefficient_R) / FzR_cal
cal_MxR_column = (MxR_column / correction_coefficient_R) / MxR_cal
cal_MyR_column = (MyR_column / correction_coefficient_R) / MyR_cal
cal_MzR_column = (MzR_column / correction_coefficient_R) / MzR_cal
cal_FxL_column = (FxL_column / correction_coefficient_L) / FxL_cal
cal_FyL_column = (FyL_column / correction_coefficient_L) / FyL_cal
cal_FzL_column = (FzL_column / correction_coefficient_L) / FzL_cal
cal_MxL_column = (MxL_column / correction_coefficient_L) / MxL_cal
cal_MyL_column = (MyL_column / correction_coefficient_L) / MyL_cal
cal_MzL_column = (MzL_column / correction_coefficient_L) / MzL_cal

# Define filter parameters
fs = sampling_rate  # Sampling frequency in Hz
cutoff_freq = 10  # Cutoff frequency in Hz
filter_order = 4  # Low-pass

# Apply Butterworth filter for each COP column
filtered_cal_FxR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_FxR_column)
filtered_cal_FyR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_FyR_column)
filtered_cal_FzR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_FzR_column)
filtered_cal_MxR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_MxR_column)
filtered_cal_MyR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_MyR_column)
filtered_cal_MzR_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_MzR_column)
filtered_cal_FxL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_FxL_column)
filtered_cal_FyL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs / 
2)), cal_FyL_column)
```

```
filtered_cal_FzL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_FzL_column)
filtered_cal_MxL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MxL_column)
filtered_cal_MyL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MyL_column)
filtered_cal_MzL_column = filtfilt(*butter(filter_order, cutoff_freq / (fs /
2)), cal_MzL_column)

# Calculate weighted COP for AP and ML directions
# Using the filtered calibrated force and moment data
COP_AP_L = filtered_cal_MxL_column / filtered_cal_FzL_column  # Left COP AP
COP_ML_L = filtered_cal_MyL_column / filtered_cal_FzL_column  # Left COP ML
COP_AP_R = filtered_cal_MxR_column / filtered_cal_FzR_column  # Right COP AP
COP_ML_R = filtered_cal_MyR_column / filtered_cal_FzR_column  # Right COP ML

# Compute total vertical force
total_Fz = filtered_cal_FzL_column + filtered_cal_FzR_column

# Weighted COP
COP_net_AP = (
    COP_AP_L * (filtered_cal_FzL_column / total_Fz)
    + COP_AP_R * (filtered_cal_FzR_column / total_Fz)
)
COP_net_ML = (
    COP_ML_L * (filtered_cal_FzL_column / total_Fz)
    + COP_ML_R * (filtered_cal_FzR_column / total_Fz)
)
# Mean-removed COP
COP_net_AP = COP_net_AP - np.mean(COP_net_AP)
COP_net_ML = COP_net_ML - np.mean(COP_net_ML)
# Correct RMS calculation for AP and ML directions
RMS_AP = np.sqrt(np.sum(np.square(COP_net_AP)) / len(COP_net_AP)) * 1000  #
Convert to mm
RMS_ML = np.sqrt(np.sum(np.square(COP_net_ML)) / len(COP_net_ML)) * 1000  #
Convert to mm

# Calculate MSV (Mean Sway Velocity) for AP and ML directions
MSV_AP = np.sum(np.abs(np.diff(COP_net_AP))) / (num_data_points /
sampling_rate) * 1000  # mm/s
MSV_ML = np.sum(np.abs(np.diff(COP_net_ML))) / (num_data_points /
sampling_rate) * 1000  # mm/s

# Print results
print(f"RMS AP (mm): {RMS_AP}")
print(f"RMS ML (mm): {RMS_ML}")
print(f"MSV AP (mm/s): {MSV_AP}")
print(f"MSV ML (mm/s): {MSV_ML}")
```

Appendix B: Python Code for Beeswarm Plot of CCR Means

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load the data
file_path = r"C:\Users\arash\OneDrive\Documents\YorkU\Master's
Thesis\Research Data\Excel\Mixed Model ANOVA Spreadsheet.txt"
data = pd.read_csv(file_path, delimiter='\t')

# Renaming groups for clarity
data['Group'] = data['Group'].map({1: 'Young Adults', 2: 'Older Adults'})

# Define the conditions for comparison
conditions = ['AP COEO', 'AP NDEO', 'AP WDEO', 'AP COEC', 'AP NDEC', 'AP
WDEC',
              'ML COEO', 'ML NDEO', 'ML WDEO', 'ML COEC', 'ML NDEC', 'ML
WDEC']

# Create a new column for the type of condition (AP or ML)
data_melted = pd.melt(data, id_vars=['Participant', 'Group'],
value_vars=conditions,
                      var_name='Condition', value_name='Cross-correlation
(ρ)')
data_melted['Type'] = data_melted['Condition'].apply(lambda x: 'AP' if 'AP'
in x else 'ML')

# Set up the seaborn style
sns.set(style="whitegrid")

# Plotting
plt.figure(figsize=(14, 10))

# Create the bar plot with low opacity and bold outlines
ax = sns.barplot(data=data_melted, x='Condition', y='Cross-correlation (ρ)',
hue='Group',
                 palette='viridis', ci='sd', alpha=0.4, errcolor='gray',
errwidth=4, capsize=.22,
                 edgecolor='grey', linewidth=4)  # Added edgecolor and
linewidth

# Overlaying with swarmplot
sns.swarmplot(data=data_melted, x='Condition', y='Cross-correlation (ρ)',
hue='Group',
              palette='viridis', dodge=True, size=8, ax=ax)

# Adjusting the legend
handles, labels = ax.get_legend_handles_labels()
ax.legend(handles[0:2], labels[0:2], title='', fontsize=18, loc='upper
right', frameon=False, bbox_to_anchor=(1, 0.97))  # Moved legend lower

# Setting titles and labels
ax.set_xlabel('Condition', fontsize=22)
ax.set_ylabel('Cross-correlation (ρ)', fontsize=22)
```

```
# Adjusting the layout and displaying the plot
plt.xticks(rotation=45, ha='right', fontsize=12)
plt.tight_layout()
plt.show()
```

Appendix C: Berg Balance Scale Test

BERG BALANCE TESTS AND RATING SCALE

Patient Name ____
Date ____
Location ____
Rater ____

ITEM DESCRIPTION SCORE (0-4) Sitting to standing _____ Standing unsupported _____ Sitting unsupported _____ Standing to sitting _____ Transfers _____ Standing with eyes closed _____ Standing with feet together _____ Reaching forward with outstretched arm _____ Retrieving object from floor _____ Turning to look behind _____ Turning 360 degrees _____ Placing alternate foot on stool _____ Standing with one foot in front _____ Standing on one foot _____ TOTAL _____

GENERAL INSTRUCTIONS
Please demonstrate each task and/or give instructions as written. When scoring, please record the lowest response category that applies for each item.

In most items, the subject is asked to maintain a given position for a specific time. Progressively more points are deducted if the time or distance requirements are not met, if the subject's performance warrants supervision, or if the subject touches an external support or receives assistance from the examiner. Subjects should understand that they must maintain their balance while attempting the tasks. The choices of which leg to stand on or how far to reach are left to the subject. Poor judgment will adversely influence the performance and the scoring.

Equipment required for testing are a stopwatch or watch with a second hand, and a ruler or other indicator of 2, 5 and 10 inches (5, 12 and 25 cm). Chairs used during testing should be of reasonable height. Either a step or a stool (of average step height) may be used for item #12.

1. SITTING TO STANDING
INSTRUCTIONS: Please stand up. Try not to use your hands for support.
( ) 4 able to stand without using hands and stabilize independently
( ) 3 able to stand independently using hands
( ) 2 able to stand using hands after several tries
( ) 1 needs minimal aid to stand or to stabilize
( ) 0 needs moderate or maximal assist to stand

2. STANDING UNSUPPORTED
INSTRUCTIONS: Please stand for two minutes without holding.
( ) 4 able to stand safely 2 minutes
( ) 3 able to stand 2 minutes with supervision
( ) 2 able to stand 30 seconds unsupported
( ) 1 needs several tries to stand 30 seconds unsupported
( ) 0 unable to stand 30 seconds unassisted

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If a subject is able to stand 2 minutes unsupported, score full points for sitting unsupported. Proceed to item #4.

3. SITTING WITH BACK UNSUPPORTED BUT FEET SUPPORTED ON FLOOR OR ON A STOOL

INSTRUCTIONS: Please sit with arms folded for 2 minutes.
( ) 4 able to sit safely and securely 2 minutes
( ) 3 able to sit 2 minutes under supervision
( ) 2 able to sit 30 seconds
( ) 1 able to sit 10 seconds
( ) 0 unable to sit without support 10 seconds

4. STANDING TO SITTING

INSTRUCTIONS: Please sit down.
( ) 4 sits safely with minimal use of hands
( ) 3 controls descent by using hands
( ) 2 uses back of legs against chair to control descent
( ) 1 sits independently but has uncontrolled descent
( ) 0 needs assistance to sit

5. TRANSFERS

INSTRUCTIONS: Arrange chairs(s) for a pivot transfer. Ask subject to transfer one way toward a seat with armrests and one way toward a seat without armrests. You may use two chairs (one with and one without armrests) or a bed and a chair.
( ) 4 able to transfer safely with minor use of hands
( ) 3 able to transfer safely definite need of hands
( ) 2 able to transfer with verbal cueing and/or supervision
( ) 1 needs one person to assist
( ) 0 needs two people to assist or supervise to be safe

6. STANDING UNSUPPORTED WITH EYES CLOSED

INSTRUCTIONS: Please close your eyes and stand still for 10 seconds.
( ) 4 able to stand 10 seconds safely
( ) 3 able to stand 10 seconds with supervision
( ) 2 able to stand 3 seconds
( ) 1 unable to keep eyes closed 3 seconds but stays steady
( ) 0 needs help to keep from falling

7. STANDING UNSUPPORTED WITH FEET TOGETHER

INSTRUCTIONS: Place your feet together and stand without holding.
( ) 4 able to place feet together independently and stand 1 minute safely
( ) 3 able to place feet together independently and stand for 1 minute with supervision
( ) 2 able to place feet together independently but unable to hold for 30 seconds
( ) 1 needs help to attain position but able to stand 15 seconds with feet together
( ) 0 needs help to attain position and unable to hold for 15 seconds

8. REACHING FORWARD WITH OUTSTRETCHED ARM WHILE STANDING
INSTRUCTIONS: Lift arm to 90 degrees. Stretch out your fingers and reach forward as far as you can. (Examiner places a ruler at end of fingertips when arm is at 90 degrees. Fingers should not touch the ruler while reaching forward. The recorded measure is the distance forward that the finger reaches while the subject is in the most forward lean position. When possible, ask subject to use both arms when reaching to avoid rotation of the trunk.)
( ) 4 can reach forward confidently >25 cm (10 inches)
( ) 3 can reach forward >12 cm safely (5 inches)
( ) 2 can reach forward >5 cm safely (2 inches)
( ) 1 reaches forward but needs supervision
( ) 0 loses balance while trying/requires external support

9. PICK UP OBJECT FROM THE FLOOR FROM A STANDING POSITION
INSTRUCTIONS: Pick up the shoe/slipper which is placed in front of your feet.
( ) 4 able to pick up slipper safely and easily
( ) 3 able to pick up slipper but needs supervision
( ) 2 unable to pick up but reaches 2-5cm (1-2 inches) from slipper and keeps balance independently
( ) 1 unable to pick up and needs supervision while trying
( ) 0 unable to try/needs assist to keep from losing balance or falling

10. TURNING TO LOOK BEHIND OVER LEFT AND RIGHT SHOULDERS WHILE STANDING
INSTRUCTIONS: Turn to look directly behind you over toward left shoulder. Repeat to the right. Examiner may pick an object to look at directly behind the subject to encourage a better twist turn.
( ) 4 looks behind from both sides and weight shifts well
( ) 3 looks behind one side only other side shows less weight shift
( ) 2 turns sideways only but maintains balance
( ) 1 needs supervision when turning
( ) 0 needs assist to keep from losing balance or falling

11. TURN 360 DEGREES
INSTRUCTIONS: Turn completely around in a full circle. Pause. Then turn a full circle in the other direction.
( ) 4 able to turn 360 degrees safely in 4 seconds or less
( ) 3 able to turn 360 degrees safely one side only in 4 seconds or less
( ) 2 able to turn 360 degrees safely but slowly
( ) 1 needs close supervision or verbal cueing
( ) 0 needs assistance while turning

12. PLACING ALTERNATE FOOT ON STEP OR STOOL WHILE STANDING UNSUPPORTED
INSTRUCTIONS: Place each foot alternately on the step/stool. Continue until each foot has touched the step/stool four times.
( ) 4 able to stand independently and safely and complete 8 steps in 20 seconds
( ) 3 able to stand independently and complete 8 steps in >20 seconds
( ) 2 able to complete 4 steps without aid with supervision
( ) 1 able to complete >2 steps needs minimal assist
( ) 0 needs assistance to keep from falling/unable to try

13. STANDING UNSUPPORTED ONE FOOT IN FRONT

INSTRUCTIONS: (DEMONSTRATE TO SUBJECT) Place one foot directly in front of the other. If you feel that you cannot place your foot directly in front, try to step far enough ahead that the heel of your forward foot is ahead of the toes of the other foot. (To score 3 points, the length of the step should exceed the length of the other foot and the width of the stance should approximate the subject's normal stride width)

( ) 4 able to place foot tandem independently and hold 30 seconds
( ) 3 able to place foot ahead of other independently and hold 30 seconds
( ) 2 able to take small step independently and hold 30 seconds
( ) 1 needs help to step but can hold 15 seconds
( ) 0 loses balance while stepping or standing

14. STANDING ON ONE LEG

INSTRUCTIONS: Stand on one leg as long as you can without holding.

( ) 4 able to lift leg independently and hold >10 seconds
( ) 3 able to lift leg independently and hold 5-10 seconds
( ) 2 able to lift leg independently and hold = or >3 seconds
( ) 1 tries to lift leg unable to hold 3 seconds but remains standing independently
( ) 0 unable to try or needs assist to prevent fall

TOTAL SCORE (Maximum = 56: _______

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Appendix D: Activity-Specific Balance Confidence Scale Test

The Activities-specific Balance Confidence (ABC) Scale ©

Instructions: For each of the following activities, please indicate your level of balance confidence by choosing one of the points on the scale below from 0% to 100%.

If you do **not currently do the activity**, try and imagine how confident you would be if you had to do the activity. If you **normally use a walking aid to do the activity or hold onto someone**, rate your confidence as if you were using these supports. If you have any questions, please ask the administrator.

0%	10	20	30	40	50	60	70	80	90	100%
No Confidence										**Completely Confident**

"How confident are you that you can maintain your balance and remain steady when you...."

1. walk around the house? ____ %
2. walk up or down stairs? ____ %
3. bend over and pick up a slipper from the front of a closet floor? ____ %
4. reach for a small can off a shelf at eye level? ____ %
5. stand on your tip toes and reach for something above your head? ____ %
6. stand on a chair and reach for something? ____ %
7. sweep the floor? ____ %
8. walk outside the house to a car parked in the driveway? ____ %
9. get into or out of a car? ____ %
10. walk across a parking lot to the mall? ____ %
11. walk up or down a ramp? ____ %
12. walk in a crowded mall where people rapidly walk past you? ____ %
13. are bumped into by people as you walk through the mall? ____ %
14. step onto or off an escalator while holding onto a railing? ____ %
15. step onto or off an escalator while holding onto parcels such that you cannot hold onto the railing? ____%
16. walk outside on icy sidewalks? ____ %

Total Score: ____ % (add all percentages and divide by 16 or number of items completed)

1/1

Appendix E: Medical History Form

Subject ID:____________________ **Date:**____________________

Age: ________________ **Height:** ________________

Sex: _____________ **Highest level of Education Attained:** ___________________

CURRENT & PAST MEDICAL HISTORY FOR BALANCE ASSESSMENT

Instruction to participant: "Before we start the tests for your balance and walking, I would like to ask if there are any previous medical conditions or current symptoms that might influence the results of your balance or walking test or that we should be aware of for safety."

Balance/mobility status
Falls in the last 6 months? ❑ (1) yes ❑ (2) no How Many? _______ Circumstances: ____ ____ 'Near-falls' in the last 6 months e.g. slipped, tripped, stumbled or needed assistance to prevent a fall? ❑ (1) yes ❑ (2) no Circumstances: ____ ____ Current Functional Mobility Status : ❑ Independent ❑ No Aid ❑ Aid, specify: ____________ ❑ AFO, specify:____________
Do you exercise 30 mins/day 5 days per week? ❑ (1) yes ❑ (2) no Type of exercise: ________________________ Do you participate in sports? ❑ (1) yes ❑ (2) no Type of sport (s): ________________________ If yes, what level do you play? ❑ (1) Recreational ❑ (2) Competitive ❑ (3) Elite ❑ (4) Professional

Past or current diagnoses/conditions that may influence balance or walking assessment	
1. Central Nervous System (check all that apply)	
(a) Previous Head injury / Concussion	❑ Date:
(b) Stroke	❑
(c) Parkinson's/movement disorder	❑
(d) Multiple Sclerosis	❑
(e) Psychiatric /Mental Health (e.g. depression, anxiety)	❑
(f) Epilepsy/Seizure disorder	❑
(g) Cerebral Palsy	❑
(h) Other, specify:	❑
2. Vision/visual perception (check all that apply)	
a) Acuity	❑
b) (a) Cataracts	❑
c) (b) Glaucoma	❑
d) (c) Visual field deficit	❑
e) (d) Neglect	❑
f) (e) Other, specify:	❑

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3. Vestibular/ Hearing	
(a) Hearing problem	❑
(b) Vertigo and dizziness	❑
(c) Middle ear infection	❑
(d) Inner ear disorders	❑
(e) Gait and ataxia	❑
(f) Other, specify:	❑
4. Musculoskeletal	
(a) Osteoporosis	❑
(b) Arthritis (OA or RA)	❑
(c) Joint replacement/fusion	❑
(d) Previous orthopaedic surgery	❑
(e) Lower limb pain (e.g. joint muscle, limited ROM)	❑
(f) Back pain	❑
(g) Misc. joint or muscle disorder	❑
(h) Prosthetics	❑
(i) Other, specify:	❑
5. Other	
(a) Diabetes/Peripheral Neuropathy	❑
(b) Cancer	❑
(c) Migraines	❑
(d) Low blood pressure	❑
(e) Medications (sedatives, antidepressants, blood pressure medications)	❑
(f) Other, specify:	❑