Validation of Centre of Pressure Trajectory Measurement from a Pressure Tile System during Standing and Locomotor Tasks

by

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ABSTRACT

This study validated a portable pressure tile system (StepScan™) by comparing its centre of pressure (CoP) measurements to those from in-floor AMTI™ force plates during a dynamic Step-Up Step-Down (SUSD) task. Thirty healthy adults completed the task while data were collected simultaneously from both systems. Intraclass Correlation Coefficient analysis showed strong agreement across CoP metrics ($r > 0.88$, $p < 0.001$), with Bland-Altman plots indicating moderate agreement and no systematic bias. A secondary aim explored age-related differences in spatiotemporal parameters. Older adults exhibited significantly higher step width variability ($p < 0.05$), particularly in the mediolateral direction, suggesting reduced stability. A weak but positive correlation ($r= 0.44$, $R^2 = 0.191$) was observed between age and postural sway. Finally, time-varying CoP data from StepScan™ demonstrated reliable error estimates, supporting its use in clinical balance assessments outside lab settings. This is the first study to validate StepScan™ against a gold-standard force plate during a functional mobility task.

DEDICATION

I dedicate this paper to my loving parents and sister, who have always supported me throughout my journey and never once doubted my potential.

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I would like to express my deepest gratitude to Dr. Chris McGibbon for his invaluable supervision and guidance throughout these years. I also extend my heartfelt thanks to Luke Dillman and Brooke Peters for their support and assistance with this project.

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List of Symbols, Nomenclature or Abbreviations

AP: Anteroposter

CNS: Central Nervous System

CoM: Centre of Mass

CoP: Centre of Pressure

GLP: Double Integration Technique

GRF: Ground Reaction Force

LPF: Low-Pass Filter Method

ML: Mediolateral

PNS: Peripheral Nervous System

STEADI: STop Elderly Accidents, Deaths and Injuries

SUSD: Step Up/Step Down

TUG: Timed Up and Go

WFG: World Falls Guidelines

BoS:Base of Support

STS: Sit to Stand

SS: Static Stand

1. Introduction

1.1 Background and Rationale

Falls are the leading cause of injury-related hospitalizations in Canada, particularly among older adults (1). Fall-related injuries among Canadian seniors rose from 12.6% in 2003 to 16.2% in 2017–2018, highlighting a growing public health concern. Most falls led to broken or fractured bones, with hip fractures accounting for over one-third of fall-related hospitalizations among seniors (1). Impaired balance is a key risk factor for falls among older adults, along with other factors such as cognitive function impairments, hypotension, pain, certain medications, visual impairments, co-morbid disorders like diabetes, reduced muscular strength, and vitamin D insufficiencies (2, 3).

Falls can lead to significant adverse outcomes such as injuries, hospitalizations, and deaths (4). However, measuring fall risk among community-dwelling seniors presents significant challenges. The absence of a universally endorsed evaluation method complicates the process, as an assessment proven effective in one context may not be applicable in another (5, 6). Therefore, it is essential to develop a standardized approach for measuring fall risk.

Clinical fall risk assessment tools like the STEADI (STop Elderly Accidents, Deaths and Injuries) use simple algorithms to assess the risk of falling in the next 12 months (7). Still, research has shown that the STEADI assessment is not a reliable predictor of falls (7, 8). Clinical scales such as the Berg Balance Scale (BBS) and Mini Balance Evaluation System Test (BESTest) are commonly used for assessing functional

balance; however, their results may be influenced by the skills of different evaluators (10).

Researchers have used sophisticated tools like motion capture systems with highly precise optical tracking and in-floor force platforms to study gait and balance in older adults (11,12). Yet, these systems are expensive and lack portability, posing significant access challenges for clinics and nursing homes to acquire and utilize them effectively.

Wearable sensor systems have been instrumental in collecting data on gait characteristics in community settings (13–15), however, to our knowledge, wearable sensor systems have not been adopted by clinicians for routine fall risk assessment. Recent advancements in artificial intelligence enabled human body pose estimation from inexpensive cameras (16) hold promise for human movement tracking, but they have yet to be proven acceptable for clinical applications (17).

Portable gait analysis systems that consist of sensorized floor mats have been commercially available for decades, and include products such as GaitRite (CIR Systems, Inc, NJ, USA) and Zeno (ProtoKinetics LLC, PA, USA). While suitable for hospital clinics with adequate space (these devices require several meters of clear, well lit, space), they still pose challenges for use in homes or private clinics where older adults are more likely to be assessed for fall risk.

Pressure sensing floor tiles, such as StepScan™ (StepScan Technologies, Inc., Charlottetown, PEI, Canada) offer a potential solution to falls risk assessment in the home or community, as they possess the portability of other products like GaitRite and Zeno, but consist of user configurable 60cm x 60cm tiles (5mm sensor resolution), that

can be used individually or in combination to measure foot pressure distribution as well as foot-floor interactions (such as heel strike and toe-off events) during movement tasks.

Previous studies have used the StepScan™ as a gold standard tool for validating marker-less motion capture systems in walking gait (18). However, the validity of the StepScan™ CoP measurements and the ability of the device to detect age-related changes in postural sway during locomotor and balance tasks has not been established. The purpose of this thesis was to fill this gap in knowledge.

1.2 Aims and Objectives

The aims of this study were threefold: 1) to validate StepScan™ centre of pressure (CoP) measurement against CoP measurement from in-floor "force plates" which represent the industry gold-standard in human motion capture; 2) to evaluate whether balance and stepping stability parameters derived from StepScan™ CoP can discriminate between healthy young and older adults; and 3) to explore stepping stability responses to an auditory perturbation.

Healthy adults between 19 and older with no previous chronic health issues performed static standing (SS), five-times chair rise task (STS), and a repeated step-up/step-down (SUSD) task, where CoP measurement was being acquired simultaneously from StepScan™ and in-floor AMTI™ force plates. This allowed direct head-to-head comparison of CoP time series trajectories during standing and locomotor tasks, as well as comparison of parameters derived from the CoP trajectories that are commonly used to evaluate postural stability during standing and locomotor tasks. Accuracy threshold relative to the gold-standard force plate-based CoP (5mm) was then used to evaluate the

fidelity of StepScan™ measures and various statistical analysis (Intraclass Correlation Coefficient (ICC) and Limits of Agreement (LoA) analysis) used to evaluate equivalency. An Accuracy threshold of 5 mm, based on the gold-standard force plate CoP, was applied to assess the fidelity of StepScan™ measures. Equivalency was further evaluated using statistical analyses, including the Intraclass Correlation Coefficient (ICC) and Limits of Agreement (LoA)

Our secondary aim involved investigating the sensitivity of StepScan™ stability parameters to age-related changes in balance during the standing and locomotor tests. For healthy older adults these changes may not be severe enough to place them at risk for falling, but the ability to detect these subtle changes in stability would be an indicator that more significant changes due to pathology are likely to be detected. The objective therefore was to assess if there were between-group differences in StepScan™ stability measures for young and older adults in the study.

While tests of standing and locomotor performance can be helpful, another approach to studying stability is to perturb the system and measure the system's response (19). Perturbations during walking come in many forms and have been studied many ways (20). During a stepping task such as the SUSD, the stepping pace is controlled with a metronome, which allows the cadence cueing to be perturbed – speeding up or slowing down – hence requiring a motor response that temporarily "perturbs" the stepping pattern but in a safe manner (21). The tertiary aim was to study an auditory-cued cadence

perturbation during the SUSD to explore approaches for measuring dynamic stability of stepping in older adults.

This study is novel and important because the StepScan™ is already being utilized in research and clinical practice, but its measurement fidelity has yet to be reported. Nor has an ecologically feasible yet physically challenging protocol – the SUSD and the auditory-cued cadence perturbation test – been evaluated as a sensitive assessment of dynamic balance that can be performed in any limited space environment. This thesis addresses these important gaps in knowledge.

2. Literature Review

2.1 Importance of fall prevention in seniors.

Falls constitute the primary cause of injury-related hospitalizations in Canada, especially among older adults (1). Between 2010 and 2014, there were 304,610 admissions to emergency departments due to fall-related injuries, with nearly one-half of these patients subsequently requiring hospitalization (1). Notably, hospitalization rates escalate with age, reaching their peak among individuals aged 90 years and above. Females represent the majority of both emergency department and hospital admissions in this regard (22). These statistics highlight the significant impact of falls on older adults in Canada, emphasizing the need for preventive measures to reduce the burden on families and the healthcare system.

Impaired balance stands out as a significant risk factor for falls among older adults. Additionally, cognitive function impairments, hypotension, pain, certain

medications, visual impairments, reduced muscular strength, co-morbid disorders such as diabetes, and socio-economic factors such as poor nutrition, contribute to the risk (1, 2). Given these factors, falls demand careful consideration for effective prevention strategies.

Falls can have serious consequences, including injuries, hospitalizations, and fatalities. Even without causing significant trauma, falls can instill a fear of falling and lead to functional decline, further elevating the risk of hospitalization due to falls. This issue not only affects individual well-being but also places a substantial burden on the healthcare system (17, 18).

Falls often occur during routine daily tasks (25). According to a 2013 study by Robinovitch et al. (26), incorrect weight shifting during activities such as standing, sitting down, and walking was identified as the primary contributing factor to falls in nursing homes. Understanding these mechanisms is essential for informing the design of effective fall prevention strategies. However, relying on passive observation of real-life falls provides partial information necessary for designing prevention strategies. Using a proactive approach and identifying individuals at greater risk of falling is necessary to reinforce fall prevention strategies and reduce the long-terms costs of fall-related injuries.

2.2 How is fall risk assessed?

Various methodologies are available for assessing fall risk but they can be largely classified into non- or minimally-instrumented clinical scales based on timed physical tests or questionnaires (27), and instrumented approaches using motion capture technology (28–30). These assessments and devices are extensively utilized in both

research settings to determine an individual's risk of falling based on gait and movement characteristics (23, 25).

2.2.1 Clinical measures

Functional tests, such as the Timed Up and Go (TUG), have been utilized to predict potential fall incidents among older adults, yet the outcomes have yielded conflicting findings (9). While some studies support the TUG as a predictor of falls, others report limited sensitivity and specificity, leading to conflicting evidence regarding its predictive value (9). Clinical scales, including the Berg Balance Scale and the Mini Balance Evaluation System Test, are commonly employed for assessing functional balance; however, their results may be influenced by the skills of different operators (10). Another clinical tool, the Tinetti Scale, is used to evaluate balance and gait characteristics with the goal of identifying individuals at risk of falling; however, evidence of its predictive accuracy is mixed.(32).

Falls among older adults are a significant concern, leading to injuries, loss of independence, and death. Stopping Elderly Accidents, Deaths, and Injuries (STEADI) is a clinical fall risk screening and prevention method designed to address this issue. Utilizing clinical algorithms, these assessments integrate multiple risk factors to estimate an individual’s likelihood of falling. Such algorithms commonly evaluate a combination of demographic and medical factors. STEADI helps healthcare professionals identify fall risk in older adults and implement preventive measures to reduce this risk (33). Similarly, the World Falls Guidelines (WFG) use a stratification algorithm to classify community-dwelling older adults, aiding healthcare professionals in identifying and preventing falls

(34). By adopting these evidence-based approaches, we can better protect our older adult population and improve their quality of life.

Wearable sensor systems have proven invaluable in gathering data on gait characteristics and postural stability in community-dwelling environments, providing valuable insights into fall risk assessment. These systems have also been utilized in training machine learning models to predict fall risk, showing varying levels of success (35). Reported accuracy ranges from 62% to 100%, specificity from 35% to 100%, and sensitivity from 55% to 99%. While wearable sensor systems hold promise, further refinement is necessary, especially in assessing frailty in free-living conditions or during short walking segments (9).

2.2.2 Motion capture and wearable technologies.

Motion capture technology and wearable sensors are utilized in both clinical and research settings to facilitate the development of rehabilitation devices and enable fall prediction and prevention. These technologies play a pivotal role in monitoring body movements and physiological parameters to enhance conventional rehabilitation therapies (36). Furthermore, motion capture systems offer valuable feedback to both patients and therapists, allowing for the customization of training regimens for athletes and patients recovering from injuries or surgeries (36).

Motion capture systems offer high-end systems such as Vicon cameras, OptiTrack, and Xsense MVN, particularly in healthcare and clinical examination settings (1, 2). They play a pivotal role in assessing gait abnormalities across various conditions, including Parkinson's disease, stroke, neuromuscular disease, multiple sclerosis, cerebral

palsy, balance disorders, sports-related injuries, aging-related issues, falls, autism spectrum disorder, and performance analysis (33, 34). These systems enable real-time and comprehensive muscle evaluation during diverse activities, both indoors and outdoors, highlighting their potential applications in diagnosing skeletal muscle problems, evaluating musculoskeletal disorders, and assessing balance and gait control both before and after rehabilitation training or orthotic management (41).

These devices utilize infrared cameras to triangulate the location of retroreflective rigid bodies attached to the targeted subject, creating a 3D model of the body in space. This integration represents a significant advancement in motion capture technology, promising unparalleled precision and efficiency in analyzing human movement (42). Recent approaches, such as objective falls risk assessment using markerless motion capture combined with representational machine learning, further enhance this potential by enabling automated, non-invasive analysis of movement patterns to identify individuals at higher risk of falls, bridging the gap between laboratory-grade measurement and practical clinical applications (43).

2.2.3 Gaps in measuring fall risk in community-dwelling adults.

Muir et al. (2010) highlight a potential underreporting of fall events, particularly injurious falls, and note that the volunteer-based study sample may not represent the broader population of community-dwelling older adults (5). In a study by Wang et al. (2020), participants were among the healthiest older adults, raising uncertainty about the applicability of findings to frail individuals more susceptible to falls (6). The challenge persists in measuring fear of falling among high-risk, community-dwelling older adults

(44). Moreover, addressing the challenges of underreporting and sample representation in fall research is crucial for developing effective interventions and support systems for community-dwelling older adults at risk of falls. This necessitates better fall risk assessment technologies that can be deployed in the community.

Most studies lack clarity on outcome definitions and whether outcome assessors were blinded (45). The absence of a universally recommended test for fall risk assessment further complicates matters, as assessments validated in one setting may not hold in others (46). Overall, these limitations underscore the complexity and variability in studying fall risk among community-dwelling elderly, necessitating comprehensive and context-specific approaches.

2.3 Falls from a physical standpoint

Clinically, a fall is defined as "an event that results in a person coming to rest inadvertently on the ground or floor or other lower level" (47). This definition excludes events resulting from a major medical event such as a stroke or an overwhelming external hazard such as being pushed (41, 42). Whatever their cause, falls result from the inability to stabilize the total-body centre of mass (CoM) with respect to the base of support (BoS). While this can include slips and trips, many falls in older adults occur during simple weight transfer when transitioning between steps (50). Understanding the physiological factors contributing to falls is essential for effective fall prevention strategies and interventions, which requires an understanding of human dynamic balance.

2.3.1 Physiology of balance and postural control

Balance and posture maintenance relies on the harmonious integration of sensory information from various systems, including visual, vestibular, proprioceptive, and somatosensory. Weakness or impairment in any of these systems heightens the risk of falling and diminishes postural control (15, 19).

The vestibular system, situated within the peripheral nervous system, plays a crucial role in regulating body orientation and balance. The vestibular sensory system is located within the inner ear and serves as the body's mechanism for balance and spatial orientation. Specifically, the vestibular apparatus detects angular velocity of head rotations, linear acceleration of translational movements, and head displacement relative to gravity, while also contributing to non-motor functions such as regulating blood pressure to maintain posture (21). Responsible for detecting both head and body movements in three-dimensional space, the vestibular system also contributes to non-motor tasks such as regulating blood pressure to maintain posture (20). Detecting changes in head movement, including rotation and straight-line motion, provides the Central Nervous System (CNS) with information regarding one's movement, head placement, and spatial alignment in relation to gravity. Impairments to this system can disturb body orientation and control (21–23).

According to Mulavara et al. (2015), the vestibular system is involved in stabilizing the body in unsteady situations while standing and walking (24). Interference with the operation of the vestibular system during walking can particularly affect the coordination of head and torso movements, as well as overall mobility performance (24).

Recognizing the critical role of the vestibular system underscores the significance of minimizing external disruptions to enhance mobility performance.

The somatosensory system is a part of the nervous system responsible for various sensory functions, including proprioception and kinesthesia (51). According to Weber et al. (2012), somatosensory functions play an important role in normal motor planning and control (52). Additionally, Liu et al. (2023) emphasize that lower extremity muscle strength, proprioception, and tactile sensations are key factors for postural stability (53). Proprioception is a cumulative neural input to the CNS, which is located on the joints, skin, and tendons. Proprioception is important for balance and postural control (54).

The peripheral nervous system (PNS) includes several categories such as olfactory, auditory, and gustatory systems. These senses work in tandem to collect information about the body's environment (55). CNS on the other hand organizes the information being received (56). Timing and coordination are controlled by the cerebellum. The cerebellum is an area of the brain responsible for these functions. Damage to the cerebellum may cause discontinued movements (57).

2.3.2. Biomechanics of balance and posture

The CoM is an imaginary point in space that represents the central point of the body's mass. The CoP is the specific location where the ground reaction force (GRF) is applied on the contact surface between the body and the ground. The CoM and CoP, as fundamental parameters in biomechanics, provide crucial insights into human movement and balance (58,59). Coordinated movements of body segments play a crucial role in controlling the trajectory of the CoM during walking (49) and significant variability in

segmental configurations, impacting CoM stability in the vertical direction, is closely associated with the likelihood of future falls (49).

2.3.3 Centre of Mass (CoM)

Understanding the CoM trajectory is crucial in human movement, particularly during standing and walking, as it serves as an indicator of stability and fall prediction. The position of the CoM can be influenced by the shape and orientation of connecting body segments, and its estimation involves various methods, such as segmental kinematics, and double integration of GRF. These methods provide insights into CoM dynamics, aiding in the assessment of balance and movement control (60,61).

The CNS is pivotal in regulating the CoM concerning the BoS to maintain postural stability and balance. It achieves this by minimizing body tilts, ensuring the CoM projection stays within the BoS, and counteracting external forces such as gravity and inertia that could destabilize the body's posture. Additionally, the CNS influences CoM movement by managing the leg stance and adjusting foot placement in the leg swing to enhance ML gait stability. Moreover, the CNS is believed to possess an internal representation of the body's CoM relative to the BoS, formed through prior experiences (62). This internal model enables the CNS to execute rapid and reactive motor responses when exposed to external perturbations, contributing to the overall maintenance of postural control (63,64).

Whereas individual body segments of the human form may be considered to have fixed CoM’s in a body segment coordinate system, the whole-body CoM is not a fixed point in a body frame of reference, but rather reflects the instantaneous combined centre

of gravity of all the body segments (39) as illustrated in Figure 1. Although it is common practice in motion capture to use the centre of the pelvis (via pelvis markers) as a proxy measure of the CoM (65), Figure 1 demonstrates why this assumption is limited. As such, considerable resources are needed to estimate whole-body CoM during human activity, such as wearable sensor systems (eg. XSens motion capture suit) or multi-camera optical systems with whole-body marker tracking (eg. Vicon, Qualysis, Optitrak, etc.), which makes the CoM trajectory largely infeasible as a routine clinical measure.

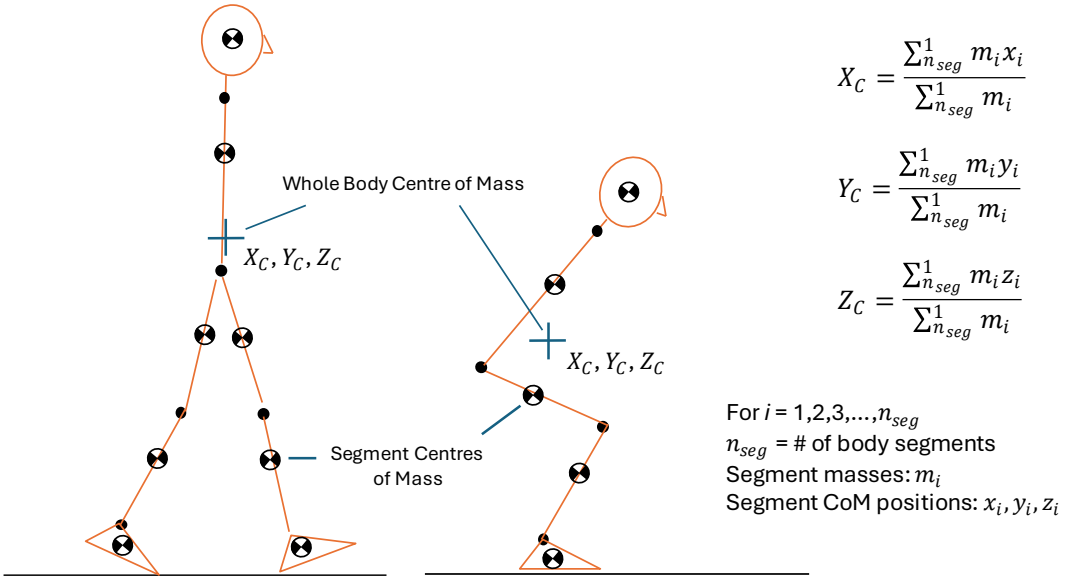

Figure 1. Whole body centre of mass (CoM) estimation from individual body segment masses and centres of mass.

Measurements assessing static postural sway also utilize force platforms, which include evaluating CoP coordinates (66). The postural control system must generate stabilizing moments to dynamically adjust the CoM over a shifting CoP within the base of support (BoS). Consequently, numerous methods for assessing postural stability have emerged, focusing on both CoM and CoP movements (67). Notably, however, there has

been a significant emphasis on measuring CoP due to its convenient evaluation using force plates, fostering active development in this area (68). Also notable is that portable gait systems like the StepScan™ system can only measure the CoP and therefore justifiably the primary focus of this thesis.

2.3.4 Centre of Pressure (CoP) and base of support (BoS)

The CoP is a key parameter used in many studies related to balance and is regarded as a significant clinical measure of postural stability, as evidenced by its application as a fundamental posturographic parameter used to assess postural stability (69–73). The CoP is used to measure neuromuscular control during posture and gait and can be used to identify balance control, foot function, and treatment efficacy (59,74,75). It is also the starting point for methods such as inverse dynamic analysis for computing joint moments and forces during movement (76).

In the context of human biomechanics and foot-floor interactions, the CoP is functionally defined as the point of intersection of the GRF vector on the plantar surface of the foot (77,78). More generally, however, the CoP is the projection of the body's CoM to a point intersecting the support surface, as shown in Figure 2. During single support of gait (or one limbed stance), the CoP of the plantar surface of feet and the CoM projection to the support surface are coincident. However, during the double support phase (or two limbed stance), while each plantar surface has a CoP, the CoM projection now represents a point between the foot CoPs, weighted to the vertical GRF under each foot.

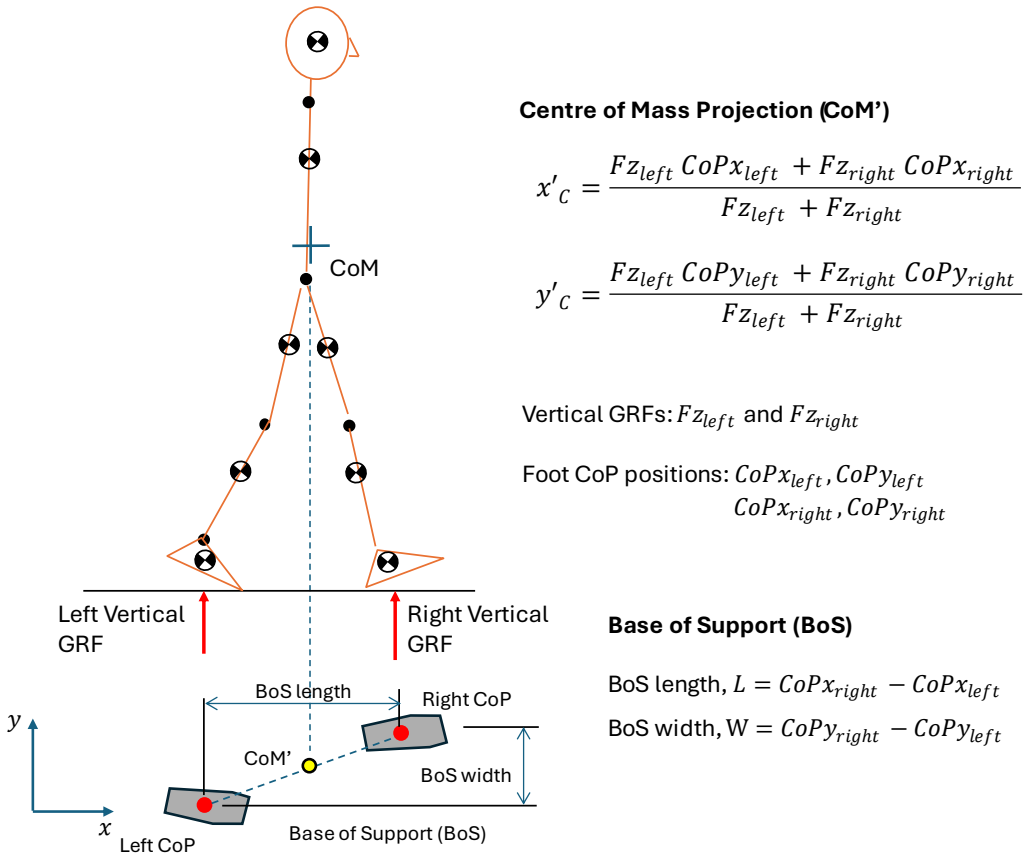

Figure 2. Centre of pressure (CoP) and Centre of mass projection (CoM') and base of support (BoS).

The method for calculating the CoP depends on how measurements are acquired. When using a force platform, the measured reaction forces and moments on the plate are used to estimate the centre of force, which is commonly termed "centre of pressure", as illustrated in Figure 3. When a single foot is in contact the force plate, the calculated CoP represents the CoP of the plantar surface of foot. In many applications, such as computerized posturography, both feet are either in contact with a single platform or the data from the two platforms will be combined (as shown in Figure 2), since the end goal is quantifying how the CoM moves within the BoS.

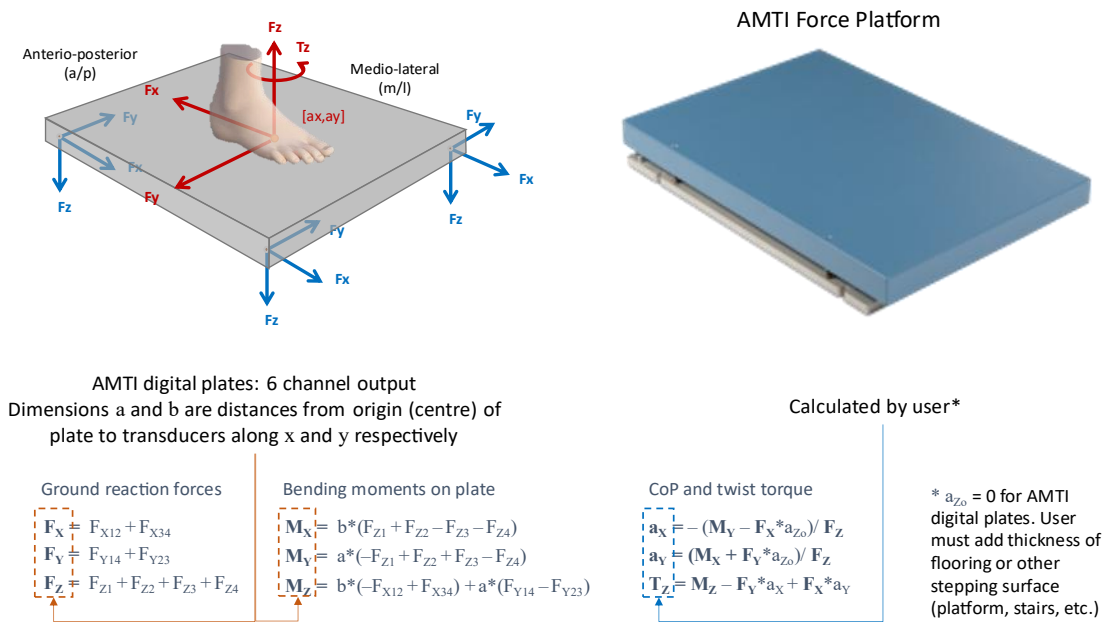

Figure 3. Force plate-based centre of pressure (CoP) estimation. AMTI™ digital plates output 6 channels (3 forces and 3 moments). Centre of pressure and twisting torque are calculated given a_{z0} which is the distance between the support surface (flooring, platform, stairs, etc.) and the force plate top.

When the measurement device is a pressure sensing instrument, such as the StepScan™ system, pressure in kPa is measured in each of the pressure sensing cells (120x120 for StepScan™, or 14400 piezoresistive sensors). Centre of pressure (CoP) for such a device is calculated from locating the "centre of force" based on the distribution of pressures measured between the object (foot) and the tile surface, as illustrated in Figure 4. Cells with pressure less than a given threshold (10kPa) are assigned zero and the data summated and shown the Figure 4 to calculate the total vertical force and the CoP coordinates.

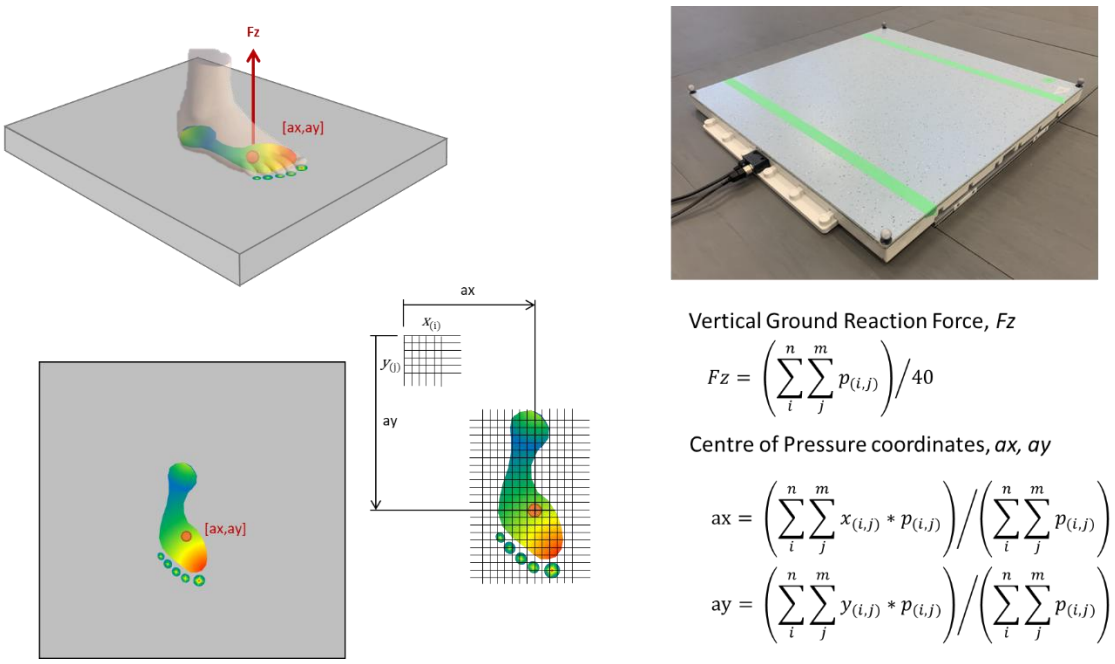

Figure 4. Pressure tile-based centre of pressure (CoP) calculation.

Regardless of the approach used, analyzing the CoP trajectory can allow researchers to understand how the body maintains stability and adjusts its movement in response to perturbation (60, 61), when measurements of the body CoM are unavailable or not feasible to acquire, such in a clinic. In fact, many research studies have focused solely on the CoP trajectory (ie. time-series of CoP X-Y coordinates) to assess body sway. The CoP coordinates, derived from GRF registered with a force platform, reflect the overall stability and organization of an individual's automatic postural responses.

For tests of standing balance, the standard deviation about the mean of the CoP in the mediolateral (M/L) and anteroposterior (A/P) directions is often used to quantify postural stability (80), as illustrated in Figure 5. Since abnormal sway direction may not

necessarily be isolated to M/L and A/L directions, a more recent approach suggests fitting the CoP X-Y trajectory to an ellipse that encloses 95% of the observations (81,82)

This is accomplished by first using a Principal Components Analysis to identify the major and minor axes of the CoP X-Y trajectory, and then estimating the major and minor diameters of the best-fitting ellipse, also shown in Figure 5. Another common parameter is the mean velocity of the CoP during quiet standing (82). As such, various kinematic parameters can be derived from the CoP trajectory in the ML and AP directions, hence it is a key measure in assessing postural control and any deviations therein (80,83,84).

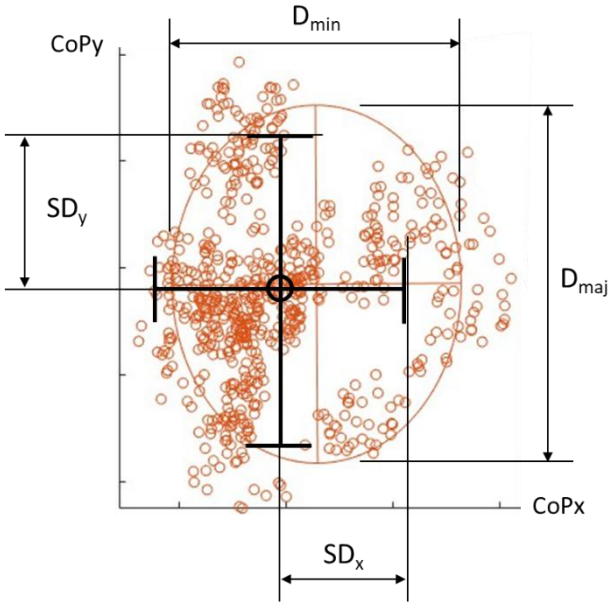

Figure 5. CoP X-Y trajectory during static standing showing different metrics for quantifying standing stability, such as the standard deviation of the mean (SD_x, SD_y) and the major and minor diameters of a best-fit ellipse (D_{maj}, D_{min}).

The BoS is closely related to stability. The BoS is defined as the area within the contact points of the body with the supporting surface, and stability requires that the

projection of the CoM of the body falls within this region (85). In static standing, stability increases with increases in BoS (86). In dynamic conditions, such as during gait, the CoM is in motion, while the BoS remains constant or changes dynamically during different standing stances (87), as shown in Figure 2. The majority of the gait cycle is spent in single-limb support (SLS), during which BoS is minimized to the area of the supporting foot (86) and the CoM temporarily moves outside the BoS, resulting in a forward acceleration of the CoM, which is arrested by the opposite foot, which then repeats the cycle. Dynamic stability is therefore achieved by controlling the CoM with respect to the ever-changing BoS (88).

2.3.5 Sit-to-stand analysis

Kinematics of the CoM during the STS, and by extension, the horizontal trajectory of the resulting CoP (at the intersection of the CoM force vector and the support surface) is a common measurement that is parameterized for assessing balance and mobility in older adults. Studies of chair rise performance in healthy and older adults have shown that the sit-to-stand (STS) task yields a rich set of spatiotemporal parameters including total rise time, trunk-flexion duration, weight-shift latency, peak vertical centre-of-mass (vCoM) velocity, and first-step latency—whose alterations signal declining balance control (89–91). Research shows that longer momentum-transfer and extension phases, along with greater horizontal CoM excursion, accompany age-related reductions in knee power (89), and that a longer weight-shift period and a delayed first step latency were linked to balance impairment in older adults. (91). As such, excursion

of the CoP and timing between repeated sit-to-stand cycles are variables easily acquired with force plates or pressure tiles.

2.3.6 Stepping parameter analysis

Spatiotemporal parameters in overground stepping analysis refer to the measurements that capture the spatial (distance) and temporal (time) aspects of human walking (76,92–94). These parameters are crucial in understanding the mechanics of human locomotion, diagnosing abnormalities, and evaluating the effectiveness of treatments or interventions (77, 79). Spatial parameters include stride length (the distance covered in one gait cycle), step length (the distance between the heel strike of one foot and the heel strike of the other foot), and width of the base of support (the distance between the two feet when standing). These parameters provide information about the distance covered in each step and the stability of the gait, and quite critically rely on the CoP when a floor-based measurement system is being used to measure gait parameters. They also provide critical information about "temporal parameters" which include stride time (the time taken for one gait cycle), step time (the time between the heel strike of one foot and the heel strike of the other foot), stance time (the time during which the foot is in contact with the ground), and swing time (the time during which the foot is not in contact with the ground) (77, 79), all of which require detecting CoP-related events.

In summary, while there are many important variables in human biomechanics, by all accounts the CoP ranks among one of the most utilized for research and for clinical translation.

2.4 Technologies for stepping stability analysis

Many studies explore the stepping stabilities using various technologies, such as force plates, motion capture systems, instrumented treadmills, pressure insoles, and wearable inertial sensors (96–101). The advantages of these instruments are that they have been used in research for a long time and they have been well validated. However, most of the gait analysis technologies mentioned are expensive and not portable.(102,103)

2.4.1 Motion capture laboratory research (CoP and CoM)

Motion capture laboratories play a pivotal role in studying human locomotion and balance, where key elements like the CoM and CoP take center stage (104,105). The CoM, a crucial parameter for understanding movement dynamics, is commonly estimated through intricate motion capture systems (106). Simultaneously, the CoP, essential for assessing balance and weight distribution, finds measurement through specialized force platforms within these research settings (107). These technologies work in tandem, offering comprehensive insights into the intricate mechanics underlying human movement, aiding in a deeper comprehension of locomotion and balance control.

2.4.2 Wearable sensors to measure CoM

Wearable devices that include micro-electronic machined (MEMs) sensors such as accelerometers, gyroscopes and magnetometers packaged as Inertial Measurement Units (IMU)s, have been studied for decades. In a study conducted by Park et al. (2015), accelerometer sensors were used in walking gait to estimate the CoM. Furthermore, the study found a high correlation between the CoM of the accelerometer system and the

CoM of the foot pressure sensor system for measuring gait characteristics (108) and can be used to estimate the CoM Velocity (VCoM) (109). In a study conducted by Gonzalez et al. (2012), researchers employed Microsoft Kinect sensors in conjunction with the Wii Balance Board to assess and estimate the CoM (61).

2.4.3 Portable gait analysis systems

StepScan™, developed by StepScan Technologies, Inc. based in Charlottetown, PEI, Canada, markets modular interconnectable tiles for gait analysis and balance assessment. This technology has the potential to be widely used in medical and sports settings to assist in diagnosing and treating movement and balance-related conditions. In rehabilitation contexts, this technology could be useful for assessing treatment outcomes in people with lower-extremity musculoskeletal impairments. However, limited research has been conducted to assess the accuracy and consistency of the StepScan™ system.

GaitRite is considered the 'gold standard' in portable gait parameter measurement and analysis, having been utilized in over 400 studies (110). The GaitRite system is a portable tool for automated gait analysis, enabling precise measurement of gait parameters. It consists of a 5.2 m long, and 90 cm wide carpet embedded with 16,128 sensors in a grid, which are activated by mechanical pressure. This setup allows for the measurement of various temporal and spatial parameters (111). However, the device has some limitations, including its requirement for significant space and its weight, making it challenging to manipulate.

Another gait analysis device that can be used is Zeno. It requires participants to walk along a specific path, turn around, and walk back. The Zeno system uses a camera

to record video of each walking bout and the ProtoKinetics Movement Analysis Software (PKMAS) software suite to synchronize and record both video and Pressure data (112). In contrast, the RehaGait system uses mobile inertial sensors attached to the shoes to measure linear acceleration, angular velocity, and the magnetic field of the foot (113). However, Zeno and other portable gait analysis devices often require a controlled environment and prescribed walking patterns, which may not accurately reflect a person's natural gait. These systems can be expensive and complex, requiring specialized training to use, which limits their accessibility (114).

While the advancements in portable gait analysis systems like StepScan™, GaitRite, and Zeno offer significant promise in clinical and sports settings, their practical application is often hampered by various limitations such as cost, complexity, and the need for controlled environments. These constraints highlight the need for further innovation and research to enhance the accuracy, usability, and affordability of gait analysis technologies. Addressing these challenges is crucial, especially given the broader context of falls among seniors, which necessitates effective and accessible tools for balance assessment and fall prevention.

2.5 Gap statement

Falls among seniors pose a significant threat to both individual well-being and the healthcare system, with Canada witnessing a considerable number of fall-related hospitalizations among older adults. Impaired balance, alongside various risk factors such as cognitive impairments, hypotension, and visual impairments, underscores the urgency for effective prevention strategies. Falls not only result in injuries and hospitalizations but

also instill a fear of falling and contribute to functional decline, exacerbating the risk of further falls. Understanding the mechanisms behind falls, including the role of the vestibular sensory system and the assessment of parameters like the CoM and CoP, is paramount for implementing targeted preventive measures.

Various assessment techniques, including clinical scales, motion capture systems, and wearable sensors, offer valuable insights into fall risk assessment, paving the way for tailored interventions. Furthermore, the advent of portable gait analysis systems like StepScan™ and GaitRite holds promise for enhancing gait assessment and rehabilitation, although further research is needed to quantify their accuracy and consistency.

For example, in a prior investigation conducted by McGuirk et al. (2022), StepScan™ was employed as the "gold standard" measurement to validate the Theia™ markerless motion capture system (18), for measuring 3D gait in a community setting. It is noteworthy to mention that to our knowledge StepScan™ itself has not undergone validation itself against an accepted industry gold standard. Consequently, the primary objective of this study is to fill this gap by validating the StepScan™ CoP measurement.

To our knowledge, no studies have been published yet to determine if StepScan™ tile measurements have the sensitivity to detect age-related changes in stepping dynamics during a prolonged stepping task, nor are there yet tested analytical techniques for utilizing StepScan CoP trajectories for quantifying dynamic balance.

Through this comprehensive endeavour, we aimed to significantly advance fall prevention and rehabilitation strategies, envisioning a safer and healthier environment for older adults. This work is not merely a prelude; it is a call to address the multifaceted issue of falls and harness the potential of advanced technology and precise gait analysis

for the benefit of older adults. Importantly, our study provides valuable insights into the potential advantages and limitations of the StepScan™ system in assessing stability during standing and locomotor tasks.

3. Methods

3.1 Aims and Hypotheses

3.1.1 Aim #1 – Validating StepScan™ CoP measurement

A convenience sample of thirty healthy participants performed static standing (SS), 5x sit-to-stand (STS) and step-up/step-down (SUSD) trials while data were collected simultaneously from StepScan™ pressure tiles positioned on top of synchronized in-floor AMTI™ force plates (see Figures 6 and 7). There were two objectives related to this aim:

3.1.1.1 Aim #1.1 – Time-Series Measurement Analysis

The first objective was to quantify the accuracy of CoP time-series data during standing and locomotor activities. Accuracy of the CoP is critical for many biomechanical and clinically important outcomes. While there is no singular accepted tolerance level on CoP accuracy, the StepScan™ tiles have a sensor resolution of 5mm, and therefore the target mean accuracy value was set at 5mm for error in CoP-X (A/P) and CoP-Y (M/L) coordinates.

Both the absolute error (in laboratory coordinates) and the relative error (after removing the bias) was compared to the target value using a one-sample *t*-test. Absolute

position error is a combination of random and systematic error, and would be relevant to studies or tests where the foot CoP position is needed relative to body coordinates tracked by other motion capture systems (eg. IMUs, motion cameras, etc.), such as an inverse dynamic analysis. The relative error is the random error component, and would be relevant to studies or tests where the absolute position is inconsequential, such as variability about a mean or stability of a trajectory.

Hypothesis H1.1a: *The mean absolute error in CoP will be 5mm or less in A/P and M/L directions for SS, STS and SUSD tests*. ***Hypothesis rejection criteria****: The mean absolute error is significantly more than 5mm.*

Hypothesis H1.1b: *The mean relative error in CoP will be 5mm or less in A/P and M/L directions for SS, STS and SUSD tests*. ***Hypothesis rejection criteria****: The mean relative error is significantly more than 5mm.*

The above analysis was then used to determine which functional activities (SS, STS and SUSD) had sufficient CoP accuracy for parameterization to derive stability scores: Activities where the relative CoP error met the 5mm threshold then went on to the next stage of analysis.

3.1.1.2 Aim #1.2 – Balance/Stability Measurement Analysis

While the CoP time-series may be of interest to researchers, clinicians are more likely to be interested in key parameters that can be derived from the CoP X-Y trajectory that are of interest for assessing balance and stability (82). For example, the spread of the CoP trajectory during a "static standing" balance test is often parameterized by

calculating the standard deviation in A/P and M/L directions (82,115), fitting the trajectory to an ellipse and quantifying the major and minor diameters and/or calculating the mean velocity of the CoP (82,116).

The chair-rise manoeuvre imposes high torque demands on the knees and hips, making it sensitive to age-related declines in lower-limb strength and balance control that may not be detected in static standing tasks (90). In particular, spatiotemporal parameters derived from CoP and CoM trajectories—such as prolonged rise time, delayed weight-shift initiation, and reduced vertical CoM velocity—have been associated with impaired postural transitions and increased fall risk in older adults. Scarborough et al. (2007) demonstrated that balance-impaired individuals exhibit prolonged weight-shift and first-step latency following chair rise, suggesting that temporal and CoP-based metrics are effective in differentiating mobility status when arm use is restricted (91).

Overground stationary stepping tasks, such as the SUSD have been studied where stepping stability was quantified as variability in the repeated pattern of CoM trajectory during the test (21). The CoM produces a relatively smooth trajectory, whereas the CoP has discontinuities and/or sharp transitions, but which can be parameterized in terms of variability in A/P excursion of the CoP (step length variability) and variability in M/L excursion of the CoP (step width variability), both of which are measured in units of mm and therefore have the same agreement criteria of 5mm.

Agreement between calculated stability parameters from StepScan™ and from the AMTI force plates was also evaluated with Intraclass Correlation Coefficient (ICC) analysis and Limit of Agreement (LoA) analysis. These data were used to test the following hypotheses:

Hypothesis H1.2a: *The mean difference between stability parameters derived from StepScan™ and force plate CoP for SS, STS and SUSD tests will be 5mm or less*. ***Hypothesis rejection criteria****: The mean difference is significantly more than 5mm*.

Hypothesis H1.2b: *ICC analysis (*$ICC_{(2,k)}$ *from* (117)*)between stability parameters derived from StepScan™ CoP versus force plate CoP will yield an ICC with lower bound of the 95% confidence interval* $\geq .7$. ***Hypothesis rejection criteria****: The lower-bound of the 95% confidence interval is* $<.7$.

Hypothesis H1.2c: *Limits of agreement analysis (via Bland-Altman plots* (118)*) between the StepScan™ and force plate derived stability parameters, will have a non-significant (*$p>.05$*) Kendall's tau-β correlation between difference scores and mean of scores.* ***Hypothesis rejection criteria****: Tau-β correlation is positive (*$\tau_\beta > .2$*) and significant (*$p<.05$*)*.

Parameters that met all three criteria (ie. were not rejected) then advanced to Aim 2 for group comparison analysis to quantify age-related effects in stability measures from the StepScan™ system.

3.1.2 Aim #2 – Sensitivity of StepScan™ to detect Age-Related Decline in Stability

It is well understood and documented in the literature that there are age-related changes in stability during standing and gait in the later years of life, even for older adults that are otherwise healthy and fit (119). Generally, these changes are not due to pathology or impairment but rather reflect the age-related decline in sensory organization (ie.

vestibular-visual-somatosensory) in vertebrate animals (120). As such these age-related changes can be subtle and often require a variety of investigative approaches to gain a clear picture of whether the changes are meaningful.

Such investigations often require posturography assessment using highly sensitive technologies such as the NeuroCom (121), or force plates in a clinical motion laboratory (122), both of which are expensive and lack accessibility. Here in Atlantic Canada, the closest location for computerized posturography assessment is in Halifax, NS. While these examinations are typically done to diagnose or to assess a known diagnosis of a movement-related disorder, the minimal sensitivity required to detect disability-related change would be the ability to detect declines with normal aging.

The purpose of Aim 2 was to determine if standing and locomotor stability measures from StepScan™ are sensitive enough to detect age-related declines in balance among otherwise healthy adults. Stability parameters that met all the above validity criteria were then compared between the younger (n=15, 19-64yrs) and older (n=15, >65 yrs) participants, to test the following hypotheses:

Hypothesis 2.1: *There will be a significant between-group difference ($p<.05$) in StepScan™ stability measures where older adults will be less stable during standing and locomotor activity than younger adults.* ***Hypothesis rejection criteria****: The null hypothesis is accepted that no significant difference is found ($p>.05$).*

Hypothesis 2.2*: There will be a significant ($p<.05$) and meaningful ($r>.3$) correlation between the age of participant and their StapScan™ stability scores.* ***Hypothesis rejection criteria****: The correlation is non-significant ($p>.05$) or explains too little variance ($r<.3$).*

Parameters that show age-related changes may also be good candidates for mobility and/or balance outcomes in older adults with aspecific balance issues with either standing or walking.

3.1.3 Aim #3 – Explore the SUSD auditory perturbation test

The tertiary aim was to explore approaches for utilizing time-varying CoP data from StepScan™ for studying postural control during the SUSD perturbation task, where the participants were asked to step to the metronome beat, initially at their preferred pace, and which switched to two different rates over the course of 90s (30s @ prefrred pace → 30s @ 120% preferred pace → 30s @ 80% preferred pace). While no formal analyses were planned for this aim, a variety of descriptive analyses were done to illustrate the potential of using a relatively subtle and easily implementable perturbation such as changing cadence during the SUSD test.

In summary, executing these aims will provide, for the first time, a direct comparison of StepScan™ measurement performance against an industry gold standard (AMTI™ force plates), and we will advance our understanding of the utility of the selected balance and mobility tests that can be performed in a home or clinic using the portable StepScan™ technology.

3.2 Participants

3.2.1 Human Subjects Sample

A convenience sample of 30 healthy adults between 19 to 64 years of age and older was asked to participate in the study. Although the activities being studied were common activities that people perform in their daily life, there are always risks inherent in activities that can challenge people, such as stepping repeatedly up onto and back off of a 10cm (4 inch) platform. For this reason, we first recruited and tested 15 younger adults (19-64 yrs), and having no issues or adverse events such as tripping or losing balance, then went on to recruit and test 15 older adults (65 yrs or older).

3.2.2 Recruitment and Screening

Recruitment was conducted via poster, email, and word of mouth by the PI and supervisor. Participation was strictly voluntary, and participants were informed they are able to withdraw from the study at any time, without penalty.

Potential participants were contacted by the Study Investigator by email, phone or in person to express interest in participating. The study Investigator initiated the “First Contact Script” which the Study Investigator used as a guide to explain their participation in the study and give the individual an opportunity to ask questions.

To ensure that the individual is eligible to participate without acquiring detailed information about their health, the first stage of screening was the “Healthy Subject Pre-Screening Form”. The pre-screen form asked the following questions:

1. which age category they fall into (under 19, between 19 and 65, and over 65)

2. whether they have one or more health conditions that could increase the risk of harm from participating in the study.

Participants 19 years old or older who answered no to the health screening questions and indicated their ascent to participate were provided with the "Informed Consent Form" (ICF) and the "Get Active Questionnaire" (GAQ). After completing the consent process (see below), participants completed the Canadian Society for Exercise Physiology GAQ as a final step in participant screening.

3.2.3 Inclusion and Exclusion Criteria

Participants included healthy adults aged 19 or older with no previous chronic injuries.

People with health conditions that could affect their ability or willingness to perform repetitive movement tasks that challenge their physical and mental capacity were excluded from the study. Examples include having a chronic (lasting longer than 6 months) musculoskeletal, neurological, cardiovascular, or other condition that causes pain, dizziness, or fatigue.

This exclusion included health conditions that are not actively being treated, if that condition could affect their ability or willingness to perform repetitive movement tasks that challenge their physical and mental capacity. Examples include pain or inflammation of the feet, legs or back, healing from recent injuries or other limb, body, or head trauma (concussion), or physical or mental fatigue from physical exercise.

3.3 Instrumentation

3.3.1 Motion Laboratory Set-up

Two StepScan™ tiles were placed on the force plates as shown in Figure 6. The "low" StepScan™ tile was placed directly on force plates #1 and #2. The "high" tile was placed on top of a rigid wooden box having a height of 10 cm (4 inches) which sat on force plates #3 and #4. Because the tiles are 60cm long x 60cm wide, and two adjacent force plates measure 60cm long x 80cm wide, the low and high tiles could be carefully aligned in the A/P (X) direction with the edges of the forces plates as a reference. Care was taken to position the tiles approximately along the centre line in the M/L direction.

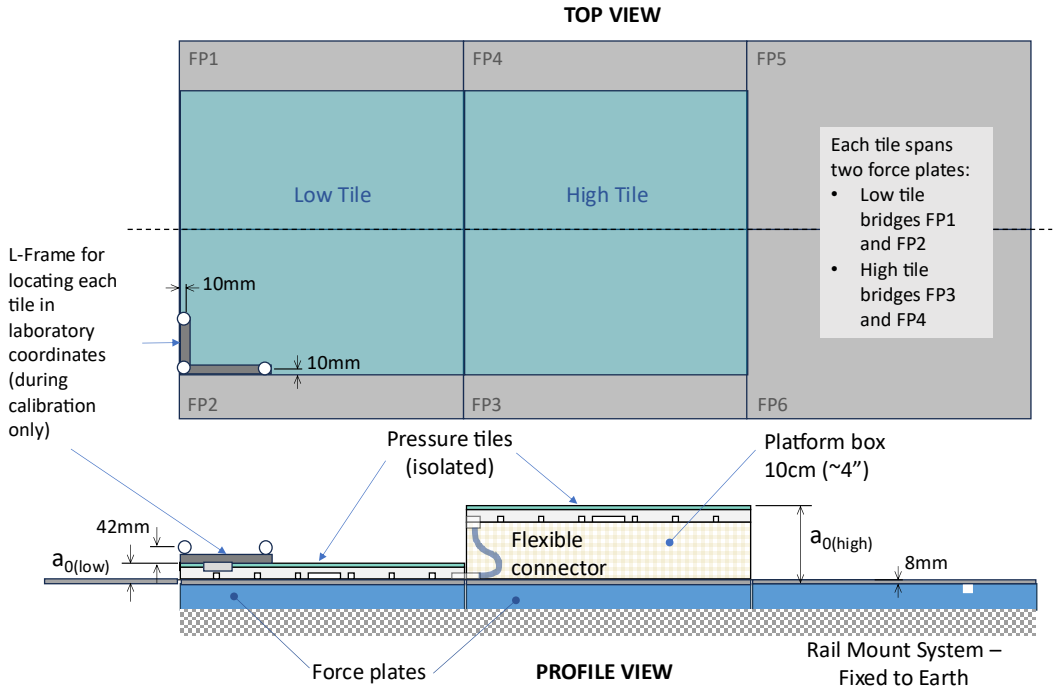

Figure 6. Experimental set-up of StepScan tiles on top of AMTI force platforms.

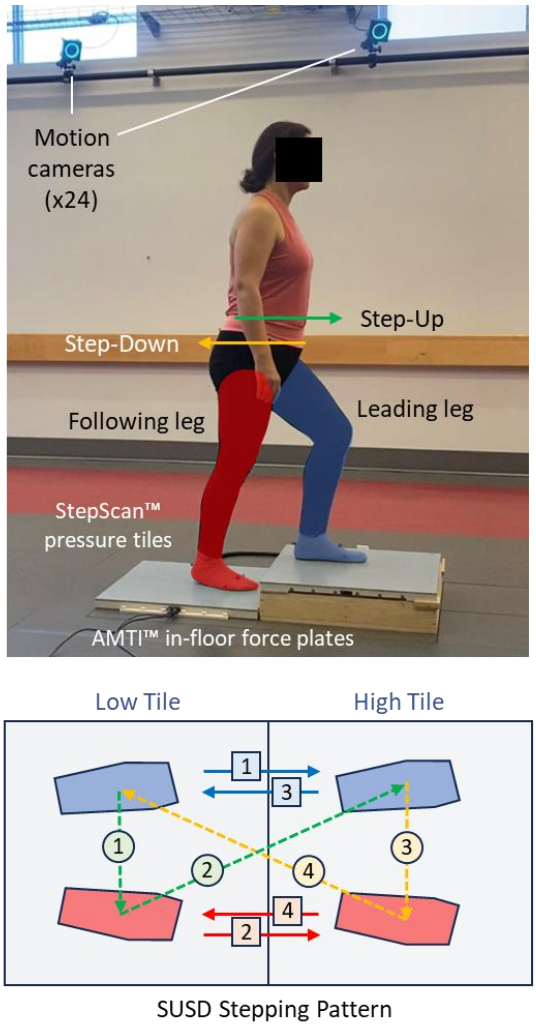

Figure 7. Step-up/Step-down (SUSD) test.

At the beginning of each data collection session, a calibration frame (L-Frame, Figure 6) was positioned on the right hand lower corner of each tile to precisely register its local coordinate (x-y-z) system in the global laboratory coordinate (X-Y-Z) system. Additional motion capture markers were initially attached to the outer edges of the tiles in order to correct any tile movement that might occur during testing; however, after the first 15 participants it was determined to be unnecessary. Due to the weight of the tiles

and their large contact surface with the underflooring, they were found to be very stable and did not shift position during any testing sessions with study participants.

3.3.2 StepScan™ Technology

StepScan™, developed in Charlottetown, PEI, is a pressure-sensitive electronic floor tile system designed to capture and analyze balance and mobility during standing and walking tasks. What makes the StepScan™ system unique compared to other portable gait mat technologies (e.g., GaitRite, Zeno) is that the tiles are modular (60cm x 60cm, or 2' x 2') and interconnectable on all four sides (see Figure 4). Tiles can also be connected on different levels with a custom flexible cable (as illustrated in Figure 6).

3.3.3 AMTI™ force plate technology

The IBME CARE mobility lab currently has 6 AMTI force platforms (400mm x 600mm) installed in sunken pits in the centre of the laboratory. AMTI™ force plates were installed by AMTI technicians, which involved epoxying a metal rail system to the bottom of the concrete (ground level) pit, which secures the plates to the earth's mass.

Unlike the StepScan™ tile which measures surface pressure, the force platform measures a single resultant force acting through the centre of pressure of the foot, based on force and moment readings from the four transducers (3 axis) located near the corners of the force plate top (see Figure 4). Because the StepScan™ tile sits upon two force plates, effectively bridging them, the signals from the x, y and z transducers were further combined as if the two plates were one by summing the forces and moments of the two plates. As such, FPs 1+2 corresponded to the Low tile, and FPs 3+4 corresponded to the High tile, and the CoP coordinates calculated as shown in Figure 4, where the term "a_0"

was the distance between the AMTI surface and the plantar surface, defined by the height of each tile as determined during calibration.

3.3.4 Metronome for pacing trials

Critical for executing the SUSD perturbation trials is an auditory cue for controlling the participant's step pacing. An electronic metronome was custom-built using an Arduino™ board. The device outputs a 5v pulse at pre-set intervals, and was integrated with the Motive data collection system for synchronous analog recording (1000Hz) with force platforms.

3.4 Data collection procedures

Following consent and enrollment procedures, participants was scheduled for a one-time visit to the IBME CARE facility for testing.

3.4.1. Preparation

Prior to participant arrival, the StepScan tiles were first arranged on the force platform array and the Optitrack L-Frame calibration device was then used to reference the corner origin of the Low and High tile, as shown in Figure 6.

Upon arrival at the CARE facility, participants changed from their street clothes into clothing appropriate for data collection, using a private change room with lockers. Participants were informed at enrollment of the dressing requirements: a tight-fitting T-shirt or tank-top, tight-fitting shorts (or yoga pants), and a pair of indoor soft-sole shoes or sneakers. Pre-laundered clothing and footwear were available for those who did not possess the required clothing.

A qualified researcher attached the reflective markers to the participants' feet, and pelvis as shown in Figure 8.

Marker Label	Description
Pelvis	
RASIS	Right Anterior Superior Iliac Spine
RPSIS	Right Posterior Superior Iliac Spine
LASIS	Left Anterior Superior Iliac Spine
LPSIS	Left Posterior Superior Iliac Spine
Right Foot	
RFM	Right 1st Metatarsal
RVM	Right 5th Metatarsal
RSM	Right 2nd Metatarsal
RCA	Right Calcaneus (Heel)
Left Foot	
LFM	Left 1st Metatarsal
LVM	Left 5th Metatarsal
LSM	Left 2nd Metatarsal
LCA	Left Calcaneus (Heel)

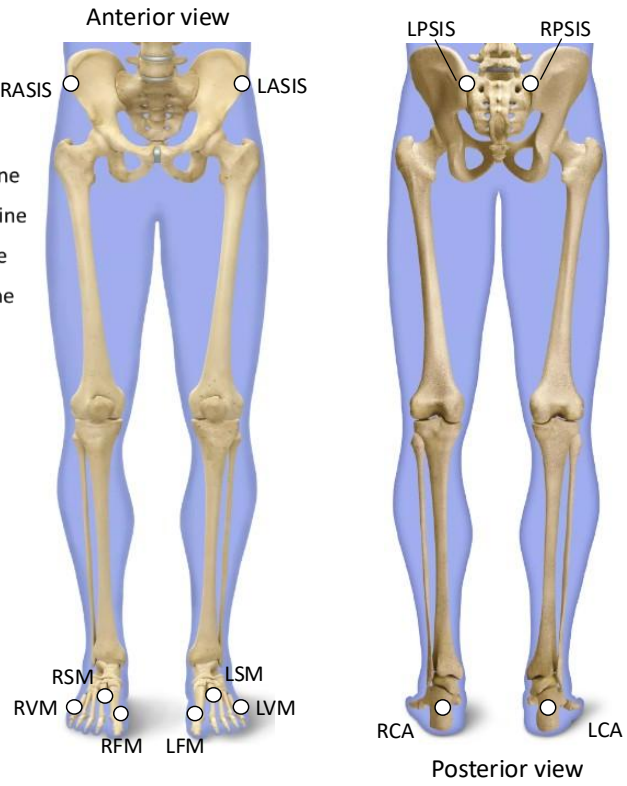

Figure 8. Marker set used for motion tracking.

3.4.2 Procedures

Participants then performed a series of activity trials consistent with the three common activities performed for clinical assessment of balance and mobility in older adults: standing, sit-to-stand, and stepping.

3.4.2.1 Static standing

Participants performed three sets of quiet standing tests with their feet shoulder-distance apart and their eyes open. Each standing test was conducted for 10 seconds. One test was

performed while standing on FPs 5 and 6 (no tiles), one while standing on the Low tile (on top of FP 1+2), and one while standing on the High tile (on top of FP 3+4).

3.4.2.2 Five times Sit-to-Stand

Participants performed a test requiring five repeated sit-to-stands from an armless and backless chair, while their feet were placed on the StepScan™ Low tile (on top FP 1+2) and chair (wooden box) positioned on the High tile (on top of FP 3+4).

3.4.2.3 Step-up/Step-down protocol

Participants were first asked to identify their dominant limb by identifying which leg they would use to kick an imaginary ball rolled toward them. This was necessary because the SUSD task required only one leg to perform all the upward motion during the task.

Next, participants were asked to walk around the indoor track in the lab, completing a full circuit counter-clockwise three times. These data were used to determine the participants' self-selected walking pace, or cadence (steps/min). The operator then entered the participants' cadence values into the metronome software, plus two additional metronome settings: one that was 20% faster (denoted as "fast") and another that was 20% slower (denoted as "slow") than their preferred walking pace. To control for potential order effects, the starting leg (dominant or non-dominant) was randomized across participants.

The protocol then proceeded as follows:

1. **SUSD Dominant**: With the metronome set at the participant's preferred pace, the participant started the SUSD protocol by stepping up with their dominant limb and continued stepping up and back down for 30 seconds.

2. **SUSD Non-dominant**: With the metronome set at the participant's preferred pace, the participant started the SUSD protocol by stepping up with their non-dominant limb and continued stepping up and back down for 30 seconds.
3. **SUSD Dominant w/ perturbation**: Stepping first with their dominant limb, the trial started at the preferred pace for 30 seconds, transitioned to the slow pace for 30 seconds, and then transitioned to the fast pace after another 30 seconds.
4. **SUSD Non-dominant w/ perturbation**: Stepping first with their non-dominant limb, the trial started at the preferred pace for 10 seconds, transitioned to the slow pace for 10 seconds, and then transitioned to the fast pace after another 10 seconds.

Participants were allowed to rest for 1-2 minutes (as needed) between trials.

3.5 Data processing

The IBME CARE facility has fully integrated force plates with the OptiTrack motion capture system via Motive software, with synchronized triggering of StepScan and the accompanying metronome. After each data collection session, raw motion capture trials were first reviewed and labeled in Motive. Markers were identified and labeled manually as needed, followed by gap-filling and basic trajectory cleaning. Once trials were finalized, they were exported in C3D format for further analysis. A custom Matlab application was then used to process the StepScan and Motive data, ensuring a consistent and efficient workflow to preserve data fidelity. Additional custom Matlab programs were used to conduct the analyses specific to this project.

3.5.1 Statistical analysis

As detailed in 3.1, each aim of the project has an associated data analysis plan. The primary outcome for Aim 1.1 was the mean unsigned difference (herein referred to as the "mean error") between StepScan™ and in-floor AMTI™ force plate CoP measurements. Mean error was evaluated for CoP coordinates in the X (anterior-posterior or AP) and Y (medio-lateral or ML) directions using the entire CoP trajectory for each task. The mean errors were calculated two ways: 1) "Absolute error" refers to mean error in CoP X-Y coordinates in the global (laboratory) frame of reference, and 2) "Relative error" refers to the mean error in CoP X-Y coordinates after removing the mean from the trajectory.

For Aim #1.2, the main statistical analysis was the ICC, which was used to assess the absolute agreement between CoP measurements from StepScan™ and CoP measurements from in-floor force plates, with a lower bound of .7 prescribed for the 95% confidence interval on the ICC. In addition, we examined the mean absolute error relative to an accepted tolerance (1 sensor dimension or 5mm) using a one-sample t-test, and we analyzed Bland-Altman plots and tested for heteroscedasticity (relationship between mean difference and the sample mean) using a Tau-Beta correlation analysis.

For Aim #2, we conducted independent samples t-tests between young and older participants groups for each of the StepScan™ parameters that met the error tolerance criteria for each of the performed tasks (standing, sit-to-stands and SUSD). In addition, Pearson correlations were conducted to quantify the relationship between participant age and the magnitude of the StepScan™ parameters. This analysis was used to determine which, if any, StepScan™ output metrics were sensitive to healthy aging, which will

provide insight for interpreting data from future studies in older adults with medical conditions affecting walking and/or balance.

Aim #3 was exploratory, and while no specific plans existed for statistical approaches, the goal was to test the idea of incorporating an auditory perturbation (changing metronome beat) into the SUSD protocol as a further challenge task for quantifying dynamic motor response in older adults. Results of this exploratory analysis are descriptive only.

4. Results

4.1 Participants

Thirty healthy volunteers between the ages of 19 and 86 participated in the study, as summarized in Table 1. Participants were recruited through word of mouth or by responding to posters placed throughout the city of Fredericton. The younger adult group consisted entirely of students from the University of New Brunswick. The older adult group was recruited through other ongoing research projects at the University of New Brunswick, as well as through local community groups. Most participants learned about the study through word of mouth, often from friends who had already taken part.

Table 1. Participant characteristics and starting limb randomization for SUSD.

Group† (N)		Age (years)		Weight (kg)		Height (cm)		Starting limb*	
		Mean	SD	Mean	SD	Mean	SD	D	ND
19-64 yrs (15)	F (9)	27.7	8.8	62.2	12.1	166.1	8.7	4	5
	M (6)	26.8	7.4	74.8	6.9	176.5	7.1	3	3
65+ yrs (15)	F (11)	73.2	5.5	61.8	11.1	159.4	6.4	5	6
	M (4)	71.5	2.9	94.1	21.8	181.8	7.5	3	1

* D=Dominant limb; ND=Non-dominant limb; † F=Female; M=Male.

4.2 Aim #1 – Validation of StepScan™ CoP Measurement

4.2.1 Aim #1.1 – Time-Series Measurement Analysis

CoP position errors with respect to the "gold standard" AMTI™ force plates are summarized in Figure 9 for both absolute (top panel) and relative (bottom panel) position errors.

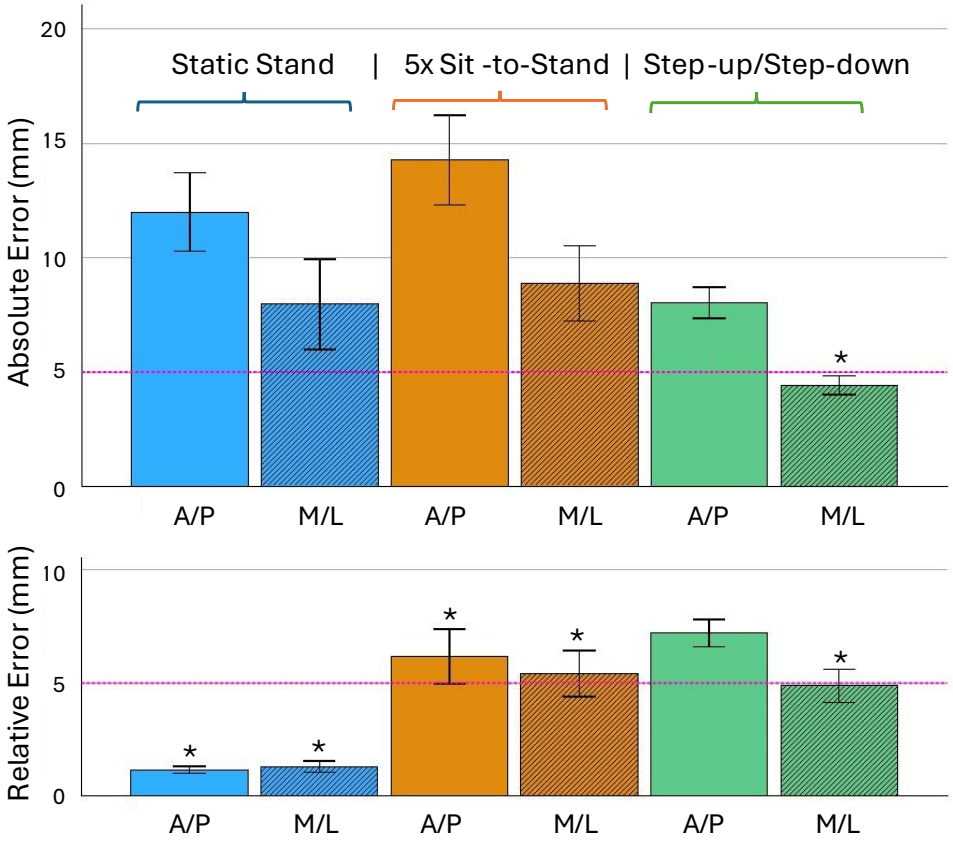

Figure 9. CoP errors in X (A/P) and Y (M/L) directions for Static Standing, 5x Sit-to-Stand, and Step-Up/Step-Down test. Top panel shows absolute errors calculated from global CoP x-y coordinates. Bottom panel shows relative errors calculated from removing the mean from the CoP x-y trajectories. The horizontal dashed line shows the 5mm threshold. * Error meets threshold of ≤ 5mm.

Results of H1 hypothesis tests are shown in Tables 2 and 3, as detailed below.

4.2.1.1 Mean Absolute Error in CoP

Hypothesis H1.1a: *The mean absolute error in CoP will be 5mm or less in A/P and M/L directions for SS, STS and SUSD tests*. ***Hypothesis rejection criteria****: The mean absolute error is significantly more than 5mm.*

Mean absolute errors are shown in Table 2, for **static standing**, the absolute CoP error was significantly higher than 5 mm in both the X (11.67±4.76 mm, $p < .001$) and Y direction (7.96±5.19 mm, $p = .005$), indicating poor agreement with force plate measures. Similarly, during the **sit-to-stand** task, absolute CoP errors were above threshold in both X (14.14±5.09 mm, $p < .001$) and Y (8.72±4.31 mm, $p < .001$) directions. For the **SUSD task**, the X direction error was greater than 5mm (8.03±1.78 mm, $p < .001$), while the Y direction error was significantly below the threshold (4.42±1.08 mm and $p = .007$), suggesting acceptable agreement in the M/L direction for this task.

Table 2. Absolute (global position) CoP error during standing and locomotor activities.

Absolute CoP error (mm)				Test Value = 5mm One-sample t-test	
		Mean	Std. Deviation	Diff [95% CI]	p-value
Static stand	X	11.67	4.76	6.67 [4.90, 8.45]	<.001
	Y	7.96	5.19	2.96 [0.99, 4.93]	.005
Sit-to-stand	X	14.14	5.09	9.14 [7.24, 11.04]	<.001
	Y	8.72	4.31	3.72 [2.11, 5.33]	<.001
Step-up/down	X	8.03	1.78	3.03 [2.35, 3.71]	<.001
	Y	4.42	1.08	-.58 [-.99, -.17]	.007*

* Meets accuracy requirement of ≤ 5mm.

4.2.1.2 Mean Relative Error in CoP

Hypothesis H1.1b: *The mean relative error in CoP will be 5mm or less in A/P and M/L directions for SS, STS and SUSD tests*. ***Hypothesis rejection criteria****: The mean relative error is significantly more than 5mm.*

When subtracting off the trial mean for StepScan and AMTI trajectories, the relative CoP error was well below the 5 mm threshold for **static standing** in both the X (1.14±.42 mm, $p < .001$) and Y (1.31±.64 mm, $p < .001$) directions, indicating excellent agreement. However, for the **sit-to-stand** task, relative CoP errors were not different from the threshold in X (6.06±3.18 mm, $p = .077$) and Y (5.39±2.64 mm, $p = .423$) directions. In the **SUSD task**, error in the X direction exceeded the threshold (7.22±1.58mm, $p < .001$), but did not differ significantly from the threshold in the Y direction (4.88±1.90 mm, $p = .728$).

Table 3. Mean relative CoP error during standing and locomotor activity.

Relative CoP error (mm)				Test Value = 5mm One-sample t-test	
		Mean	Std. Deviation	Diff [95% CI]	p-value
Static stand	X	1.14	.42	-3.86 [-4.01, -3.70]	<.001*
	Y	1.31	.64	-3.69 [-3.93, -3.44]	<.001*
Sit-to-stand	X	6.06	3.18	1.06 [-.13, 2.24]	.077*
	Y	5.39	2.64	.39 [-.59, 1.38]	.423*
Step-up/down	X	7.22	1.58	2.22 [1.62, 2.82]	<.001
	Y	4.88	1.90	-.12 [-.85, .60]	.728*

* Meets accuracy requirement of ≤ 5mm.

The above analyses showed that the relative CoP trajectory measured by StepScan™ was sufficiently accuracy to parameterize CoP trajectories in both X (A/P) and Y (M/L) for static standing, and at least in the Y (M/L) direction for locomotor tests.

4.2.2 Aim # 1.2– Balance/Stability Measurement Analysis

4.2.2.1 Static Standing Balance Parameters

Acording to the Table 4, all five static standing parameters—standard deviation in both A/P (SDy) and M/L (SDx) directions, major and minor diameters of an ellipse (Dmaj, Dmin), and mean CoP velocity (Vel)—showed **mean differences under 1 mm**, all well below the 5 mm threshold. ICC values were **exceptionally high** (ranging from .936 to .978), with all lower bounds of the 95% confidence intervals above. The 1-tailed t-tests confirmed that differences were statistically significant but not practically meaningful, as they remained within the 5 mm threshold.

Table 4. Static stand stability measures from StepScan and AMTI centre of pressure (CoP) measurements.

Static Stand balance parameter		Mean	SD	Diff (SD)	Diff < 5mm 1-tail t-test p-value	Absolute agreement ICC(2,k)	[95% CI]
SDx	SS	8.52	4.41	0.59 (1.13)	<.001	.977	[.942 - .990]
	FP	7.97	3.88				
SDy	SS	6.01	3.06	0.44 (1.15)	<.001	.959	[.910 - .981]
	FP	5.57	3.03				
Dmaj	SS	17.8	10.12	0.89 (4.64)	.003	.936	[.866 - .969]
	FP	16.9	8.71				
Dmin	SS	8.34	4.23	0.17 (1.45)	<.001	.968	[.933 - .985]
	FP	8.17	3.92				
Vel	SS	16.1	6.89	0.17 (2.07)	<.001	.978	[.954 - .989]
	FP	15.9	7.01				

SDx,y = Standard deviation of CoP in x and y directions; Dmaj,Dmin = Major and minor diameters of an ellipse fit to CoP trajectory; Vel = mean resultant velocity of CoP.
SS=Based on CoP from StepScan tile; FP=Based on CoP from AMTI force plate

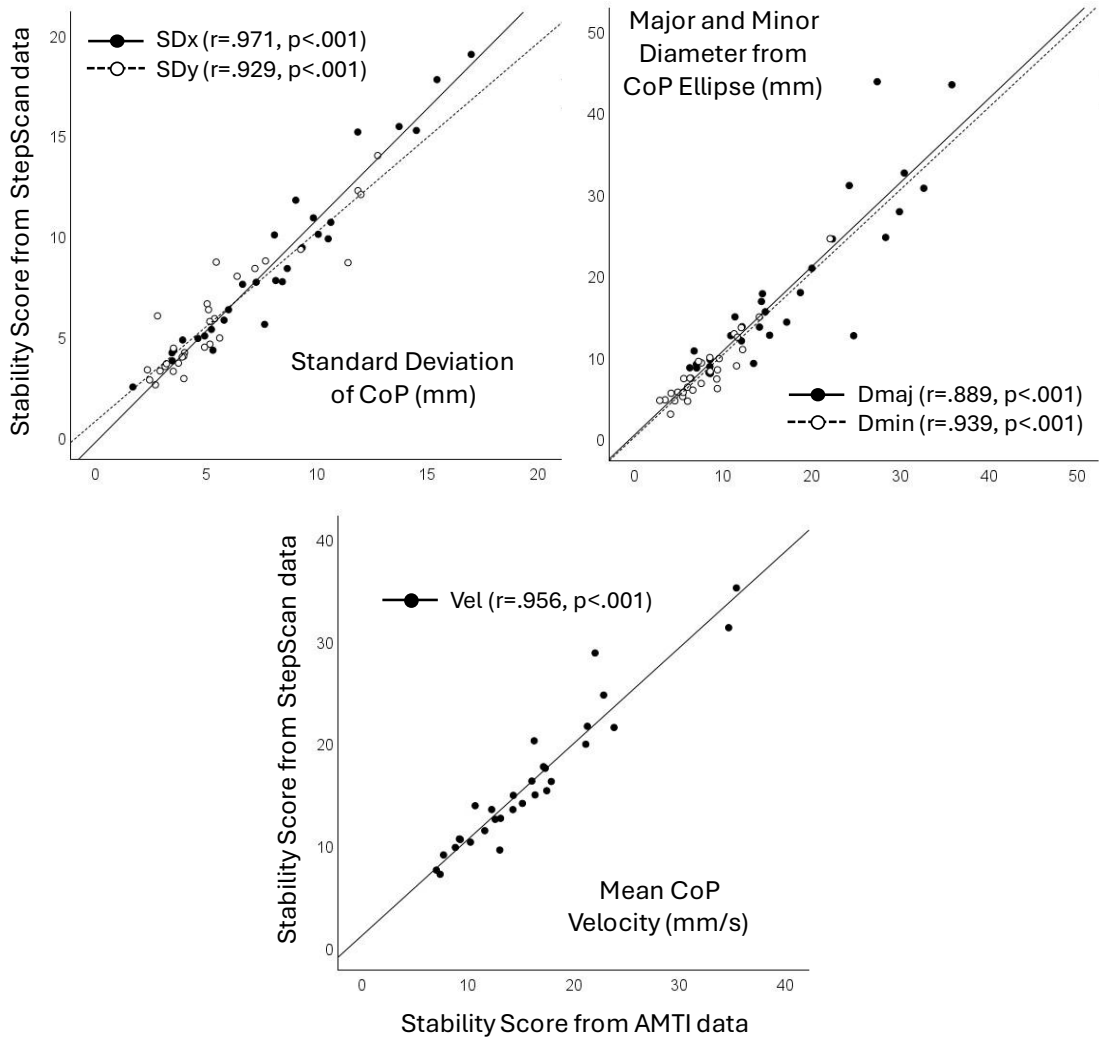

Figure 10. Scatter plots with Pearson correlation tests between StepScan (Y axis) and AMTI (X axis) for balance parameters: SDx,SDy = Standard deviation of CoP; Dmaj,Dmin = Major and minor diameter of 95% ellipse; Vel = mean CoP velocity.

Correlation plots for standing balance parameters are shown in Figure 10 and LoA plots are shown in Figure 11. Consistent with the ICC analysis, Pearson correlation coefficients shown in Figure 10 were found to be high for all the parameters analyzed

(r>.88) and LoA plots in Figure 11 showed no significant bias or heteroschedasticity for the major and minor diameter parameters (Dmaj, Dmin) and the mean CoP velocity (Vel). Conventional standard deviations scores (SDx, SDy) also passed Kendall's tests, but did however show significant bias (p=.011 and p=047, respectively).

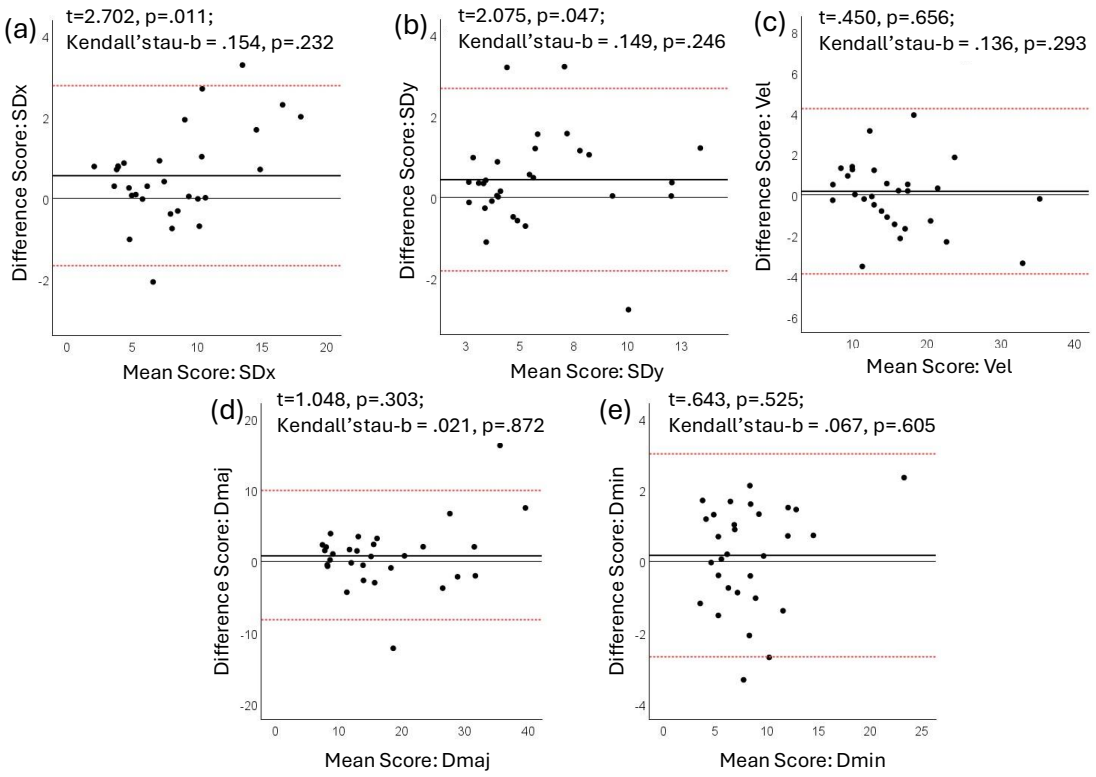

Figure 11. Limits of agreement plots for static standing balance parameters. (a) CoP X excursion variability (SDx); (b) CoP Y excursion variability (SDy); (c) mean CoP velocity; (d) Ellipse major diameter (Dmaj); (e) Ellipse minor diameter (Dmin). Single-sample t-test result (diff=0) and Kendall's tau-beta correlation are included. The heavy horizontal line is the mean difference score and the red dashed lines are the +/- boundaries defined by 1.96 x standard deviation of the mean difference.

4.2.2.2 Five times Sit-to-Stand (5xSTS) CoP Excursion Variability

Table 5. 5x sit-to-stand stability measures from StepScan and AMTI centre of pressure (CoP) measurements.

Sit-to-Stand balance parameter		Mean	SD	Diff (SD)	1-tail t-test p-value	Absolute agreement ICC(2,k)	[95% CI]
APvar	SS	19.4	6.76	3.87 (3.71)	.119	.816	[.120 - .939]
	FP	15.5	5.55				
MLvar	SS	14.4	5.50	1.22 (3.81)	<.001	.826	[.626 - .919]
	FP	13.1	4.58				
Var	SS	24.6	7.36	3.85 (4.10)	.150	.825	[.244 - .940]
	FP	20.7	6.00				
tVar	SS	.233	.202	-.011 (.036)	.946	.992	[.983 - .996]
	FP	.243	.216				

APvar = Standard deviation of CoP excursion in x direction (test value=5mm); MLvar = Standard deviation of CoP excursion in y direction (test value=5mm); Var = Combined APvar and MLvar (test value=5mm); tVar = Standard deviation in chair sit-to-stand time (test value=.01s).
SS=Based on CoP from StepScan tile; FP=Based on CoP from AMTI force plate

Among the 5xSTS balance parameters, **MLvar** showed a statistically significant difference between StepScan™ and force plate measurements ($p < .001$), indicating potential measurement bias in the medial-lateral direction. However, **APvar**, **Var**, and **tVar** did not differ significantly from the 5 mm or 0.01 s thresholds ($p > .05$), suggesting acceptable agreement. Notably, **tVar** demonstrated excellent reliability with an ICC of .992, indicating near-perfect agreement.

As shown in Figure 12, the Pearson correlations were still relatively high (>.73), and LoA plots in Figure 13 shows that only **tVar** and **MLvar** passed the test for bias (p=.101 and p=.142, respectively) and had non-significant Kendall's tau-b (p=.0323 and p=.609 respectively). **APvar** and the combined **Var** did not pass either the test for bias

(p<.001 for both) and significant tau-b (tau-b=.275, p=.04 and tau-b=.291, p=.030, respectively).

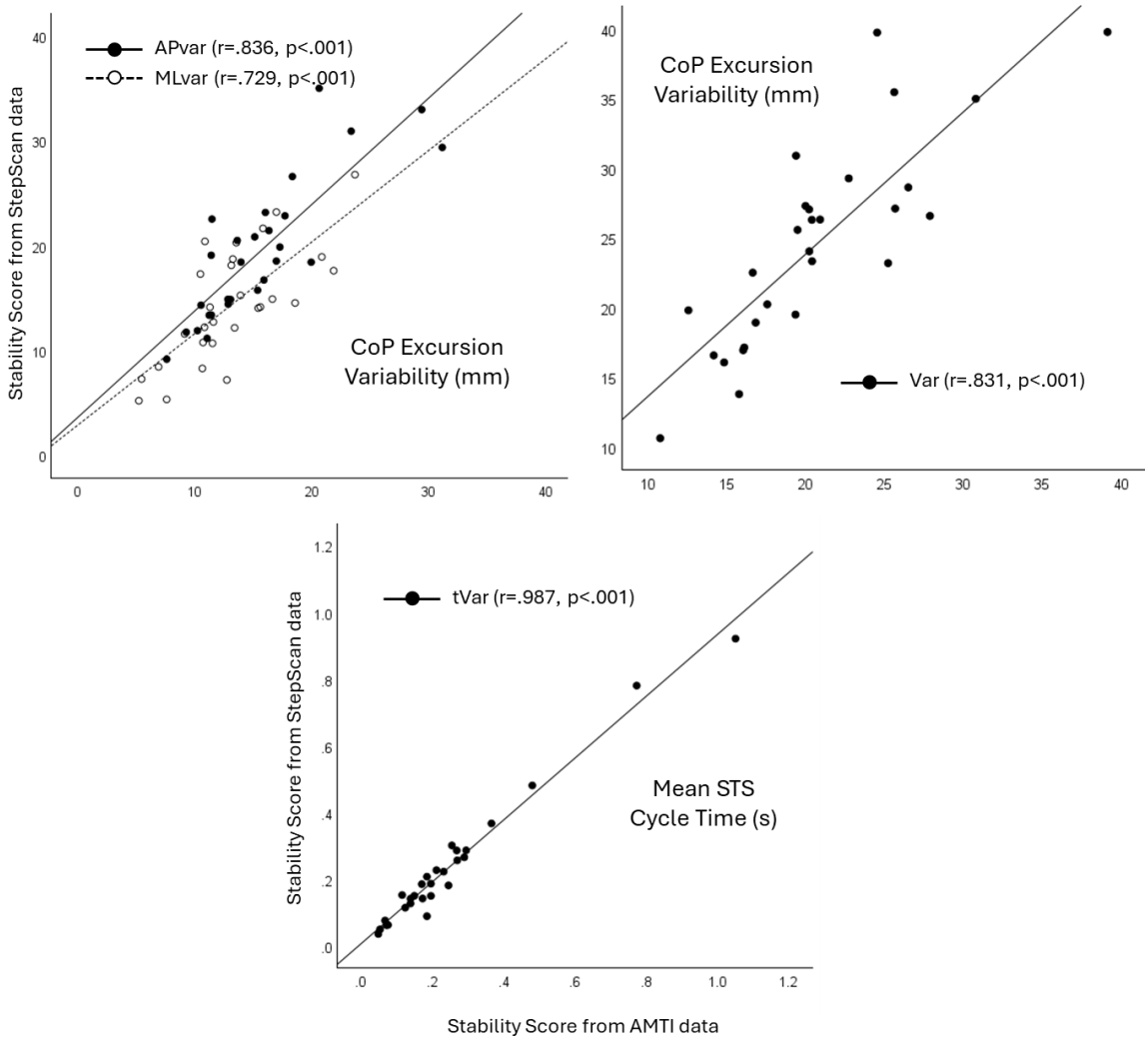

Figure 12. Scatter plots with Pearson correlation tests between StepScan (Y axis) and AMTI (X axis) for sit-to-stand stability parameters: APvar = Standard deviation of CoP excursion in x direction; MLvar = Standard deviation of CoP excursion in y direction; Var = Combined APvar and MLvar; tVar = Standard deviation in chair sit-to-stand time.

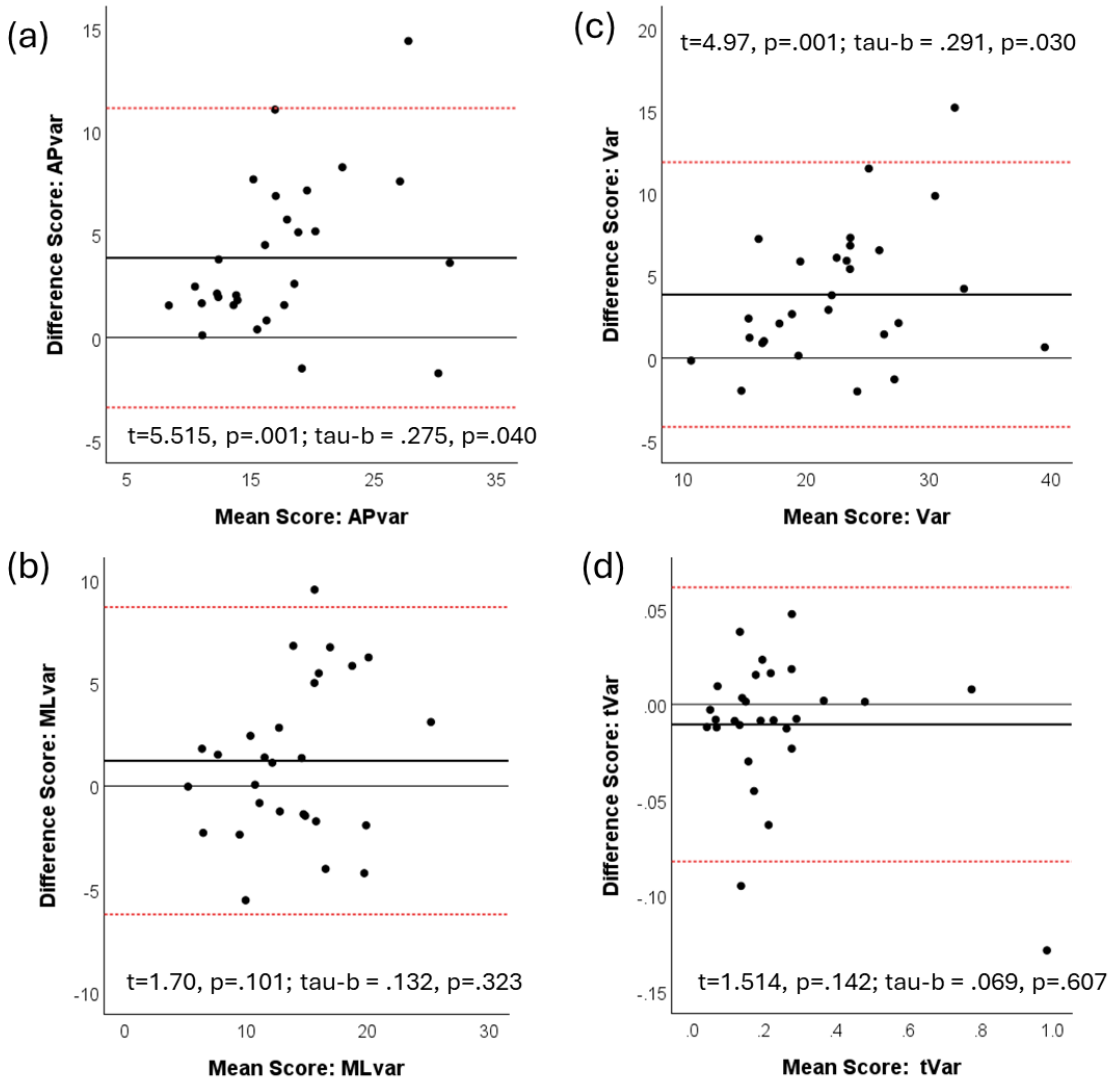

Figure 13. Limit of agreement plot for Sit-to-Stand parameters: (a) CoP X excursion variability (APvar); (b) CoP Y excursion variability (MLvar); (c) combined AP and ML variability (Var); and (d) sit-to-stand cycle time variability (tVar). Single-sample t-test result (diff=0) and Kendall's tau-beta correlation are included. The heavy horizontal line is the mean difference score and the red dashed lines are the +/- boundaries defined by 1.96 x standard deviation of the mean difference.

4.2.2.3 Step-Up/Step-Down (SUSD) Step Width Variability

Step width variability was evaluated for both dominant and non-dominant legs during the upward and downward phases of the SUSD test. All four conditions (Dom-Up, Dom-Down, NDom-Up, NDom-Down) demonstrated mean differences ranging from -2.01 mm to 0.30 mm. ICC values were again strong (.968 to .982), with all ICC lower bounds ≥ .796.

Table 6. Step-width variability during Step-up/Step-Down test from StepScan and AMTI centre of pressure (CoP) measurements.

SUSD test: Lead leg, step up/down		Mean	SD	Diff (SD)	Diff < 5mm 1-tail t-test p-value	Absolute agreement ICC(2,k)	Absolute agreement [95% CI]
Dom-Up	SS	19.7	5.61	-0.21 (1.48)	<.001	.982	[.962 - .992]
	FP	19.9	5.60				
Dom-Down	SS	27.0	7.77	-2.01 (2.21)	<.001	.968	[.796 - .990]
	FP	29.0	8.68				
NDom-Up	SS	17.2	5.11	0.30 (1.36)	<.001	.981	[.960 - .991]
	FP	16.9	4.97				
NDom-Down	SS	22.8	6.10	0.10 (1.64)	<.001	.981	[.960 - .991]
	FP	22.7	5.82				

Dom = Dominant leg is leading; NDom = Non-dominant leg is leading; Up = Step-up portion of the SUSD; Down = Step-down portion of the SUSD; SS=Based on CoP from StepScan tile; FP=Based on CoP from AMTI force plate.

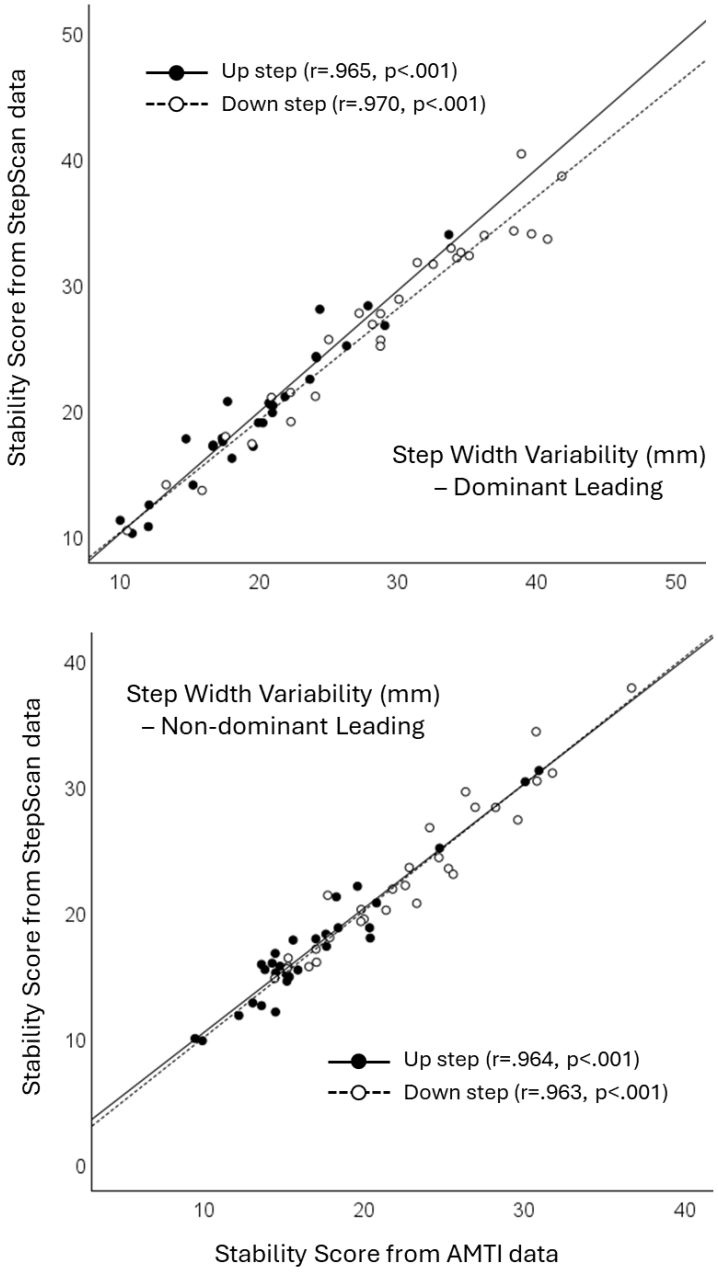

Figure 14. Scatter plots with Pearson correlation tests between StepScan (Y axis) and AMTI (X axis) for SUSD step width stability parameters. Top: Domninant limb leading; Bottom: Non-dominant limb leading. Filled circles represent the "up step" and open circles represent the down step.

Correlation plots in Figure 14 show that Pearson r-values were all high (r >.96). The LoA plots in Figure 15 revealed significant difference between the systems and proportional bias only for the dominant leg down step. Otherwise no systematic or proportional bias was detected in the other variables.

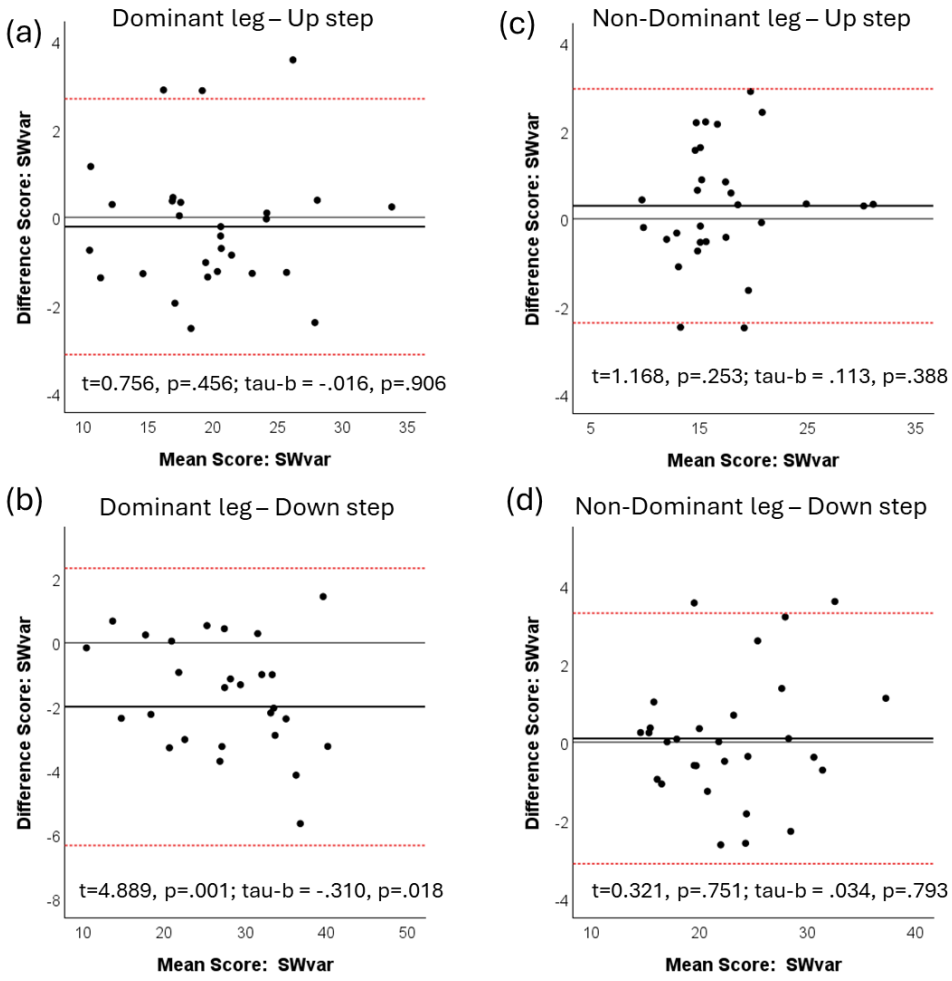

Figure 15. Limits of agreement plots for Step Width Variability from StepScan and AMTI during SUSD with Dominant leg leading, for the up step (a) and down step (b), and Non-dominant leg leading, for the up step (c) and down step (d), including the single-sample t-test result and Kendall's tau-beta correlation.

4.3 Aim #2 – Sensitivity of StepScan™ to detect Age-Related Decline in Stability

Table 7. Relationship between age and StepScan balance and stability parameters.

Stability Parameter	Age Group	Mean	SD	Student t-test			Pearson Corr.	
				t	*df*	*p*	*r*	*p*
Standing Stability Parameters								
SDx (mm)	Y	7.13	3.43	-1.796	28	.042†	.347	.030†
	O	9.91	4.93					
SDy (mm)	Y	4.93	1.84	-2.038	20.6*	.027†	.321	.042†
	O	7.09	3.68					
Dmaj (mm)	Y	13.5	5.91	-2.557	20.7*	.009†	.437	.008†
	O	22.1	11.7					
Dmin (mm)	Y	7.87	2.61	-.601	28	.276	.112	.278
	O	8.81	5.46					
Vel (mm/s)	Y	13.5	5.48	-2.139	28	.021†	.357	.026†
	O	18.6	7.39					
5xSTS CoP Excursion Variability								
APvar (mm)	Y	19.5	6.97	.102	26	.460	.017	.465
	O	19.3	6.79					
MLvar (mm)	Y	13.8	5.43	-.519	26	.304	.067	.367
	O	14.9	5.72					
Var (mm)	Y	24.3	7.54	-.164	26	.436	.041	.418
	O	24.8	7.47					
tVar (s)	Y	.156	.084	-2.112	15.8*	.026†	.337	.040†
	O	.309	.257					
SUSD Step Width Variability								
Dom-Up (mm)	Y	19.9	6.08	-.157	26	.438	.094	.317
	O	19.9	5.27					
Dom-Dn (mm)	Y	26.8	8.00	-.132	27	.448	.060	.378
	O	27.2	7.81					
NDom-Up (mm)	Y	15.1	3.22	-2.616	27	.007†	.450	.007†
	O	19.6	5.81					
NDom-Dn (mm)	Y	21.5	4.65	-1.199	27	.121	.191	.160
	O	24.2	7.27					

* Degrees of freedom (df) adjusted for unequal variances from Levene's test
† Significant one-tailed hypothesis test at alpha = .05

Parameters analyzed in Aim #1.2 were compared between young (n=15) and older adult (n=15) participants using independent t-tests, as well as Pearson correlation analysis to quantify the relationship between age and stability scores for the different tasks. These results are summarized above in Table 7, and Figures 16 through 18.

4.3.1 Static Standing Stability Parameters

As shown in Table 7 and Figure 16, significant differences were observed between younger and older adults in several static standing stability measures—SDx ($p = .042$), SDy ($p = .027$), Dmaj ($p = .009$) and Vel ($p = .021$)—while Dmin did not differ significantly ($p = .276$). Age was also significantly and positively correlated with SDx ($r = .347$, $p = .030$), SDy ($r = .321$, $p = .042$), Dmaj ($r = .437$, $p = .008$) and Vel ($r = .357$, $p = .026$), but not with Dmin ($r = .112$, $p = .278$).

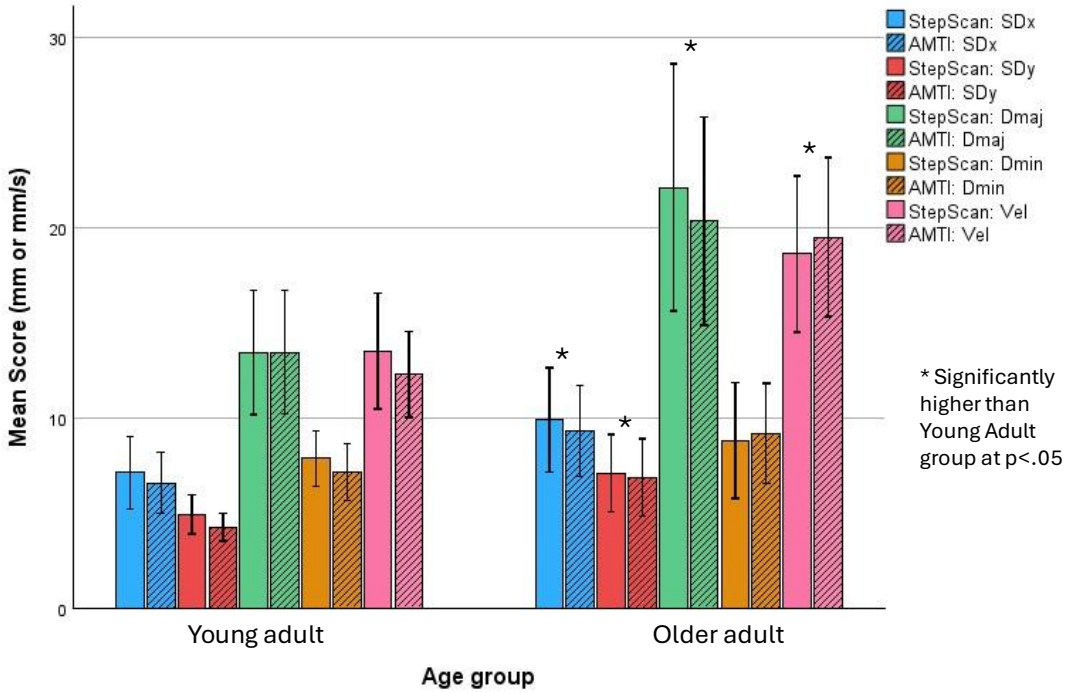

Figure 16. Age group comparison for static standing balance parameters.

4.3.2 Sit-to-Stand CoP Excursion Variability

As shown in Figure 15, among the four CoP-derived variability parameters, only **tVar (peak-to-peak sit-to-stand time variability)** was significantly greater in older adults (p = .026), indicating increased inconsistency in the timing of sit-to-stand transitions with age. However, **APvar**, **MLvar**, and **combined variability (Var)** did not differ significantly between younger and older adults (p > .05), suggesting that spatial variability in CoP excursion during sit-to-stand tasks is not markedly affected by age.

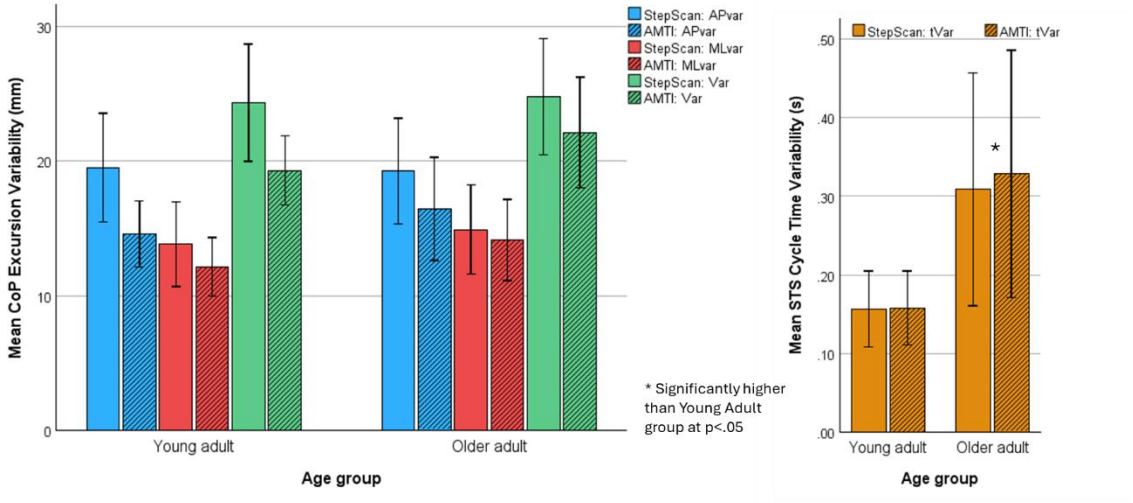

Figure 17. Age group comparison for sit-to-stand stability parameters.

4.3.3 Step-Up/Step-Down Step Width Variability

Among the step width variability measures, only the non-dominant foot during the step-up condition (NDom-Up) showed a significant difference between age groups, with older adults demonstrating greater variability (p = *.007*). No significant differences were observed for the dominant foot step-up (Dom-Up; p = *.438*), dominant foot step-down (Dom-Dn; p = *.448*), or non-dominant foot step-down (NDom-Dn; p = *.121*) conditions.

Older adults exhibited significantly higher variability in step width parameters compared to young adults ($p < .05$), particularly in the mediolateral (SDx) and vertical (Vel) directions. Additionally, they showed increased major and minor step width deviations (Dmaj, Dmin). Both StepScan and AMTI measurements demonstrated similar trends, confirming that aging is associated with reduced balance control and increased step width variability during the SUSD task.

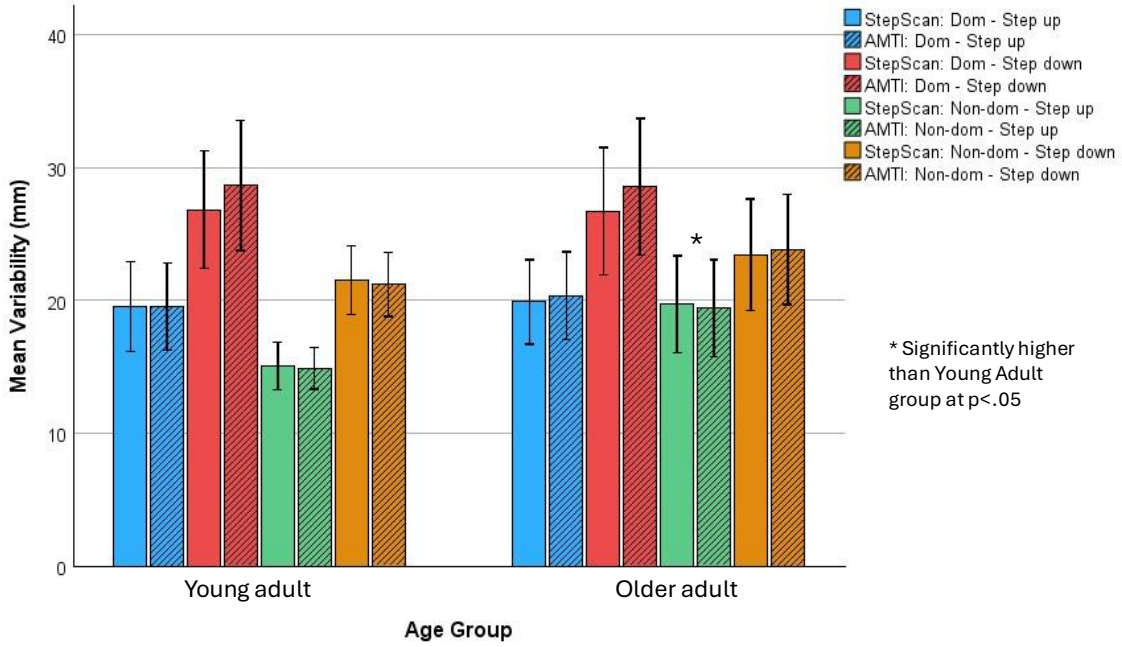

Figure 18. Age group comparison for step-up/step-down stability parameters.

As shown in Figure 18, step width variability was generally higher during the step-down phase compared to the step-up phase for both young and older adults. Older adults demonstrate greater variability than young adults, particularly in the dominant limb during the step-down phase. However, no statistically significant differences were observed between age groups or measurement systems, indicating that while aging may

contribute to increased variability, it is not the sole determinant of step width fluctuations during the SUSD task.

4.4 Aim #3 – Exploratory Study of an Auditory Perturbation Task

Although the metronome was always audible during the data collection sessions, due to technical difficulties with the Arduino's interface with the Motive system, many participants' sessions had only partial or no metronome signals saved in the exported C3D files. As such, it was not possible to analyze these trials as originally planned. Nevertheless, the trial intervals at the three different paces was known (30s each) which allowed some qualitative observation of the phase plane trajectories.

Figure 19 shows phase plots (velocity vs displacement) of the CoP excursion in the A/P and M/L directions for a young adult (top row) and an older adult (bottom row) for the SUSD perturbation trial where the non-dominant limb was the leading leg. Figure 20 shows displacement-displacement and velocity-velocity plots for the A/P and M/L CoP kinematics during the same SUSD perturbation trial where the non-dominant limb was the leading the leg. In these plots the entire trajectory was plotted as three contiguous segments color coded for pace (blue-preferred, red=20% faster, green=20% slower), with the mean trajectory overlaid as the thicker line.

Visual comparison of the plots for young and older adults indicates an increased degree of disorder of the CoP trajectory during the SUSD perturbation task for the older adult, when compared to the younger adult. This was most evident from the A/P phase plot in Figure 19 and the Velocity-Velocity plot in Figure 20.

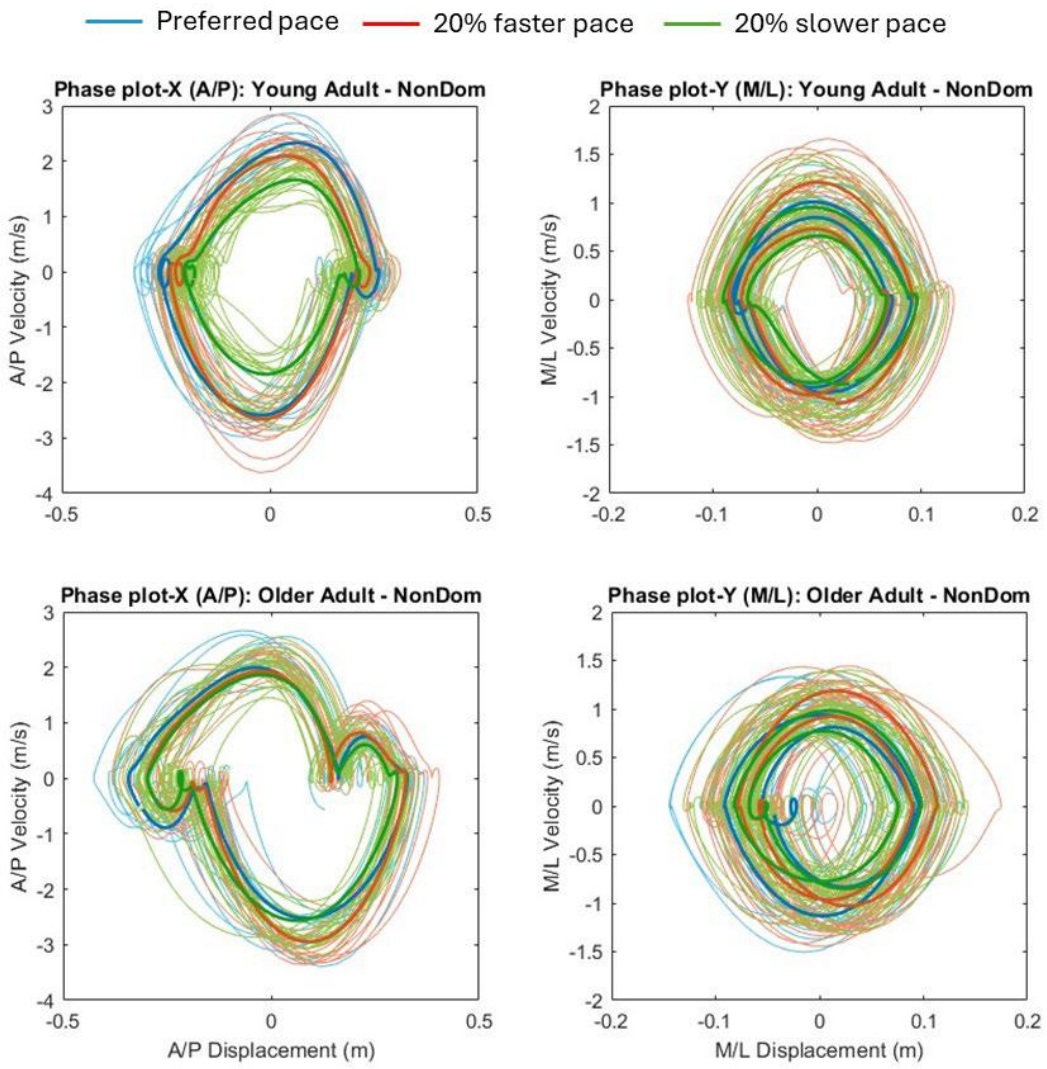

Figure 19. Phase plots (Displacement vs Velocity) of CoP A/P excursion (left column) and M/L excursion (right column) for young adult (top row) and older adult (bottom row), during SUSD perturbation task, leading with non-dominant limb.

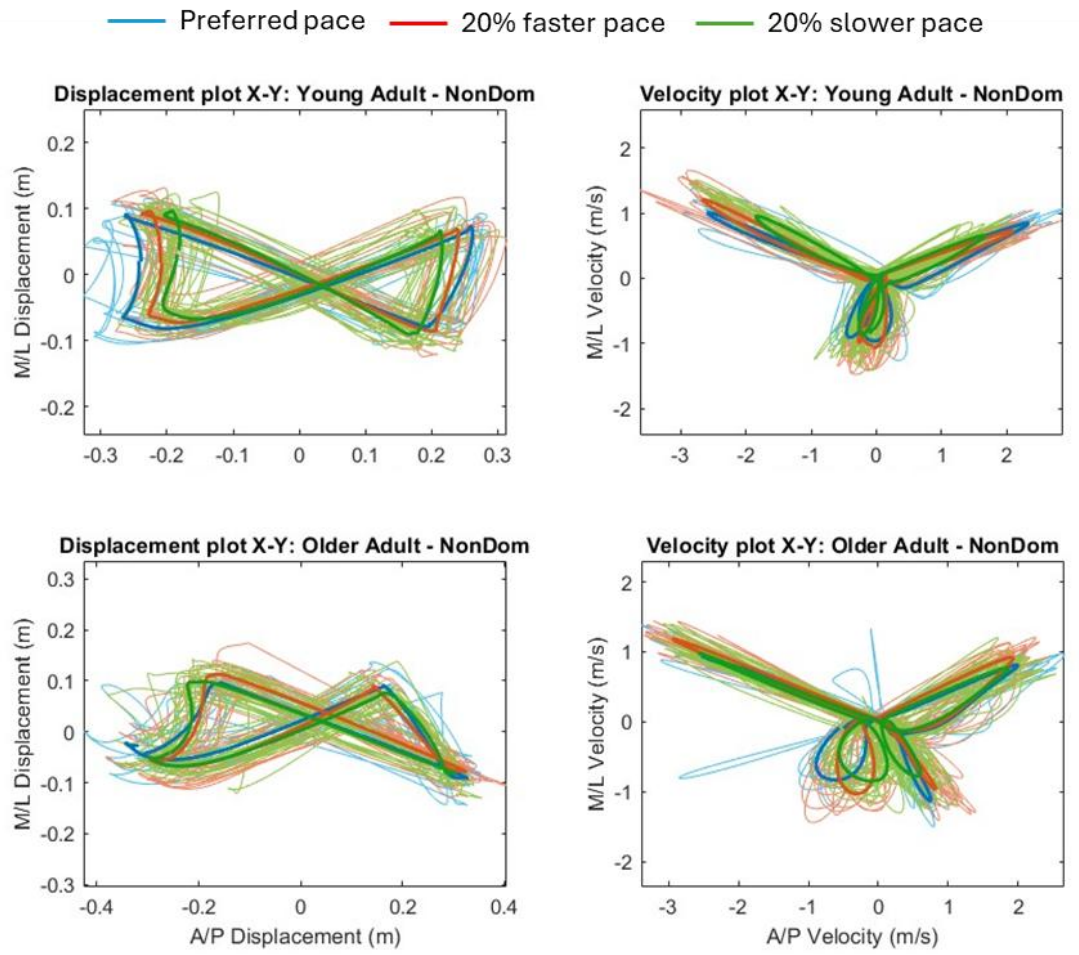

Figure 20. Displacement-Displacement plots (left column) and Velocity-Velocity plots (right column) for young adult (top row) and older adult (bottom row), during SUSD perturbation task, leading with non-dominant limb.

5. Discussion

5.1 Overview and Research Motivation

Centre of pressure excursion during standing and locomotor tasks is a commonly used measurement for deriving key indicators of balance and stepping stability, particularly in aging populations where the risk of falls increases. This study aimed to assess the accuracy of StepScan™ in measuring key balance and mobility metrics and to evaluate whether these measures can effectively detect age-related changes in standing balance and stepping stability. Given the growing need for reliable, accessible balance assessment tools, our study fills a gap by validating StepScan™ against the gold-standard AMTI force plates and analyzing its ability to differentiate balance characteristics between young and older adults.

5.2 Aim 1: Accuracy of StepScan™ in Balance and Mobility Measures

5.2.1 CoP Errors: Absolute vs. Relative

Absolute CoP position errors were task-dependent, with the smallest errors observed during static standing and the largest during dynamic transitional tasks, particularly the Sit-to-Stand (STS) task. This gradient supports the notion that static balance measurements are more robust and less susceptible to external perturbations or rapid shifts in body mass. Static trials showed consistent absolute CoP errors within the expected range of the system's sensor resolution (5 mm), suggesting that measurement deviations fall within the hardware's technical limits.

While absolute CoP errors are important for applications requiring spatial alignment across systems—such as integrating StepScan™ with optical motion capture (e.g., Motive) or inertial platforms (e.g., XSens)—they are less critical for assessing internal postural control. In contrast, relative CoP errors—which quantify the internal consistency and variability of CoP displacement over time—are more directly tied to balance performance. These metrics offer insight into sway dynamics, corrective strategies, and neuromotor control under varying conditions. As noted by Raymakers et al. (2005) temporal parameters like sway velocity, ellipse area, and displacement amplitude are better suited for detecting subtle postural instabilities than absolute position alone (123).

When comparing StepScan™ to other technologies, such as in-shoe pressure sensors or low-resolution platforms like BTrackS™, StepScan™ demonstrated competitive or superior reliability in static and semi-dynamic tasks. BTrackS™, for example, has been validated for gross postural sway assessment but has lower spatial resolution (~4 sensors under each foot) and is less sensitive to subtle CoP fluctuations (124). In-shoe systems like Moticon or Pedar are well-suited for dynamic gait analysis but may be less accurate during quiet standing due to sensor drift and foot shifting within the shoe (125). StepScan™'s higher spatial resolution and floor-level design minimize these artifacts, making it particularly effective for evaluating postural sway and CoP variability in balance assessments.

5.2.2 Agreement Between StepScan™ and AMTI for Stability Metrics

Statistical analysis revealed high agreement between StepScan™ and AMTI for key CoP-derived metrics, including standard deviation in the medial-lateral (SDx) and anterior-posterior (SDy) directions, major and minor axis lengths of the ellipse (Dmaj, Dmin), and mean CoP velocity. Correlation coefficients ($r > 0.88$) and ICC values (ranging from 0.936 to 0.978) support the robustness of StepScan™ in static conditions. Bland-Altman plots indicated minimal systematic bias between systems, though minor inconsistencies in CoP velocity were observed based on Kendall's tau-beta analysis.

These results confirm the suitability of StepScan™ for measuring postural control under static conditions. In dynamic tasks like the 5xSTS, although initial concerns about relative CoP error led to caution in early analysis, further evaluation demonstrated that meaningful balance and mobility metrics could still be extracted. While relative CoP accuracy was reduced compared to static trials, the data remained interpretable and revealed age-related patterns consistent with prior literature. This aligns with findings from Janssen et al. (2002), who emphasized the STS task's high biomechanical and postural demands (126).

5.3 Aim 2: Sensitivity to Age-Related Balance Decline

5.3.1 Standing Balance Differences Between Young and Older Adults

Older adults demonstrated significantly greater variability in static balance metrics—particularly SDx, CoP velocity, Dmaj, and Dmin—consistent with previous findings that indicate increased postural sway and reduced balance control with age. For

example, Park et al. (2016) and Stins & Roerdink (2018) reported that older adults exhibit significantly greater mediolateral CoP excursions and increased sway velocity, both of which are associated with increased fall risk (127,128).

In our study, Dmaj ($R^2 = 0.191$) and CoP velocity ($R^2 = 0.128$) showed weak positive correlations with age, suggesting that while aging contributes to postural instability, it is not the only factor. These findings align with the multifactorial model of postural decline, which implicates deterioration in visual, vestibular, and somatosensory inputs, as well as slower neuromuscular responses (129). StepScan™'s ability to capture these subtle variations underscores its utility as a practical screening tool for early balance deterioration in older adults.

5.3.2 Step Width Variability During SUSD

Step width variability was consistently higher during the step-down phase of the SUSD task, reflecting the increased postural demand associated with controlled descent. This finding supports previous research showing that stair descent requires greater balance control and is more challenging for older adults (130). Although older adults in our study displayed greater step width variability than younger adults, the differences were not statistically significant—likely due to sample size or high-functioning participants.

Further, variability increased when participants led with their non-dominant leg, suggesting lateral asymmetry in motor control. This observation corresponds with findings by Oh-Park et al. (2012), who reported that decreased confidence and strength in

lower limbs may influence stair performance and contribute to instability during descent (131).

5.4 Aim 3: Descriptive Analysis of Perturbation Responses

Preliminary analyses of perturbation responses revealed that older adults exhibited more erratic or disordered CoP control compared to younger adults. These visual differences suggest delayed or impaired sensorimotor integration and reduced capacity for rapid corrective strategies. Martelli et al. (2017) similarly observed that older adults displayed delayed and exaggerated recovery responses to slip-like perturbations (132), while Lin et al. (2015) found that these impairments were exacerbated under cognitive load (133).

Although our findings were not statistically tested, the observable patterns point to compensatory strategies—such as prolonged recovery paths or increased reliance on conscious motor planning. These trends warrant further investigation using standardized perturbation protocols and larger samples to clarify underlying mechanisms and support targeted interventions.

5.5 Conclusions and Future Directions

This study validated the StepScan™ system as a reliable tool for assessing CoP-based balance and postural control metrics during static and semi-dynamic tasks. High agreement with AMTI force plates during static balance tasks confirms StepScan™'s accuracy, while moderate agreement in SUSD step width variability and STS performance variability shows potential for dynamic applications. However, the system's

limitations in capturing absolute CoP position highlights the need for caution if integrating the StepScan)tm) system with other external body tracking systems.

Our findings are in line with recent literature confirming age-related changes in balance control across static standing, SUSD, and perturbation contexts (127,129,132) StepScan™ demonstrated sensitivity to these changes, supporting its role in early screening and monitoring of balance impairments in older populations.

Future studies should:

1. Expand the sample to include individuals with known balance impairments or fall history.
2. Investigate sensor fusion approaches by integrating StepScan™ with motion capture or IMU technologies to enhance measurement accuracy.
3. Conduct longitudinal assessments to evaluate the predictive value of StepScan™ metrics for fall risk and mobility decline.
4. Explore machine learning techniques to improve calibration and compensate for dynamic movement inaccuracies.
5. Assess limb-specific CoP dynamics using modified protocols to capture foot-specific pressure contributions.

By addressing these directions, future research can advance pressure-sensitive technology's role in comprehensive, accessible, and early balance assessment strategies for aging and clinical populations.

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Publications:

None

Conference Presentations:

1-Moradi K, McGibbon CA, Bishop E, Kerekes D, Ellsmere J, Ronsky J. Biomechanical simulation of design modifications to improve efficiency in tri-compartmental offloader brace. Canadian Society of Biomechanics, Edmonton AB, August 2024.

2- Gullison A, Haché J, Handrigan G, Moradi K, Jarrett P, McGibbon CA. Can Home-Based Exercise and Cognitive Training Improve Gait Performance in Older Adults at Risk for Dementia? Canadian Society of Biomechanics, Edmonton AB, August 2024.

3-Moradi K, McGibbon CA. Validation of Centre of Pressure Trajectory from a Portable Gait System. Canadian Medical and Biological Engineering Society, Fredericton NB, May 2025