Assessment of Postural Control in People with Type-2 Diabetes Mellitus Using a Smartphone IMU Sensor

Master's thesis by

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Preface

This project has been completed as a master's thesis during the 9th-10th semester of MSc. program in Medical Biotechnology at Aalborg University.
The work explores whether smartphones can be used as tools to assess balance in clinical populations. Specifically, I investigated the feasibility of smartphone-based postural control assessment in individuals with type 2 diabetes mellitus (T2DM), a group that faces an increased risk of falls due to disease-related complications. This topic introduced me to a new area of research that I had not previously worked with, which made this process both challenging and very exciting.

First and foremost, I would like to express my deepest gratitude to my supervisors. To Trine Rolighed Thomsen for her guidance, advice, and support throughout the entire process. To Anderson de Souza Castelo Oliveira for his tremendous help with data analysis, for asking the right questions that helped me better understand unfamiliar topics, and for his unending patience. I thank them both for always making time for me and for their continuous encouragement from start to finish.
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Abstract

Postural control impairments in individuals with type 2 diabetes mellitus (T2DM) increase the risk of falls and related injuries. Traditional balance assessments require expensive equipment and clinical settings, limiting their accessibility. Smartphones, equipped with inertial sensors, offer a portable and low-cost alternative for assessing balance.

This project investigated the feasibility of using a smartphone inertial measurement unit (IMU) to assess static postural control in individuals with T2DM, compared to a gold-standard force plate. Additionally, it explored whether the smartphone could distinguish between healthy and diabetic participants during balance tasks of varying difficulty.

Balance was evaluated under four static conditions: both-leg and single-leg stances, with eyes open and closed. A smartphone was attached to the lower back while participants stood on a force plate. RMS and mean velocity (MV) parameters were extracted from both devices. A healthy control group served as reference.

The smartphone reliably detected increased sway in more challenging conditions and captured significantly higher RMS and MV values in T2DM participants compared to healthy controls. Strong correlations between the smartphone and force plate were found, particularly in RMS parameters during the most difficult task. However, certain limitations affected comparability between devices, including the physical support required by T2DM participants during single-leg tasks, the small sample size, and the use of a younger control group.

Future research should include larger, age-matched samples, explore alternative sensor placements such as trouser pockets, and investigate the smartphone's ability to track postural changes over time through longitudinal assessments - while also evaluating the willingness and adherence of T2DM patients to long-term smartphone-based monitoring.

Contents

List of Abbreviations

BL-EC	Bipedal stance with eyes closed
BL-EO	Bipedal stance with eyes open
CNS	Central Nervous System
COM	Center of Mass
COP	Center of Pressure
DM	Diabetes Mellitus
IMU	Inertial Measurement Unit
LoA	Limits of Agreement
MV	Mean Velocity
OL-EC	One-leg stance with eyes closed
OL-EO	One-leg stance with eyes open
RMS	Root Mean Square
T1DM	Type 1 - Diabetes Mellitus
T2DM	Type 2 - Diabetes Mellitus

Introduction

1.1 Diabetes Mellitus Overview

Diabetes mellitus (DM) is a metabolic disorder defined by persistently elevated blood sugar levels. The chronic condition results from impairments in insulin secretion, insulin action, or both, affecting multiple organs of the body and disrupting their normal functions. The disruption, of both the structure and function, leads to microvascular and macrovascular complications in organs, such as the eyes, kidneys, heart, and nerves. The most common complications include retinopathy with progression to blindness, nephropathy, coronary heart disease, and the nerve-related neuropathy [1].
Diabetes is recognized as ever-increasing health problem challenging the human population worldwide [1]. The International Diabetes Federation reports 537 million adults with DM between the ages of 20 and 79, a number which is likely to increase by 20% by 2030 and almost double by 2045 [2]. These figures are likely underestimated as diabetes is underdiagnosed in 1 in 3 cases [3]. Beyond the health impact, the disorder also presents an economic burden, with total health expenditures estimated at 149 billion EUR in Europe in 2019 [4].

1.1.1 Type 2 Diabetes Mellitus (T2DM)

The type 1 diabetes mellitus (T1DM), type 2 diabetes mellitus (T2DM), gestational DM and other specific types of DM, are known as the four categories of the disease [1]. Gestational DM is developed during pregnancy and diagnosed in the second or third trimester. The other specific types of DM are associated with other causes, including diseases of the exocrine pancreas or genetic defects of β-cells function. Mostly, diabetic patients are diagnosed with either the T1DM or T2DM [5].
The autoimmune T1DM accounts for about 5–10% of all DM cases and is caused by an absolute deficiency of insulin secretion, leading to a buildup of glucose in the bloodstream instead of being utilized by cells for energy[1].
T2DM is also known as non-insulin-dependent DM and accounts for more than 90% of all DM cases. It is a continually expanding chronic metabolic disease characterized by insulin resistance and inadequate insulin secretion by pancreatic β-cells[1][2].
In the early stages of the T2DM, decreased insulin sensitivity triggers compensatory insulin overproduction by β-cells. Over time, the increased insulin levels lead to the β-cells dysfuntion, eventually resulting in insulin deficiency. T2DM is strongly associated with increasing age, obesity, family history of DM, physical inactivity, and modern lifestyle factors including unhealthy diet, sedentary behavior, and increased stress levels, which contribute to the development of T2DM [1].
Individuals with T2DM face several complications, including diabetic neuropathy, diabetic foot, osteoporosis, hyperglycemia and more. Sensory complications and development of wounds or ulcers are part of the diabetic foot complication, which, if infected, can require amputation[6]. The risk of amputation is also observed in diabetic peripheral neuropathy, which is the most common form of neuropathy and diabetic complication. Diabetic peripheral neuropathy is caused by peripheral nerve damage, occurring more frequently in T2DM patients, with studies reporting a prevalence ranging from 6% to 51% among diabetic patients in U.S and Europe [7] [8]. The disease can cause severe neuropathic pain, muscle weakness and poor body stability, resulting in compromised balance in day-to-day activities[9][10].

1.2 Falls in the Aging Population

Falls are a common and serious problem among the elderly, impacting their quality of life and independence [11]. According to European Association for Injury Prevention and Safety Promotion, every third elderly person over 65 years of age, and every second person over 80 years of age falls every year. In European countries, approximately 36,000 fatal fall-related injuries are reported annually. Additionally, an estimated 3.8 million older adults are hospitalized each year due to fall-related incidents[12]. Multiple studies have investigated the economic burden of fall-related medical care for older adults. According to European Health Association, it can be estimated that at least 25 billion EUR are spent annually on treating fall-related injuries across the EU[13].

Diabetic individuals are at an even higher risk of falling. The Longitudinal Aging Study Amsterdam compared the incidence of recurrent falls in people aged $\geq$ 65 years with and without DM. The results showed that 30.6% of the diabetic participants and 19.4% of the participants without the condition fell recurrently. The increased fall risk was partly explained by several factors, including medication use, higher levels of pain, reduced physical activity, and decreased grip strength. Cognitive impairments and limitations in activities of daily living also played a role. Furthermore, lower-extremity physical performance, which is crucial for activities like standing, walking, and balance maintenance, was found to be a significant factor[14].

The consequences of fall-related incidents can be mild, such as activity avoidance and decline in mobility, or severe from broken bones to head traumas. Falls can also lead to increased risk of institutionalization and mortality. Moreover, older adults often experience fear of falling, which can lead them to avoid activities they are still physically capable of performing, limiting their independence and contributing to functional decline [15][16].

To mitigate the impact of falls and improve the quality of life for older adults, it is crucial to address risk factors and implement effective fall prevention strategies. There are numerous factors that contribute to increased risk of falling among older adults, including muscle weakness, vestibular dysfunctions, gait and balance impairment, neurological disorders or visual and hearing impairments, Additionaly, polypharmacy, depression and environmental factors (e.g., irregular terrain, obstacles causing tripping) have been recognized as contributing factors, particularly in the elderly [17]. Impaired balance is one of the most commonly acknowledged risks and plays an important role in fall prevention [18].

1.3 Postural Control

Humans daily adopt many different configurations of the head, torso, and limbs relative to each other, collectively defined as postures. The different postures may change considerably while performing activities involved in leading an independent lifestyle, including standing up out of the bed, walking, sitting or reaching out for objects. [19]. Maintaining an upright posture is a fundamental human activity that allows individuals to interact with their environment effectively and is assured by a complex process called postural control [20].

Postural control has two main functional goals: postural orientation and postural equilibrium [21]. Postural equilibrium represents mechanical antigravity function that keeps the body balanced and stable by counteracting gravitational forces, which are acting upon the body at all times. The function requires the sensorimotor systems to maintain the center of mass (COM) within the base of support, which is the area beneath the feet that includes all points of contact with the supporting surface, during self-initiated movements and in response to external disturbances in postural stability [22]. Postural orientation refers to the active regulation of body alignment and tone in response to different factors, such as gravitational forces, support surface, visual environment, and internal reference frames [21].

1.3.1 Sensory Contributions to Postural Control

The postural control system is a complex chain of events, which includes receiving sensory information (visual, vestibular, and somatosensory), processing them by the central nervous system (CNS), and generating appropriate motor responses (figure 1) [23].

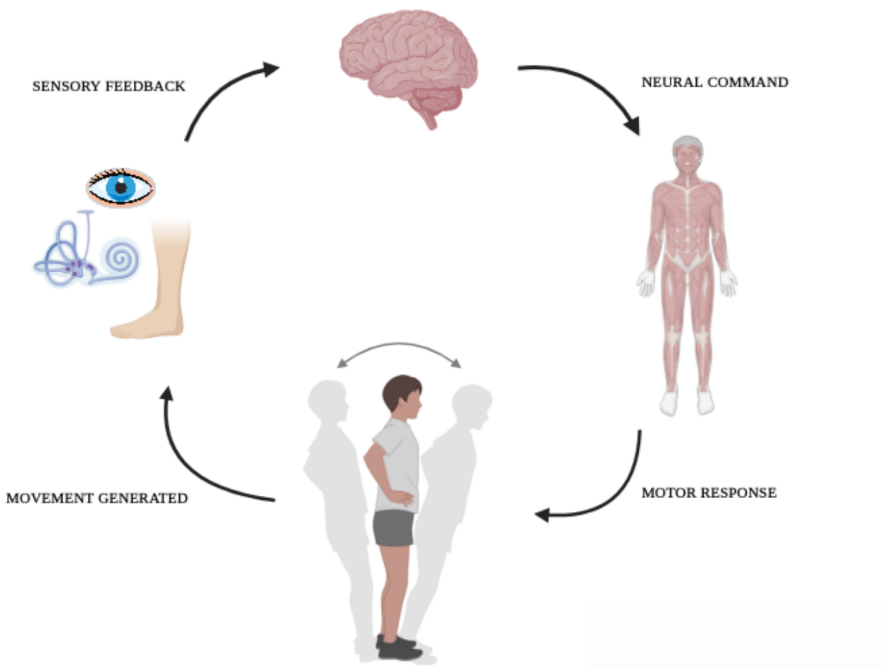


Figure 1: **Upright stance control loop.** Sensory information (visual from the eye, vestibular from the inner ear, and somatosensory from the feet/body) is relayed to the brain. The brain generates a neural command that leads to activation (motor response) and subsequent movement generation. The motor output changes the sensory input, helping the body continuously adjust and maintain balance. The figure was created with BioRender.com.

The vestibular apparatus is the organ of balance located inside the complex structure of the inner ear. The apparatus is made of two otolith organs and three semicircular canals [24]. The otolith organs play crucial role in detecting linear acceleration, while the semicircular canals respond to angular acceleration [25].
The visual system is divided into central and peripheral systems, which are responsible for identification of the surrounding objects and provide information about the overall layout of the environment, respectively [26] [27].
Lastly, the somatosensory system gathers information about the position and movement of body segments in relation to one another and the surface of support through proprioceptive and cutaneous inputs, such as joint position and touch [18].

1.3.2 Effects of Aging and T2DM on Postural Control

As balance relies on the dynamic cooperation of the visual, vestibular, and somatosensory systems, debilitation of any of the three systems can lead to instability and an increased risk of falls [28][29].
As people age, any deterioration process that causes the reduction of visual field undermines their independence and enhances their fear of falling [29]. T2DM patients often experience visual dysfunction, such as reduced contrast sensitivity, increasing the risk of falls. Another complication of persistently high blood glucose levels is diabetic retinopathy due to effect of hyperglycemia on the circulatory system of the retina[30] [18].
Age-related impairments have been reported also for the vestibular system. The otolith organs are a key for sensing verticality and body orientation in space. With age, both the number and structure of otoliths change, which becomes particularly noticeable in the saccule after the age of 60-70. Such changes occur alongside a progressive decline in postural control[29].
Evidence shows that vestibular function declines with age and estimates that falls, caused by impairments in the vestibular system, rank between the 3rd and the 10th leading cause of death among older adults in the U.S. [31]. The vestibular system is particularly important for balance maintenance in both static and dynamic conditions. Research shows significantly reduced central and peripheral vestibular function among T1DM and T2DM individuals. Agrawal et al. has found 70% higher vestibular dysfunction in patients with DM than in non-diabetic patients [32]. For instance, benign paroxysmal positional vertigo, characterized by displaced otolith organs into the semicircular canals, appears in higher rate in people with DM. One study observed this vestibular disorder in 46% of T2DM individuals compared to 37% without DM. The metabolic stress associated with DM has been shown to contribute to the otolith organs functional decline. Furthemore, T2DM patients exhibit changes in the vestibulo-ocular reflex and decrease in the optokinetic response, leading to blurred vision during head movements [33] [34].
T2DM affects the peripheral nervous system, resulting in numerous clinical presentations. The most common manifestation of diabetic neuropathy is sensory-motor neuropathy, described by proprioception loss and reduced tactile sensation in the legs and feet. However, movement impairments, including poor balance and altered gait, can occur even in diabetic patients without diabetic peripheral neuropathy [35].

1.3.3 Compensatory Strategies for Maintaining Balance

While the sensory systems provide critical information about body position and motion, it is the motor responses triggered by this input, which determine whether a person maintains balance or experiences a fall [36]. The fundamental balance recovery strategies are divided into fixed-support and change-in-support strategies [37].

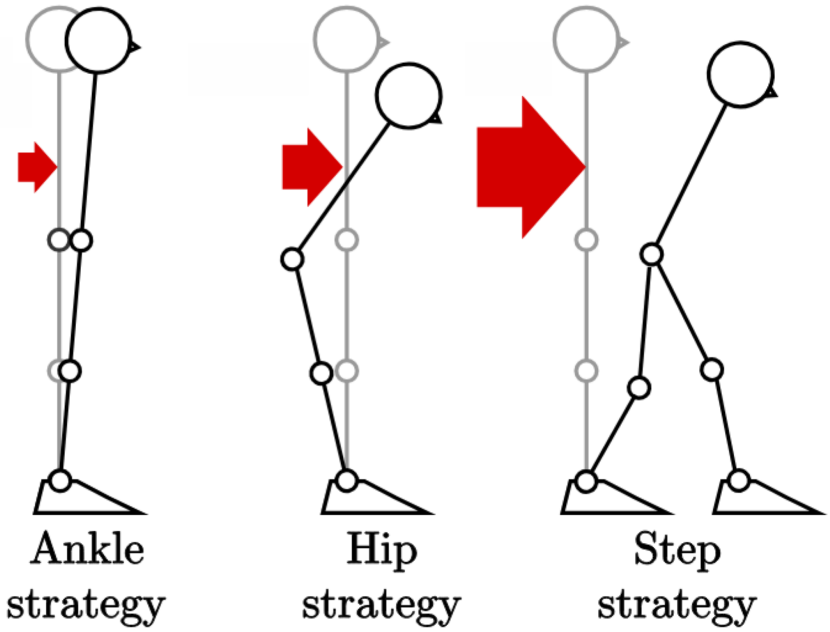


Figure 2: **Three primary postural strategies used to maintain balance following perturbations.** The ankle strategy (left) involves body movement as a rigid unit around the ankle joint; the hip strategy (middle) uses flexion or extension at the hips to restore balance; and the step strategy (right) extends the base of support by taking a step to prevent a fall. The figure was adapted from [38].

Fixed-Support strategies include the ankle and hip strategies. When ankle strategy is employed, the muscle activation starts from the ground up (distal-to-proximal activation), starting at the ankles and moving towards thighs and trunk. The rotation of the body is around the ankle joint and the strategy is limited by how much torque a foot can generate against the ground. Therefore, the ankle strategy is typically used for small, slow perturbations or during quiet standing [39].
In the hip strategy, the muscles are activated in the opposite manner (proximal-to-distal activation), starting at the trunk and moving down to the thighs. Mechanically, the upper body rotates backwards and forwards around the hip joint. It is limited by surface friction and the ability to produce horizontal force against the support surface. The hip strategy is commonly used for large disturbances and narrow or unstable surface [39].
If the fixed-support strategies become unreliable, the body will employ the stepping strategy, which shifts the base of support to contain the displaced COM after it moved due to perturbation.
The recruitment of these strategies is often altered with age or disease, leading to less efficient or delayed responses and increasing fall risk [40].

1.3.4 Postural Control Assessment

To effectively prevent falls, assessing the ability to maintain and control postural balance is crucial [41, 42]. Thorough balance evaluation is essential in clinical settings for diagnosis and treatment planning, due to the significant impact of balance disorders on affected individuals and society. The main goals of clinical balance assessments are to identify the existence of a problem and determine its underlying cause. Clinical assessments of balance can be grouped into functional tests, a systems/physiological assessments, and quantitative tools [43].
Functional balance tests usually involve performing a set of motor tasks scored on a scale, or using a stop - watch to measure how long can a person hold a position in a certain posture [43].
The Berg Balance Scale includes 14-item rating system designed to assess functional balance through both static and dynamic tasks, such as standing unsupported, reaching forward, turning 360 degrees, and stepping onto a stool. Each item receives a score from 0 to 4 points with a maximum score of 56. A score

less than 45 is associated with increased risk of falling. Even though the test is widely recognized and requires only 10 - 15 minutes to perform, the distinguishing between similar scores can be challenging [44, 43].
Timed Up and Go test is the shortest and simplest clinical balance assessment to perform, likely offering the highest reliability due to its objective stopwatch timing rather than subjective scoring. The test evaluates functional mobility, walking speed, and dynamic balance by measuring how long it takes a participant to rise from a chair, walk three meters, turn around, return to the chair, and sit down at their normal pace. If one's time to complete the tasks exceeds 13.5 seconds, they are considered at increased risk of falling. However, although it is considered a direct measure, it provides only one metric: test duration [45, 43].

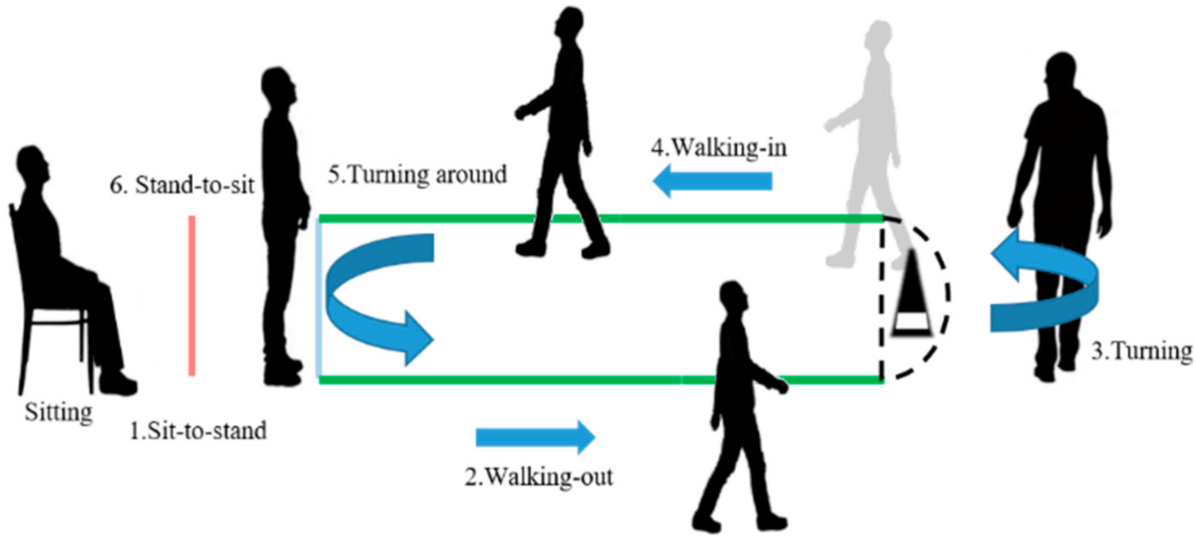


Figure 3: **Timed Up and Go test sequence.** (1) Sit-to-stand, (2) Walking out, (3) Turning, (4) Walking in, (5) Turning around, and (6) Stand-to-sit. The figure was reproduced from [46].

Functional reach test is a single-task balance assessment, which quantifies an individual's limits of stability. It involves subjects reaching as far forward as they can while standing independently and without taking a step [43].
While a functional approach to balance assessment determines whether balance impairments exist, a system approach helps to identify the specific underlying causes of balance deficits to treat them effectively [43].
The Balance Evaluation Systems Test targets 36 items categorized into 6 different balance control systems, so that specific rehabilitation approaches can be designed for different types of balance deficits: biomechanical constraints, stability limits/verticality, anticipatory postural adjustments, postural responses, sensory orientation, and stability in gait [47].
The Physiological Profile Approach focuses on the physiological impairments that contribute to fall risk rather than balance control systems. The test includes straightforward tests measuring visual function, foot sensation, leg muscle strength, reaction time, and standing postural sway [48, 43].

Unfortunately, balance scales give only rough estimates of an individual's ability to balance, and tests that rely on someone's judgment can vary a lot depending on the person doing the scoring [43].
Furthermore, while these clinical approaches are adaptable and easy to implement, they possess significant disadvantages. These assessments primarily detect obvious balance deficits, making them ineffective for identifying subtle impairments or detecting fall risk at early stage [49]. Advances in technology and computing have made it possible to objectively examine postural control through posturography [41, 42, 50].

1.4 Posturography

Posturography, literally translating to the description of posture, is one of the most frequently used methods for postural sway quantification. Essentially, the posture is being challenged across various conditions, such as tests performed with eyes open versus eyes closed or on solid versus foam surfaces, and the subject's response is evaluated [51].

Posturography can be divided into two main types: static and dynamic. Dynamic posturography covers the postural control evaluation while balance is experimentally perturbed, such as through a moving support surface or stimuli applied to upper body. Static posturography assesses postural control while the subject stands quietly in an unperturbed position. However, due to gravity and self-initiated corrective movements, even the unperturbed stance is not completely static [51].

Postural control is quantified by analyzing the trajectory of the center of pressure (COP), as the ability to maintain the COP within the limits of the base of support while standing still refers to static postural control [52, 51]. COP is the point of application of the ground reaction force vector on the support surface, reflecting the collective effect of all muscles and gravitational forces acting on the body at a given moment. The primary tools used to measure the COP are force plates [19].

1.4.1 Force plate: The Gold Standard for Postural Stability Assessment

Force plate is a dynamometric device used by researchers and clinicians to evaluate mechanical gait characteristics and assess balance with precision. The instrument records changes in ground reaction forces and the COP displacement, parameters involved in understanding human movement. Since human body is in constant subtle motion, the ground reaction forces continuously fluctuate to maintain postural stability. Force plates track and record the dynamic changes along the contact phase over time [19, 53].

A force plate consists of a platform equipped with force sensors that convert applied forces into electrical signals (figure 4). The sensors measure the force applied in three directions: the medial-lateral (ML), anteroposterior (AP), and vertical, and the three rotational force components (moments) of the ground reaction force, Mx, My, and Mz [19, 53]. Although, the force plates can measure six components, postural control is evaluated based on three key dimensions: AP and ML coordinates of the subject's orientation, and the ground reaction force in the COP [53]. The spontaneous postural sway of the human body during upright stance is challenging to notice with the naked eye. However, the oscillations cause measurable movements of the COP, which can be plotted either over time or as two-dimensional displacement pattern (figure 4) [54]. The COP trajectory parameters derived from a laboratory-grade force plate are regarded as the gold standard for postural stability assessment [55].

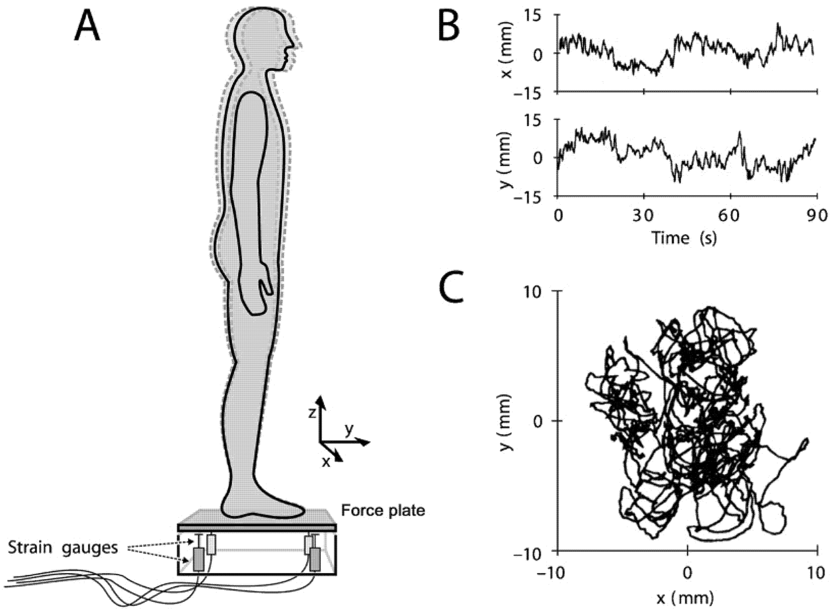


Figure 4: **Measurement of Postural Sway using a Force Plate.** (A) Schematic diagram of a subject standing on a force plate, which measures ground reaction forces in three directions: x (Medial-Lateral, ML), y (Antero-Posterior, AP), and z (Vertical). The dotted line of the subject represents spontaneous postural sway. (B) Time-series plot of COP displacement in the ML (x) and AP (y) directions. (C) The center of pressure (COP) trajectory plotted in the ML-AP plane, derived from the force plate measurements. The figure was adapted from [54]

Force plate technology, however effective, faces certain practical limitations. The price of the instrument ranges between USD 10,000 to USD 20,000, making it inaccessible for many clinics or assessments in field settings [53, 55]. The lack of portability, due to fixed installation on the ground of a laboratory, further restricts the use across different clinical locations or patients' homes [53, 56]. Additional operational limitation of external power requirement also challenges the flexibility of the location set up [55]. To operate effectively, force plates demand trained personnel for accurate data collection, which significantly decreases the broader application of the technology outside the laboratory environment [50, 57].
In response to the limitations, several alternative devices to the gold standard have been developed and utilized for evaluating postural control, gait patterns, and assessing the fall risk. Such replacements include pressure sensing platforms [58, 59], 3D motion tracking system [60, 61, 62] or inertial sensors [63, 64, 50, 65].

The European Society for the Clinical Evaluation of Balance Disorders discussed the potential of virtual reality to replace the non-portable and expensive Computerized Dynamic Posturography in diagnostic settings. Although the Computerized Dynamic Posturography effectively evaluates visual contributions to balance, it cannot fully account for the combined visual-vestibular effects that occur during real-life conditions [66]. Virtual reality creates dynamic, multisensory environments, which mirror daily life activities more accurately [67]. However, virtual reality technology alone is insufficient for comprehensive assessment of postural dysfunction [66].
Researchers are also exploring affordable balance board systems for remote assessment of postural control, since it takes time and energy for an elderly subject to visit a hospital for checking balance function. In 2022, a study used Nintendo Wii balance board and force plate to measure COP metrics under four conditions, revealing adequate to excellent reliability for the two devices [68]. A 2023 study performed static posturography assessment using a Wii Balance Board in T2DM patients with and without neuropathy, measuring COP metrics. The researchers concluded that the board can be considered a useful alternative for balance impairment screening [69].

Despite offering improved portability and reduced cost compared to traditional force plates, these alternative measurement systems are mostly restricted to indoor environments susceptible to increased noise and inconsistent data sampling rates [70].

1.4.2 Inertial Mesurement Unit

Technological progress has enabled the integration of various sensors into wearable devices and the application of the sensors into human movement monitoring. The sensors capture motion data, perform processing and analyzing functions, and ultimately contribute to posture assessment. Such systems are considered to be valuable in sports and medical fields during rehabilitation programs [71], for falls management [72], and in movement disorder assessment [73][74].
Among these sensor technologies, Inertial Measurement Units (IMUs) have emerged as particularly effective tools for human motion analysis [75]. The IMU is a device, which uses three main sensors operating in a triaxial system. The accelerometer measures linear acceleration of movements along up/down, left/right, and forward/backward directions. The gyroscope records angular velocity, tracking three types of rotations, called Euler angles: roll, pitch and yaw, while the magnetometer measures the strength and direction of the magnetic field [76].
There are multiple options for sensor placement on the body, however, the lumbar spine, particularly third to fifth lumbar vertebrae, is commonly used during posturographic assessments [76, 77]. The location closely aligns with one's COM, which has been shown to correlate with the COP measured by force platforms [70]. Research has shown that a single sensor in the L3-L5 position offers valid posturographic assessment, comparable with multiple sensors, and is useful in clinical settings [77].
The IMUs offer a long list of quantitative information on one's postural sway [49]. A study investigated the validity of an IMU sensor in healthy older individuals and showed strong correlation between COM- and force plate-derived sway measurements, and the IMU ability to distinguish between open and closed eyes conditions during the testing, validating the IMUs as an alternative to the gold standard method in postural sway evaluation [49]. Furthermore, Zhou et al [78] and D'Silva analyzed the effect of aging on gait and postural alterations in diabetic and T2DM patients using IMUs, respectively. Previously, the IMUs have been used in measuring postural stability [79], in combination with machine learning for the detection of compensatory balance responses [80] and balance evaluation [81].

1.4.3 Smartphone-Based Assessment

The objectivity of force plate measurements is a significant advantage that standard clinical assessments struggle to match. While inertial sensors offer potential for accurate and objective fall risk, balance, and gait assessment, they still require trained personnel to operate the equipment and analyze the resulting data [64]. Mobile technologies offer advantages for fall risk monitoring due to the combination of technological innovation with user-friendly design.
According to Eurostat data, smartphone usage among EU residents aged 55-74 ranged from 31.24% to 89.98% in 2024 [82]. Due to the high rate of ownership, smartphones have significant potential to address the important need of objective balance assessment outside the laboratory settings for aging individuals [64, 50].

1.4.3.1 Benefits and Challenges of Smartphone-Based Assessment

The large-scale, high-frequency daily use of smartphones allows for the recruitment of great and varied participant groups, potentially overcoming geographic constraints and traditional recruitment barriers. Smartphone-based health research can also streamline operations by reducing dependence on traditional research facilities and assistance for data collection, eliminating the need for direct contact between participants and research teams [83].

Moreover, smartphones enable uninterrupted monitoring and repeated data collection, generating longitudinal datasets that capture subtle physiological parameter variations. This continuous monitoring process tracks patients' health status in real-time, providing healthcare professionals and researchers with valuable insights including vital signs, treatment responses and adherence to therapeutic protocols [84].
Leveraging readily available smartphones can substantially decrease research expenses related to specialized equipment, participant transportation, and data collection infrastructure [85].
In Denmark, smartphone access is nearly ubiquitous — with nine out of ten families owning one or more smartphones in 2023, and 86% of the population using smartphones to access the internet [86]. However, potential concerns remain regarding data privacy, security, and the ethical handling of sensitive personal information collected through these devices [87].

1.4.3.2 Smartphone-Based Research

Given to the ubiquity and sensor capabilities, smartphones are increasingly being integrated into postural control research. Studies have validated the use of smartphones' IMUs for assessing postural sway in both young [88] and older individuals [89]. The devices have proven effective in the detection of neuromotor changes, i.e. between concussed and non-concussed individuals [90]. Studies have also demonstrated the reliability and validity of smartphones in measuring anticipatory and compensatory postural adjustments in clinical environments [91]. Moreover, smartphones have proven capable of capturing both dynamic gait patterns and static balance parameters, for example in people with conditions like orthostatic tremor [92].
Beyond assessment, smartphones are used in physical rehabilitation settings. They offer significant advantages in accessibility, remote monitoring, and patient engagement [93]. For instance, a smartphone app-based telerehabilitation program for patients aged 40-80 following total knee arthroplasty led to better outcomes, such as stronger performance on functional tests (e.g., single-leg stance) at 12 weeks [94].
Smartphone technology is also being applied in fall prevention and risk assessment. Ozinga et al. [95] and Ozinga, S.J., Alberts, J.L. [96] used 3D motion capture alongside an iPad application to measure postural decline in healthy older adults and patients with Parkinson, respectively. They found significant correlations between the iPad measurements and the 3D motion analysis system. Similarly, Cerrito et al. validated their Android application against force platform measurements during sit-to-stand tests in healthy seniors, again showing strong correlation between the devices [97]. De Groote et al. validated smartphone IMU measures, such as root mean square (RMS), velocity, and displacement, against force plate metrics in older adults, finding significant correlations between the two methods [79]. Hsieh et al. found smartphone-embedded accelerometers being able to effectively quantify static postural stability and successfully discriminate between aging individuals at low and high risk of falling [64]. Additional validation work has compared smartphone-based postural assessment against both laboratory-grade force platforms and research-quality accelerometers [89].
Beyond general aging populations, the smartphone-based assessments have been applied to evaluate postural stability across diverse conditions, including multiple sclerosis [89], Parkinson's disease [98], and individuals with stroke [99].
Prolonged sitting has been linked to adverse health outcomes in individuals with T2DM, with even light physical activity showing measurable benefits. In response, researchers have developed [100] and evaluated [101] user-centric smartphone applications to support this population in shifting from sedentary to more active lifestyles. Fernandes et al. assessed static balance control and mobility using a smartphone and instrumented TUG test among elderly population with and without T2DM. They showed that the device was capable of identifying static balance and mobility impairments often visible in people with the condition [45].
While smartphones have become valuable tools for tracking exercise, diet, weight, and plasma glucose levels [102], the research on smartphone-based postural control assessment against gold-standard force platforms in individuals with T2DM is limited.

Problem analysis

Falls are a significant health concern, particularly among older adults and individuals with T2DM. T2DM can lead to various complications, including peripheral neuropathy, which can alter postural control and increase the risk of falling. Among the contributing factors, impaired balance is one of the most acknowledged.

To maintain, achieve or restore the body balance, postural control has to be employed. Postural control is a complex chain of events and requires the integration of CNS and sensory systems to produce appropriate motor responses. However, current postural control assessments are associated with notable limitations. Subjective balance evaluation lack precision, while objective measurements lack accessibility.

While force plates are regarded as the gold standard for assessing postural control, their use is limited by cost and complex evaluation procedure. Consequently, cheaper alternatives are being considered.

Smartphones offer many advantages, with mobility being the core one. More importantly, smartphone-embedded IMU sensors are the key for enabling the devices to detect balance. The combination of mobility and built-in IMUs makes smartphones a promising solution for objective and convenient balance assessment.

Smartphones are already employed for postural sway detection, gait performance quantification and balance ability assessment. However, the application of smartphone-based IMU measurements in evaluating postural control in individuals with T2DM remains underexplored.

This project aimed to investigate the feasibility of using smartphone IMU sensors to assess static postural control in individuals with T2DM, by comparing smartphone-based balance metrics with traditional force plate measurements. A comparative analysis between the results obtained from individuals with T2DM and those of healthy control group was conducted. To explore this, the project:

- Assessed the ability of smartphone IMU sensors to discriminate between different postural conditions in a similar manner to force plates.
- Explored whether smartphone-derived postural metrics could reflect the impairments typically observed in older adults with T2DM during standard balance tasks.
- Evaluated the correlation between smartphone-derived parameters and COP metrics from force plates, in order to determine whether individuals with poor postural stability are consistently identified across both devices.
- Determined which of the extracted parameters is most reliably captured by the smartphone across both healthy and clinical populations.

To reach these aims, the methodological approach involved concurrent data collection using both force plates and smartphone IMUs during balance testing protocol under varying visual and stance conditions. Data processing and subsequent analysis was conducted using MATLAB to extract RMS and mean velocity (MV) from both measurement systems.

Materials and Methods

3.1 Paticipants

A total of 36 participants were included in this project, divided into two groups. The healthy group consisted of nine men and twelve women (age: 23.30 ± 2.03 years, height: 175.35 ± 10.01 cm, weight: 71.53 ± 14.54 kg). The T2DM group consisted of nine men and six women (age: 72.27 ± 4.95 years, height: 171.07 ± 9.29 cm, weight: 93.73 ± 15.68 kg) recruited through social media and patient lectures as part of a broader research project.
All participants were verbally informed about the experimental procedure and provided both verbal and written informed consent before participation. Ethical approval for the T2DM group was registered with the North Jutland Research department (F2024-197), the North Denmark Region Committee on Health Research Ethic (N-20240025) and ClinicalTrials.gov (NCT06745544). Written consent forms for healthy participants are provided in the Appendix. The data acquisition for the healthy control group was conducted at Aalborg University, and the T2DM group was tested at Steno Diabetes Center Nordjylland.
Exclusion criteria for both groups included the inability to stand upright without support (e.g., reliance on a wheelchair or crutches).

3.2 Instruments

3.2.1 Smartphone IMU Sensor

Samsung Galaxy A51 (Seoul, South Korea) contains a tri-axial accelerometer, which was used to perform the data acquisition. The accelerometer measures linear acceleration along the X, Y, and Z axes. The estimated sampling rate of the smartphone was $\approx$ 63 Hz. The smartphone was controlled remotely with an iPad Air 4th generation (Apple Inc., Cupertino, CA, USA) through the TeamViewer application (TeamViewer GmbH, Göppingen, Germany). In order to access the smartphone-embedded IMU sensor, Bubble App (Alexandra Institute, Denmark) was utilized.

3.2.2 AMTI Force Plate

A six-axis AMTI force plate (AMTI BMS400600-2K; Advanced Mechanical Technology, Inc., Watertown, MA, USA) (figure 5) was used for COP data collection at Aalborg University. The AMTI BMS400600-2K force plate is constructed with a solid aluminum top plate and able to collect forces and moments, each in three axis. The signal amplifier amplifies the collected data before transmitting it to a computer equipped with Qualisys Track Manager (QTM) software (version 2023.2, Qualisys AB, Göteborg, Sweden) for analysis. A sampling frequency of 500 Hz was used for each static balance measurement.

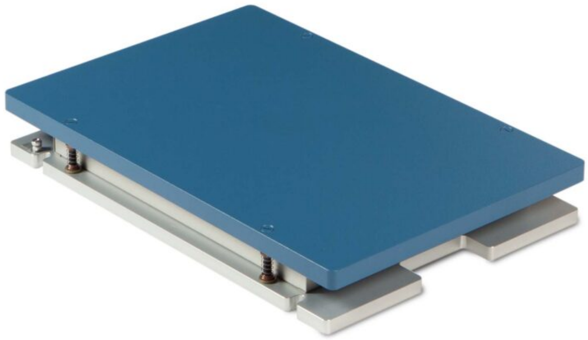


Figure 5: **AMTI Force Plate** The force plate was used to collect center of pressure (COP) data from healthy participants at Aalborg University. The figure reproduced from [103]

3.2.3 Biosignalplux Force Plate

A Biosignalplux Force Platform (Plux Biosignals S.A, Arruda dos Vinhos, Portugal) (figure 6) was used to collect COP data at Steno Diabetes Center. The platform uses four load cell sensors, each with a maximum capacity of 200 kg. The vertical forces were recorded from the force platform at a 1 kHz sampling rate and processed using Open Signals v. 1.2.8 software.

Figure 6: **Biosignalplux Force Plate** The force plate was used at the Steno Diabetes Center for center of pressure (COP) data collection in T2DM participants. The figure reproduced from [104]

3.3 Experimental procedure

After signing the consent form and providing basic information about age, height, and weight, the participants were prepared for the experiment. The smartphone was placed horizontally inside an elastic running belt, which was then adjusted and fastened to each participant's lower back in proximity to the L5 vertebrae (figure 7). Participants from the T2DM group were permitted to support themselves by touching an assistant's arm if needed. The healthy and T2DM groups underwent static balance assessment standing on the AMTI and Biosignalplux force plates, respectively. The simultaneous use of force plates for standing and smartphone placement at the lower back allowed for collection of COP and acceleration data, allowing for comparative analysis between the two measurement systems.

(a) Double-leg stance

(b) Single-leg stance

Figure 7: **Experimental setup.** The smartphone was securely positioned on the lower back of the participant using an elastic running belt while standing on a force plate. Both double-leg and single-leg stance conditions were performed as part of the balance assessment.

All participants performed four standing conditions:
1) Both legs eyes open (BL-EO)
2) Both legs eyes closed (BL-EC)
3) One leg eyes opened (OL-EO)
4) One leg eyes closed (OL-EC)
The conditions were chosen to challenge the sensory systems crucial for effective postural control and

maintaining balance. Each condition was maintained for 30 seconds and performed once. The dominant leg was determined by asking each participant for preferred kicking foot. The participants wore comfortable walking shoes throughout all testing conditions and were asked to stand relaxed with arms along the body. To minimize environmental influence during the open-eye tests, participants were instructed to focus on a fixed point on the wall ahead. Once the data were confirmed to be saved, the elastic belt was removed, marking the end of the experiment.

3.4 Data analysis

Following data collection, the smartphone inertial time series data were transferred to Google Drive for secure cloud storage, before being transferred to Microsoft Teams for accessibility. The AMTI force plate data were transferred directly to Microsoft Teams. The T2DM smartphone and Biosignalplux force plates data were anonymized for ethical considerations immediately after data acquisition and paired to prevent misidentification. All data were stored in Microsoft Teams before being processed in MATLAB R2024b (MathWorks, Natick, MA, USA).

3.4.1 Coordinate System Adjustment

To properly interpret the acceleration signals, the coordinate system of the smartphone required adjustment due to the horizontal orientation of the device during data collection. The smartphone's rotated position resulted in axis realignment where the X-axis corresponded to the vertical direction, the Y-axis to the ML direction, and the Z-axis to the AP direction. The axis realignement was verified in MATLAB (figure 8).

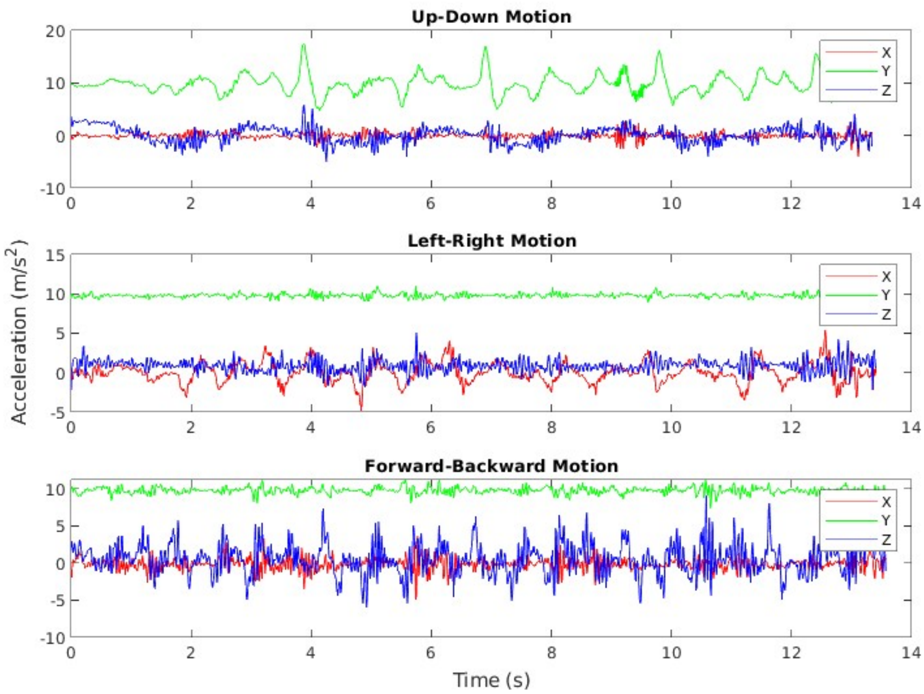


Figure 8: **The verification of axis realignment through controlled movement tests.** The plots display time-series acceleration data from the smartphone during: up-down (vertical), left-right (ML), and forward-backward (AP) movements. The dominance of the X-axis in vertical movement, Y-axis in ML movement, and Z-axis in AP movement confirms the new coordinate system.

3.4.2 Pre-processing

Prior to the analysis, the acceleration signals were low-pass filtered using a fourth-order Butterworth filter with a cut-off frequency of 10 Hz to reduce high-frequency noise (figure 9). The filter was designed by normalizing the cut-off frequency to the sampling frequency of the device. The AMTI force plate data underwent a similar filtering process, with a fourth-order Butterworth low-pass filter applied at a 10 Hz cutoff frequency (figures 10 and 11). After filtering, the raw accelerometric time series underwent detrending to remove any linear trends or drifts, followed by the extraction of specific features from the processed data.

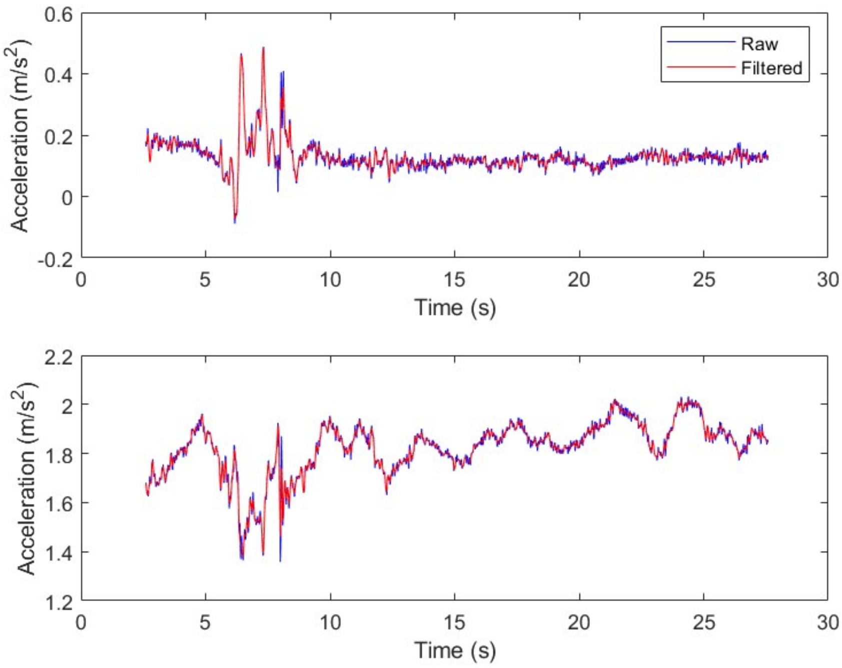


Figure 9: **Time-series plots of acceleration signals.** Time-series plot of raw (blue) and filtered (red) smartphone IMU acceleration signals in the anteroposterior (AP, top) and mediolateral (ML, bottom) directions. A 4th-order low-pass Butterworth filter with a 10 Hz cutoff was applied to reduce high-frequency noise.

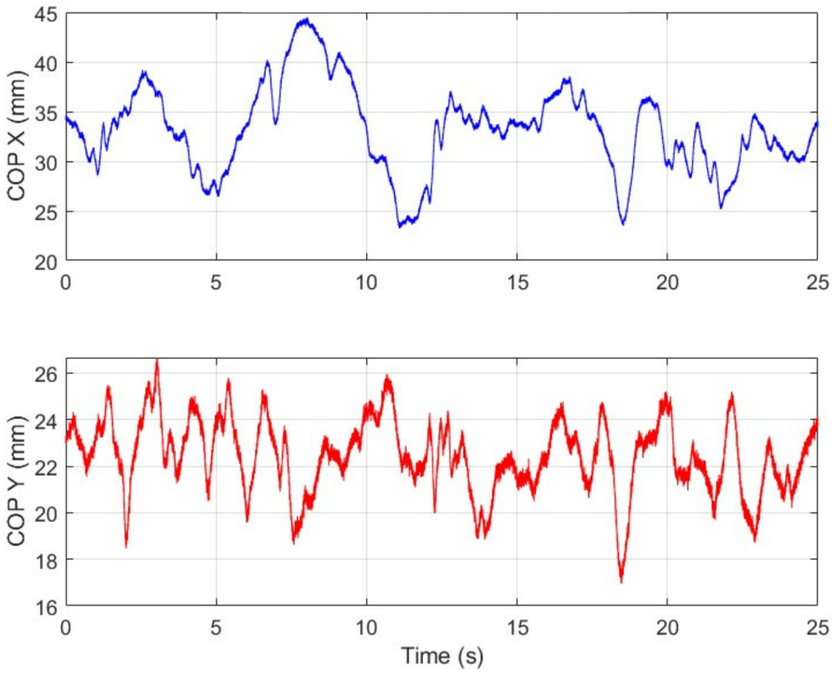


Figure 10: **Raw time-series plots of COP.** Time-series plot of raw center of pressure (COP) x (ML) and y (AP) coordinates

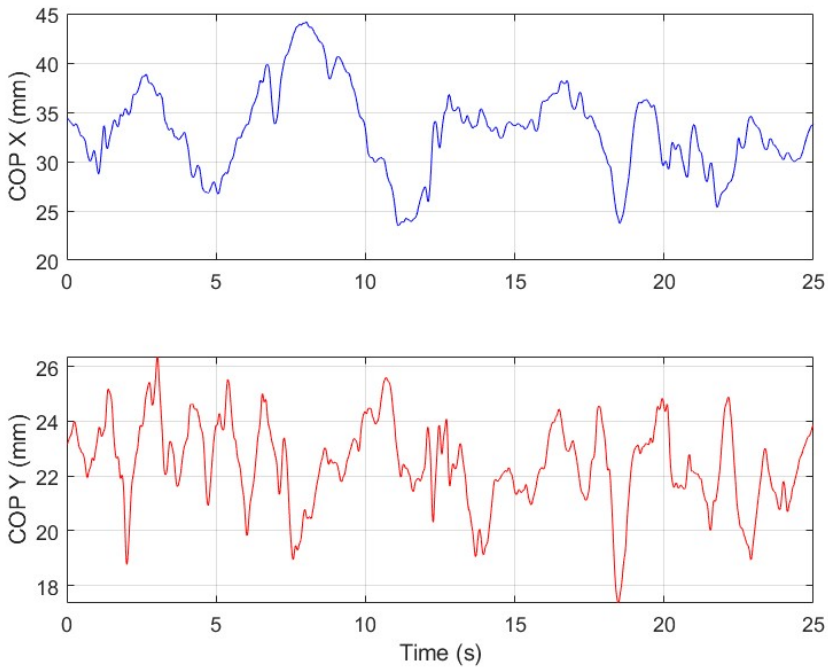


Figure 11: **Filtered time-series plots of COP.** Time-series plot of center of pressure (COP) x (ML) and y (AP) coordinates after applying low-pass Butterworth filter.

3.4.3 Processing

3.4.3.1 Acceleration Parameters

First, the resultant root mean square of the acceleration signal (RMS ACC) was computed:

$$\mathrm{RMS}_{\mathrm{AP}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \mathrm{AP}_i^2}$$

$$\mathrm{RMS}_{\mathrm{ML}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \mathrm{ML}_i^2}$$

$$\mathrm{RMS\ ACC} = \sqrt{\mathrm{RMS}_{\mathrm{AP}}^2 + \mathrm{RMS}_{\mathrm{ML}}^2}$$

The AP and ML are the filtered acceleration signals from Y and Z axis, respectively. N is the total number of samples.

Next, the velocity signal was obtained by cumulative trapezoidal integration of the detrended acceleration signal over time, following the equation:

$$\vec{v}(t) = \int \vec{a}(t)\, dt$$

The velocity signal was then detrended and only the ML and AP axes were considered. The magnitude of the 2D velocity vector was computed and the resultant mean velocity (MV ACC) was obtained by averaging the magnitude over time:

$$\mathrm{MV\ ACC} = \frac{1}{N}\sum_{i=1}^{N} |\vec{v}_{\mathrm{2D}}|$$

3.4.3.2 COP Parameters

Root Mean Square of the COP (RMS COP) was calculated as follows:

$$\mathrm{RMS}_{\mathrm{AP}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \mathrm{AP}_i^2}$$

$$\mathrm{RMS}_{\mathrm{ML}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \mathrm{ML}_i^2}$$

$$\mathrm{RMS\ COP} = \sqrt{\mathrm{RMS}_{\mathrm{AP}}^2 + \mathrm{RMS}_{\mathrm{ML}}^2}$$

The AP and ML are the displacement vectors from Y and X axis, respectively, and N is the total number of samples.

Total path length was computed as the sum of Euclidean distances between consecutive COP positions and used to calculate the mean total velocity of COP (MV COP).

$$\text{Total Path Length} = \sum_{i=1}^{n-1} \sqrt{(\mathrm{COP}_{x,i+1} - \mathrm{COP}_{x,i})^2 + (\mathrm{COP}_{y,i+1} - \mathrm{COP}_{y,i})^2}$$

MV COP was computed as Total Path length divided by duration of the test (T).

$$\mathrm{MV\ COP} = \frac{\text{Total Path Length}}{T}$$

3.5 Statistical analysis

Statistical analyses were performed using MATLAB R2024b (MathWorks, Natick, MA, USA). The normality of the data was assessed using the Shapiro-Wilk test. Based on these results, the Friedman test was performed for condition-based comparisons within each measurement group across all four balance conditions. Wilcoxon signed-rank tests with Bonferroni correction were subsequently conducted for post-hoc analyses. To evaluate the relationship between the two measurement methods, Spearman's rank correlation coefficient was used for non-normally distributed data, while Pearson's correlation coefficient was applied for normally distributed data. Correlation coefficient values were interpreted as follows: 0.3-0.5 represented low correlation, 0.5-0.7 indicated moderate correlation, and 0.7-0.9 denoted high correlation [105]. Further agreement between the force plate and smartphone measurements was assessed by generating Bland–Altman plots for RMS and MV parameters. In each plot, the average of the two device measurements was plotted against their difference for each individual trial. The mean bias and the 95% limits of agreement (LoA), defined as the mean difference ±1.96 times the standard deviation, were calculated. In addition, the 95% confidence intervals (CI) for both the bias and the LoA were reported to quantify the precision of these estimates. Before conducting the Bland–Altman analysis, a scaling factor was applied to the IMU-derived parameters to bring their magnitude in line with that of the force plate-derived values. This adjustment was empirically determined based on the observed relationship between the two modalities across multiple trials. The application of this scaling factor enabled a more meaningful and interpretable assessment of agreement between the two measurement systems. The Mann-Whitney U test was employed to compare differences in postural control between healthy participants and patients with T2DM. Effect sizes are reported as small = 0.2; medium = 0.5, and large = 0.8 [106].

Results

This section presents the findings of the postural control evaluation that compares the measurements obtained from smartphone IMU sensor with those from force plates in healthy participants (n = 19) and patients with T2DM (n = 14). Results are organized by the participant groups.
For healthy participants, all four postural conditions (BL-EO, BL-EC, OL-EO, OL-EC) were analyzed. For T2DM patients, only the first two conditions (BL-EO and BL-EC) were independently performed without external support. Although patients required assistance during single-leg stance conditions (OL-EO and OL-EC), data from these conditions were still collected and included for comparative purposes, allowing for group comparisons across all conditions

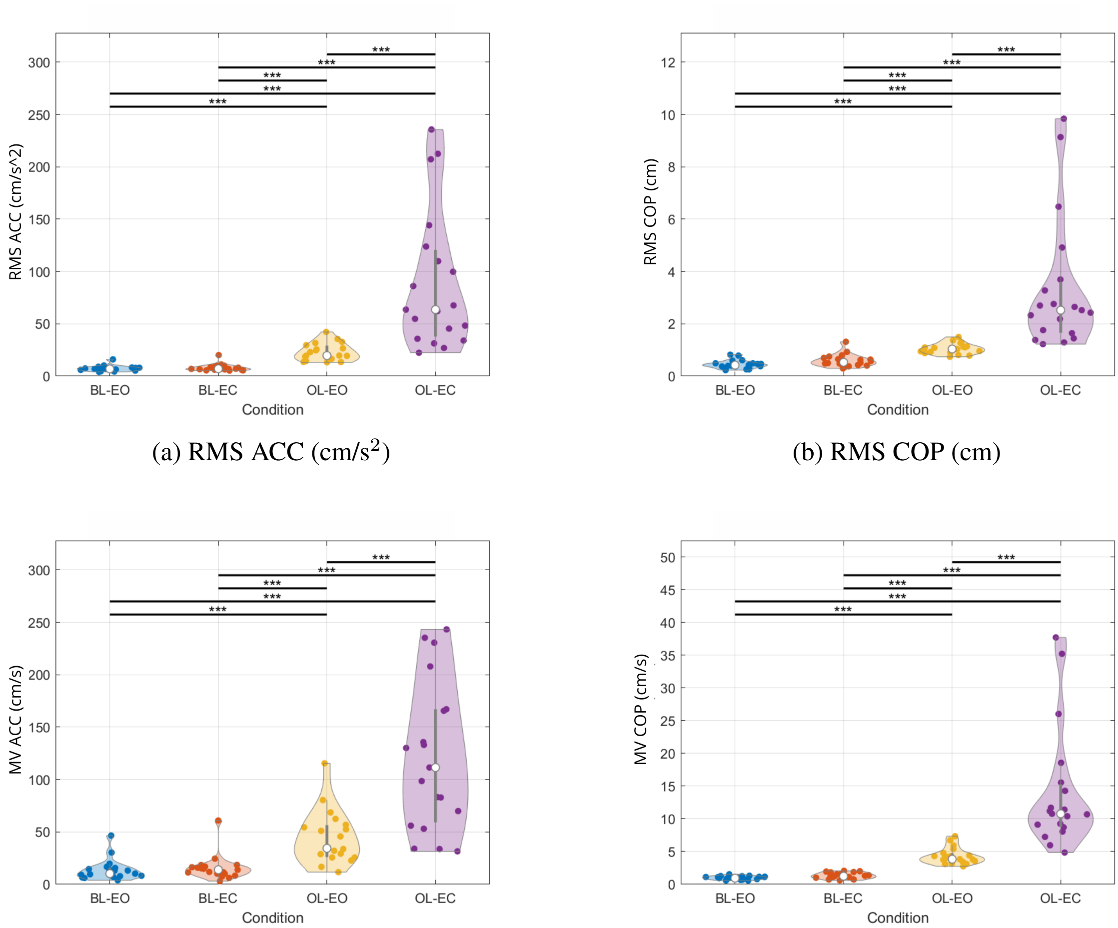
4.1 Healthy Group Results

Descriptive statistics were calculated for all postural control parameters across the four balance conditions (BL-EO, BL-EC, OL-EO, OL-EC) for both measurement methods (smartphone IMU and force plate). All parameters showed a progressive increase as visual and proprioceptive inputs were reduced and the balance conditions became more challenging (appendix 1).

4.1.1 Effects of Different Conditions on Balance Parameters

Based on the results from the Shapiro-Wilk test (appendix 1), a non-parametric Friedman test was conducted to look for differences in postural control parameters across the four balance conditions. Results were considered significant at $p < 0.05$. The test yielded statistically significant results for the smartphone-based RMS ACC and MV ACC, as well as for the force plate – based RMS COP and MV COP (appendix 3). Based on these results, a Bonferroni-corrected post-hoc Wilcoxon signed-rank test was performed between all pairwise condition combinations. To account for the increased risk of Type I errors, due to multiple comparisons, the significance level (α) was adjusted (α = 0.0083).

The variability of the data increased progressively in all parameters as the tasks got more difficult (figure 12). The most challenging condition (OL-EC) consistently exhibited the widest distribution of values for each parameter, as seen by the broader shape of the violin plots and the increased spread of individual data points. On the other hand, the least challenging balance task (BL-EO) showed the least variability, with tightly clustered data points and narrow distributions, a pattern seen across both measurement methods.
The post – hoc analysis revealed significant differences in all but one compared pairs of conditions for all parameters (figure 12). The magnitude of the differences are showed by the medium effect sizes (0.55 - 0.62) among all pairs but BL- EO vs BL – EC (0.10 - 0.42) in each parameter irrelevant of the measurement method (appendix 5).
The most pronounced difference for RMS ACC was observed between OL-EC (63.4 cm/s^2) and BL – EO (6.93 cm/s^2), following with BL – EC (7.08 cm/s^2), and OL-EO condition (19.66 cm/s^2). The force plate based RMS COP also showed significant differences ($p < 0.001$) between all conditions except between BL-EO (0.42 cm) and BL-EC (0.53 cm).
A similar pattern emerged for both MV parameters, having significant effects between all condition pairs except BL-EO (MV ACC: 10.21 cm/s and MV COP: 0.95 cm/s) versus BL-EC (MV ACC: 13.92 cm/s and MV COP: 1.25 cm/s). As the previous parameters, the velocities followed a progressively increasing trend.



(a) RMS ACC (cm/s^2)

(b) RMS COP (cm)

(c) MV ACC (cm/s)

(d) MV COP (cm/s)

Figure 12: **Distribution and Significance of Balance Parameters in Healthy Participants.** Distribution and significance of smartphone-based Root Mean Squared of Acceleration (RMS ACC) and Mean Velocity of Acceleration (MV ACC), and force plate-based Root Mean Squared Center of Pressure (RMS COP) and Mean Velocity of Center of Pressure (MV COP) across conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC). The violins illustrate the data density, with the white dot indicating the median and the grey vertical line representing the interquartile range. Asterisks denote statistically significant differences between conditions $p < 0.008$.

4.1.2 Correlation Analysis Between Smartphone and Force Plate Measurements

Next, the Spearman's rank correlation analysis was performed to assess the relationship between smartphone-derived ACC parameters and force plate-derived COP parameters across all four balance conditions. Based on the Shapiro-Wilk test (appendix 1), the Spearman Correlation analysis was applied to all pairs except one. As both RMS ACC and RMS COP in OL-EO condition were normally distributed, Pearson's correlation analysis was additionally performed [107].

The results demonstrated strong correlations in RMS parameters (figure 13). The strongest correlation was observed in the most challenging OL-EC condition (ρ = 0.90, $p < 0.001$), followed by the least challenging BL-EO condition (ρ = 0.75, $p < 0.001$). The BL-EC and OL-EO had moderate correlation coefficients of 0.55 ($p < 0.05$) and 0.65 ($p < 0.01$), respectively.

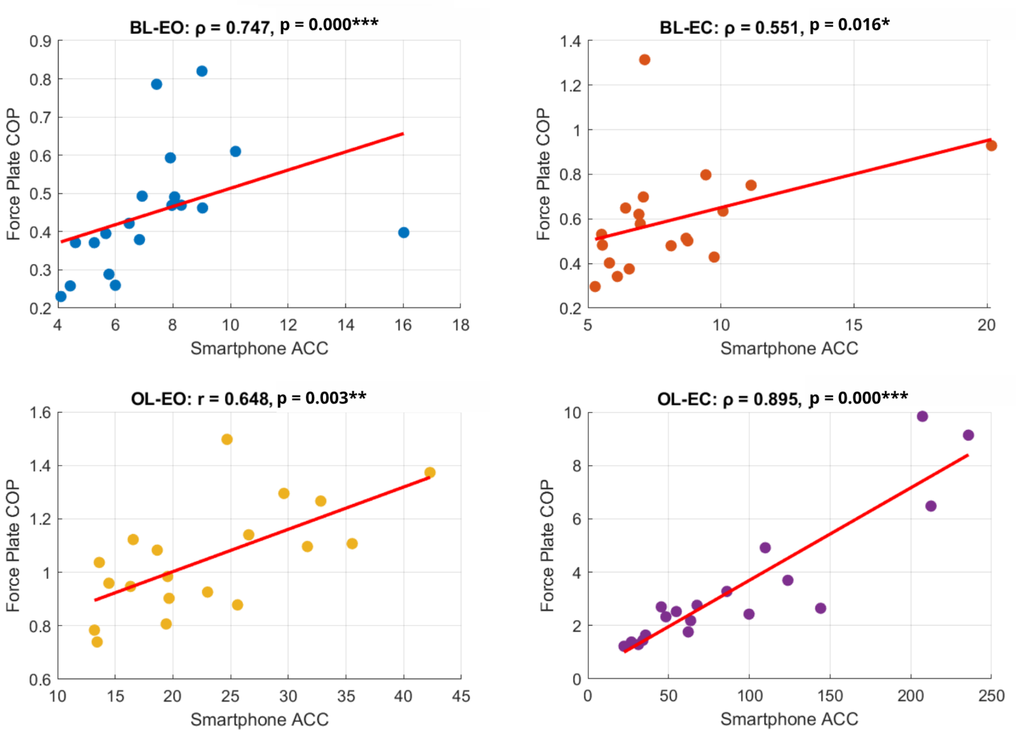


Figure 13: **Correlation Analysis of RMS ACC and RMS COP.** Correlation between smartphone-derived Root Mean Square of Acceleration (RMS ACC) and force plate-derived Root Mean Square of Center of Pressure (RMS COP) across four balance conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC). A linear regression line is shown in red for each plot. Conditions are color-coded as follows: BL-EO in blue, BL-EC in orange, OL-EO in yellow, and OL-EC in purple. Significance is denoted with asterisks: $*p < 0.05$, $**p < 0.01$, $***p < 0.001$. **Note:** r indicates Pearson's correlation coefficient.

Similarly for MV parameters, the strongest correlation could be observed after taking out the vision and challenging the base of support in OL-EC (ρ = 0.70, $p = 0.001$) (figure 14). The remaining conditions (BL-EO: ρ = 0.33, $p = 0.163$; BL-EC: ρ = 0.20, $p = 0.402$; OL-EO: ρ = 0.27, $p = 0.265$) displayed poor correlation and did not reach statistical significance.

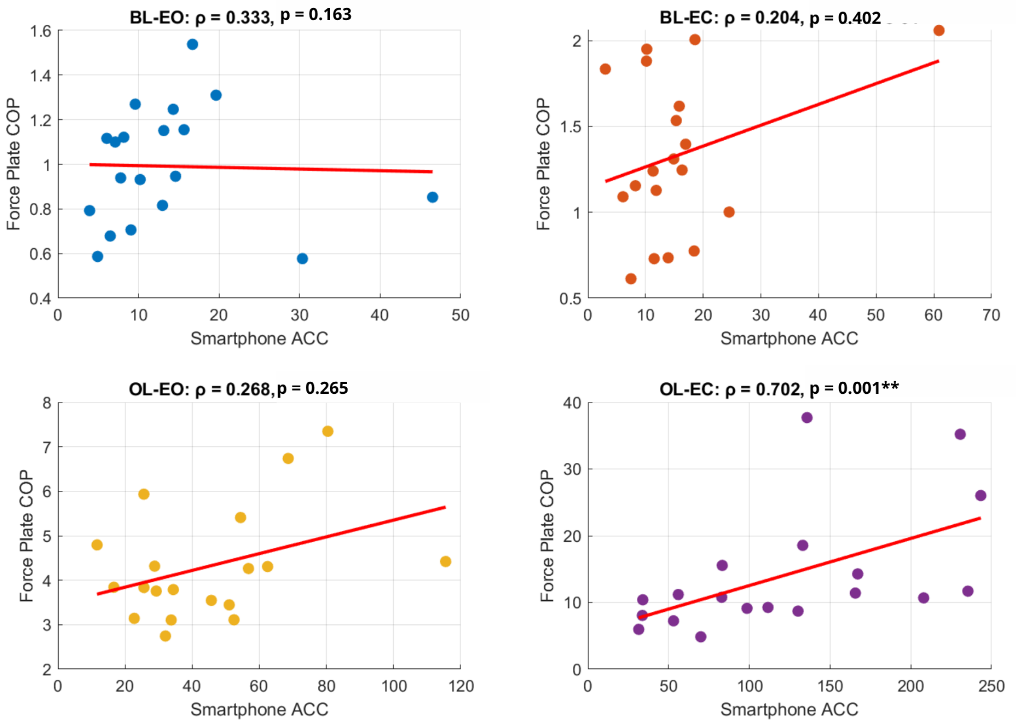
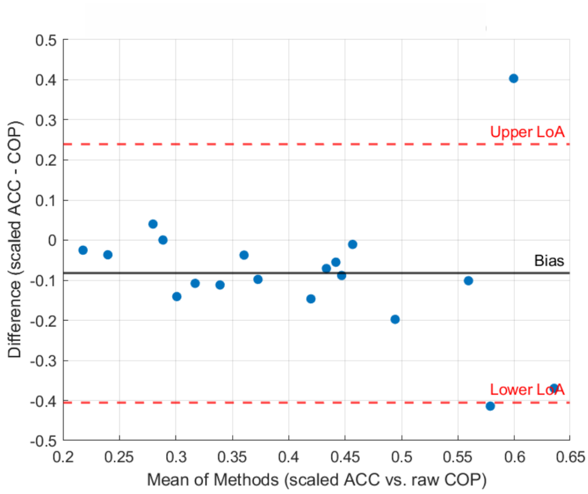


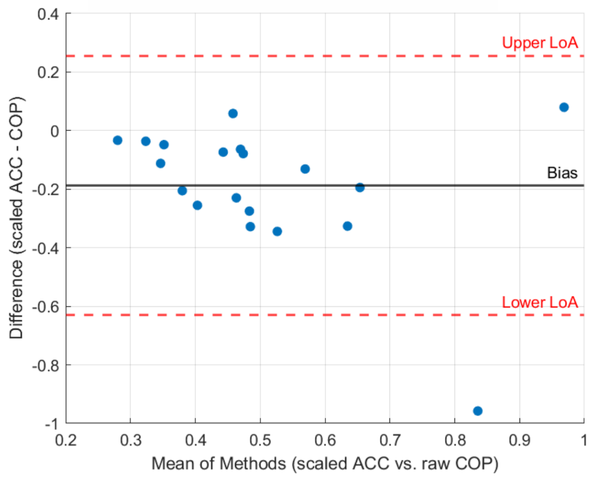
Figure 14: **Correlation Analysis of MV ACC and MV COP.** Correlation between smartphone-derived Mean Velocity of Acceleration (MV ACC) and force plate-derived Mean Velocity of Center of Pressure (MV COP) across the four balance conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC). A linear regression line is shown in red for each plot. Conditions are color-coded as follows: BL-EO in blue, BL-EC in orange, OL-EO in yellow, and OL-EC in purple. Significance is denoted with asterisks: $**p < 0.01$. **Note:** r indicates Pearson's correlation coefficient.

4.1.3 Bland-Altman Agreement Analysis

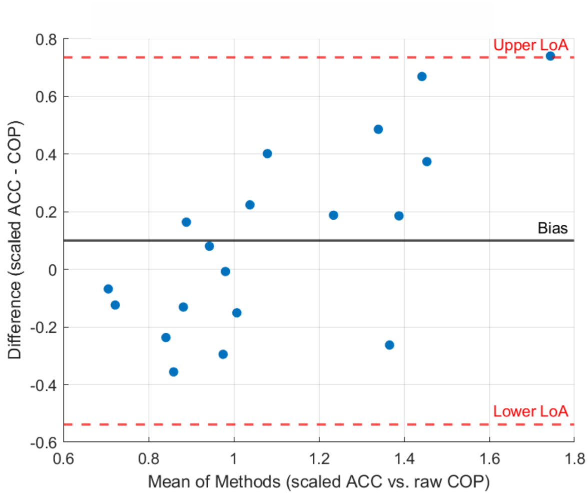
To assess the interchangeability and agreement between the smartphone IMU sensor and the force plate for measuring postural control, Bland-Altman analysis was performed (appendix 8). A scaling factor of 20 was applied to the IMU-derived parameters before conducting the analysis to allow for comparison with the force plate values, which were several magnitudes lower.
For RMS, the limits of agreement (LoA) generally increased with more challenging conditions (from BL-EO to OL-EC). The best agreement was observed in the BL-EO condition (figure 15a), characterized by a small bias (-0.08) and relatively narrow LoA (0.24 to -0.40). Agreement decreased progressively as the tasks became more challenging. The BL-EC (figure 15b) condition showed a larger negative bias (-0.19) and slightly wider LoA (0.26 to -0.63). For the OL-EO condition (figure 15c), while the average bias was small (0.10), the agreement significantly worsened, indicated by wider LoA (0.74 to -0.54) and increased scatter at higher values. The OL-EC condition (figure 15d) exhibited the poorest agreement, marked by a substantial positive bias (1.15) and very wide LoA (3.99 to -1.69), suggesting that the discrepancy between the two methods increased with the magnitude of sway during this task.



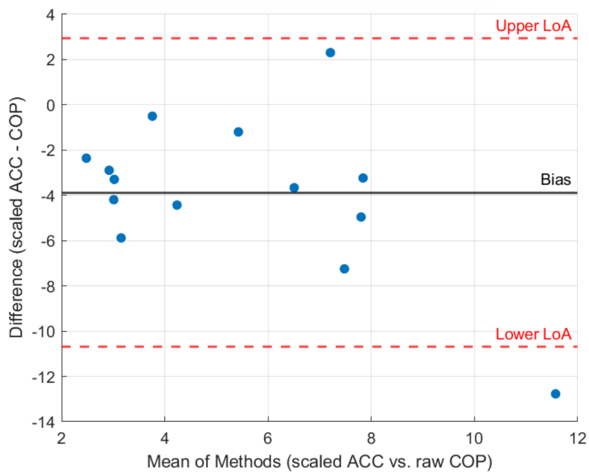
(a) BL-EO



(b) BL-EC



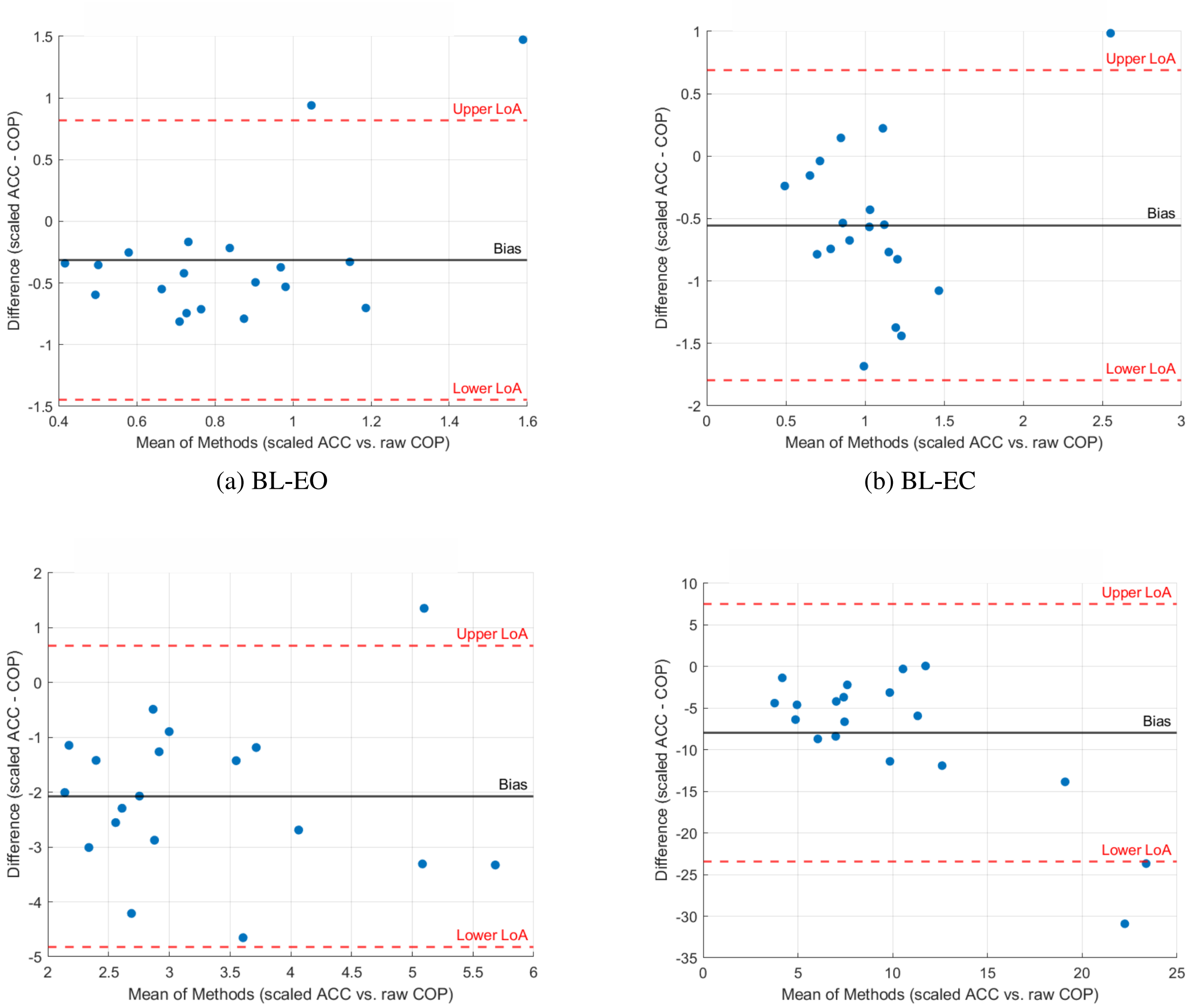
(c) OL-EO



(d) OL-EC

Figure 15: **Agreement Between RMS ACC and RMS COP in Healthy Participants.** Bland-Altman plots for each condition comparing scaled Root Mean Square of Acceleration (RMS ACC) with raw Root Mean Square of Center of Pressure (RMS COP) in the healthy group. The mean of the two methods is displayed on the x-axis and their difference (scaled ACC – COP) on the y-axis. The solid black line represents the mean bias, while the dashed red lines indicate the upper and lower limits of agreement (LoA).

Similar to the RMS parameters, there was variability in bias and LoA for MV parameters across the different balance conditions, highlighting task-dependent agreement. Among the conditions, the best agreement was demonstrated in the BL-EO condition (figure 16a) (bias: -0.31; LoA: 0.82 to -1.45). The BL-EC (figure 16b) and especially the OL-EO (figure 16c) conditions showed progressively worse agreement, with wider LoA (BL-EC: 0.69 to -1.80; OL-EO: 0.67 to -4.82) and larger negative biases (BL-EC: -0.55; OL-EO: -2.08). The OL-EC (figure 16d) condition exhibited the most prominent lack of agreement, characterized by a large negative bias (-7.97) and wide LoA (7.52 to -23.47).



(a) BL-EO (b) BL-EC

(c) OL-EO (d) OL-EC

Figure 16: **Agreement Between MV ACC and MV COP in Healthy Participants.** Bland-Altman plots for each condition comparing scaled Mean Velocity of Acceleration (MV ACC) with raw Mean Velocity of Center of Pressure (MV COP) in the healthy group. X axis depicts the mean of the two measurement methods and their difference (scaled ACC – COP) is displayed on y axis. The bias is represented by the black line and the upper and lower limits of agreement (LoA) by the dashed red lines.

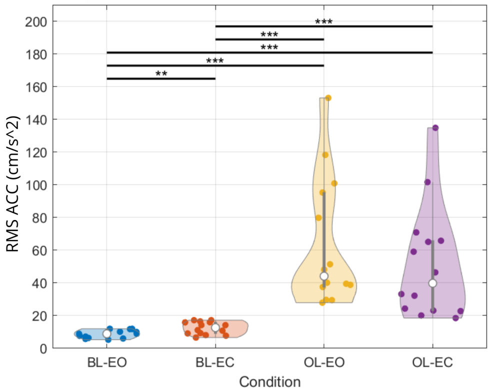
4.2 T2DM Group Results

Similarly to the healthy group, descriptive statistics were calculated for T2DM group (appendix 2).
As mentioned previously, T2DM participants were supported during the single-leg stance conditions (OL-EO and OL-EC), influencing the postural sway measurements. Despite this support, both ACC and COP parameters showed substantially higher values in the more challenging conditions, indicating increased postural instability.

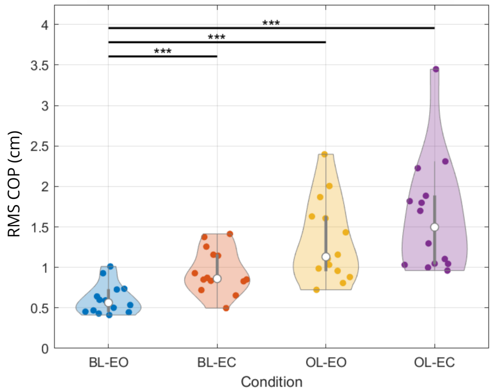
4.2.1 Effects of Different Conditions on Balance Parameters

Friedman test was conducted to assess differences in postural control parameters across the four balance conditions (appendix 3). Significant differences were observed for all parameters. The distribution of the four postural control parameters across the four balance conditions is depicted in figure (17).
RMS ACC values were lower in the first two conditions (BL-EO: 8.90 cm/s^2; BL-EC: 12.67 cm/s^2) compared to one-leg stance conditions (OL-EO: 44.12 cm/s^2; OL-EC: 39.79 cm/s^2) (figure 17a). Notably, the OL-EO condition exhibited the highest median with wider IQR, indicating greater variability in this condition.
RMS COP showed a progressively increasing trend as the balance tasks became more difficult. The median and the spread of the data were larger in the one-leg stance conditions (OL-EO: 1.13 cm and OL-EC: 1.50 cm) compared to the both-legged stance conditions (BL-EO: 0.56 cm and BL-EC: 0.86 cm), also indicating greater variability (figure 17b).
Similarly, the MV ACC values were lower in the BL-EO (19.72 cm/s) and BL-EC (14.72 cm/s) conditions, and higher in the OL-EO (86.61 cm/s) and OL-EC (73.65 cm/s) conditions (figure 17c).
The force plate-based MV COP showed directly proportional increase across the four conditions, with values progressively rising from BL-EO (1.60 cm/s) to OL-EC (6.07 cm/s) (figure 17d).

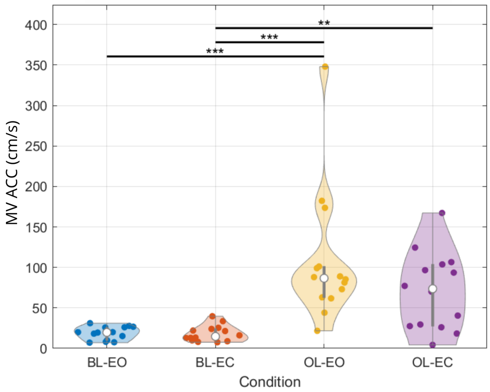
Post-hoc analysis using the Wilcoxon signed-rank test (with Bonferroni correction, significance level set at $p < 0.0083$) revealed significant differences between most condition pairs for all parameters (appendix 4). However, no significant differences were found between the OL-EO and OL-EC pair of conditions in any of the parameters. This could be due to the assistance the patients required during these two most challenging balance tasks.
For RMS ACC, comparisons of the both leg and one-leg balance conditions had moderate effect sizes (0.62), and were statistically significant at $p < 0.001$, showing a substantial increase of acceleration when visual input was removed or the base of support reduced (figure 17a). RMS COP (figure 17b) showed statistically significant differences only when BL-EO condition was compared.
The analysis in MV ACC revealed a significant increase from BL-EO to OL-EO ($p < 0.001$), BL-EC to OL-EO ($p < 0.001$), and BL-EC to OL-EC ($p < 0.01$), with moderate effect sizes (r = 0.49 - 0.62) (figure17c). No other pairwise comparisons reached statistical significance. For the force-plate based MV COP (figure17d), all the comparison except OL-EO and OL-EC showed statistically significant increase with moderate effect sizes (r = 0.50-0.62).



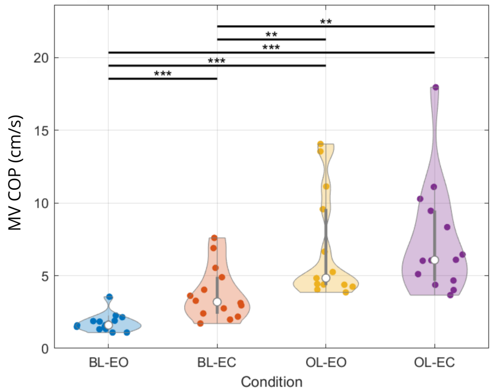
(a) RMS ACC (cm/s^2)



(b) RMS COP (cm)



(c) MV ACC (cm/s)



(d) MV COP (cm/s)

Figure 17: **Distribution and Significance of Balance Parameters in T2DM patients.** Distribution and significance of smartphone-based Root Mean Squared of Acceleration (RMS ACC) and Mean Velocity of Acceleration (MV ACC), and force plate-based Root Mean Squared Center of Pressure (RMS COP) and Mean Velocity of Center of Pressure (MV COP) for the T2DM group across four balance conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC).Significant differences between conditions are depicted with asterisks ($^{**}p < 0.01$, $^{***}p < 0.008$).

4.2.2 Correlation Analysis Between Smartphone and Force Plate Measurements

Similarly to the healthy group, correlation analyses were performed to examine the relationships between smartphone-derived ACC parameters and COP measurements obtained from the force plate across different balance conditions. The Shapiro - Wilk test revealed a mix of results across parameters and conditions, with some variables demonstrating normal distribution and others deviating from it (appendix 2). Therefore, both Spearman's rank-order correlation and Pearson's correlation analyses were performed.

RMS parameters displayed strong positive correlations across all four conditions (figure18). The correlation coefficients ranged from 0.71 to 0.79 (OL-EC, $p < 0.01$; BL-EC, $p = 0.001$).

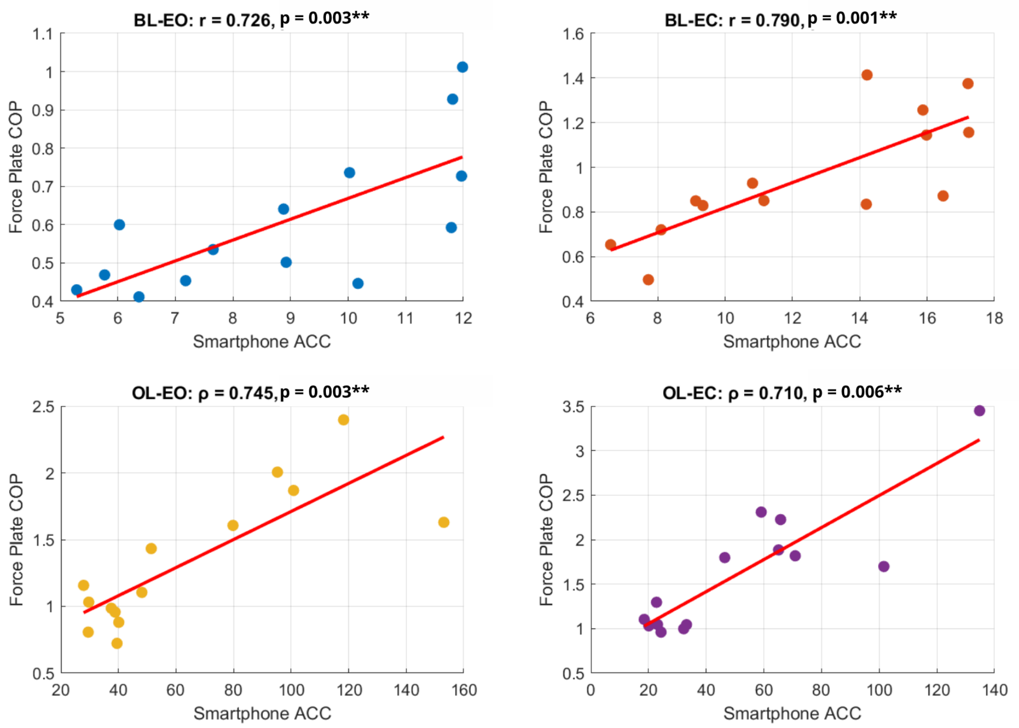


Figure 18: **Correlation Analysis of RMS ACC and RMS COP.** Correlation between smartphone-derived Root Mean Square of Acceleration (RMS ACC) and force plate-derived Root Mean Square of Center of Pressure (RMS COP) across four balance conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC). A linear regression line is shown in red for each plot. Conditions are color-coded as follows: BL-EO in blue, BL-EC in orange, OL-EO in yellow, and OL-EC in purple. Significance is denoted with asteriks: $^{**}p < 0.01$. **Note:** r indicates Pearson's correlation coefficient.

MV parameters showed moderate correlation in OL-EC condition ($\rho = 0.55$, $p < 0.05$) (figure 19). Rest of the balance tasks displayed only low correlation coefficients, which were not statistically significant.

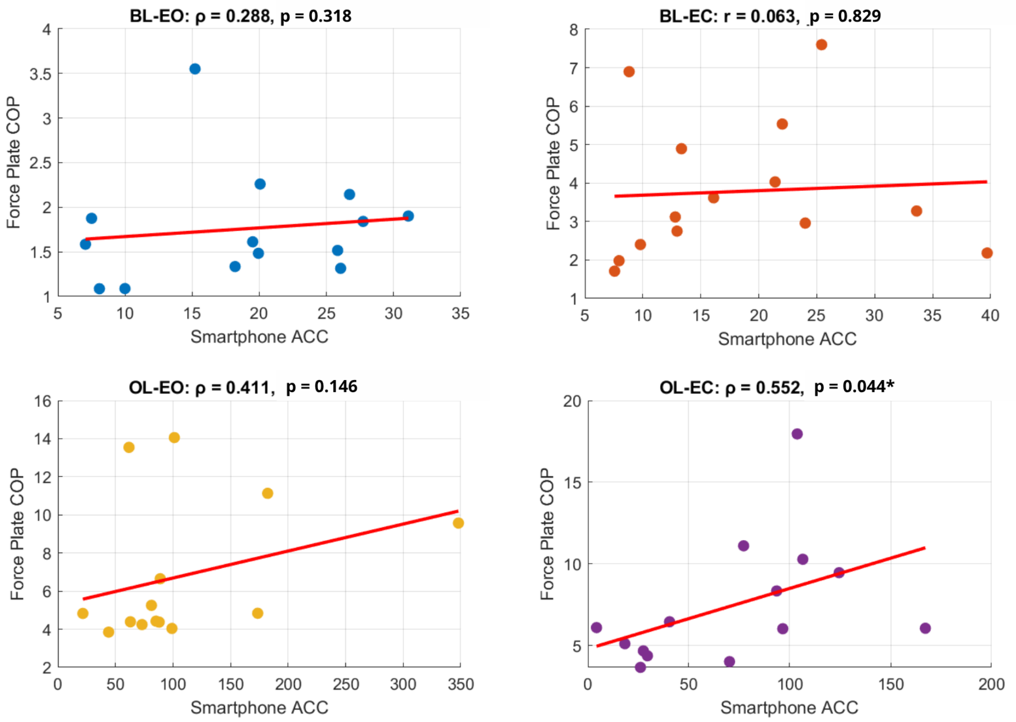
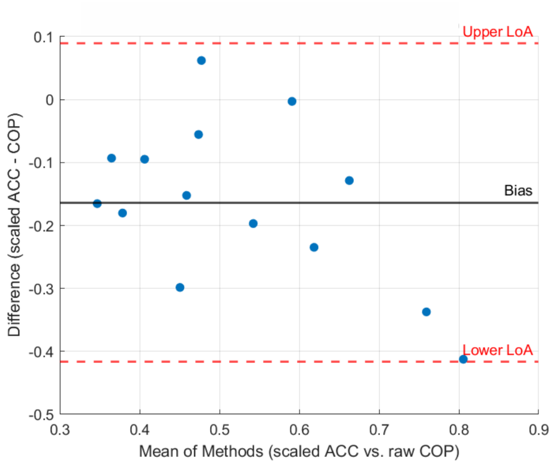


Figure 19: **Correlation Analysis of MV ACC and MV COP.** Correlation between smartphone-derived Mean Velocity of Acceleration (MV ACC) and force plate-derived Mean Velocity of Center of Pressure (MV COP) across four balance conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC). A linear regression line is shown in red for each plot. Conditions are color-coded as follows: BL-EO in blue, BL-EC in orange, OL-EO in yellow, and OL-EC in purple. Significance is denoted with asteriks: $*p < 0.05$. **Note:** r indicates Pearson's correlation coefficient.

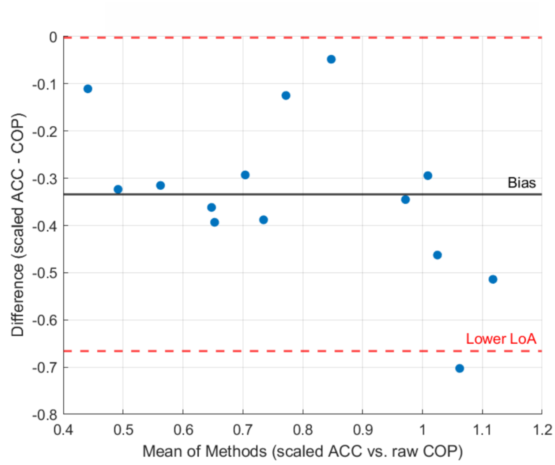
4.2.3 Bland-Altman Agreement Analysis

The Bland-Altman analysis for the T2DM group's RMS and MV parameters revealed a varied agreement, also dependent on the complexity of the balance tasks (appendix 7). A scaling factor of 20 was applied to the IMU acceleration data to enable direct comparison with COP measurements as the force plate-derived values were smaller in magnitude.

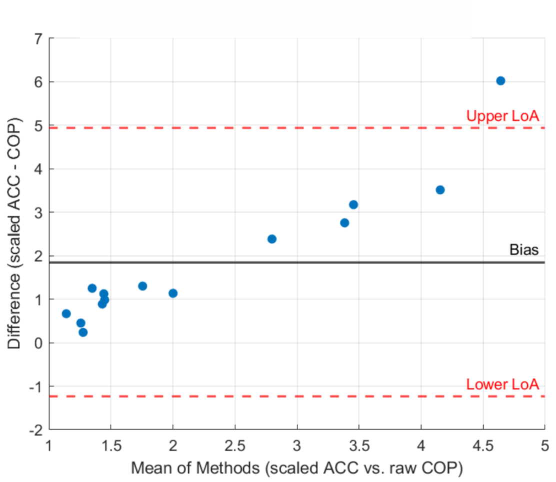
RMS showed better agreement in the less challenging balance tasks (BL-EO and BL-EC) (figures 20a and 20b) than in the single-leg conditions (OL-EO and OL-EC) (figures 20c and 20d). A notable positive bias (1.85) emerged in OL-EO condition, accompanied by wide LoA (4.94 to -1.24), indicating that the agreement between the two devices was exacerbated with increasing sway.



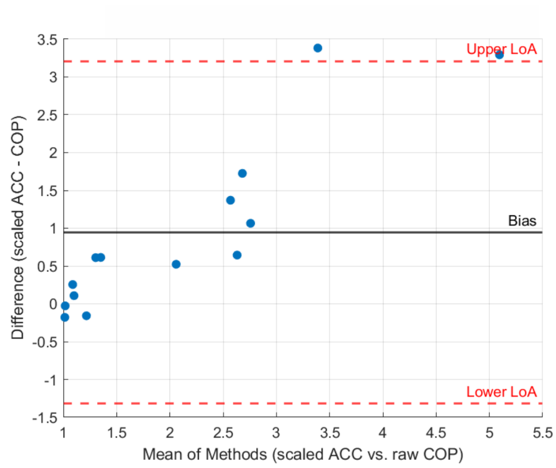
(a) BL-EO



(b) BL-EC



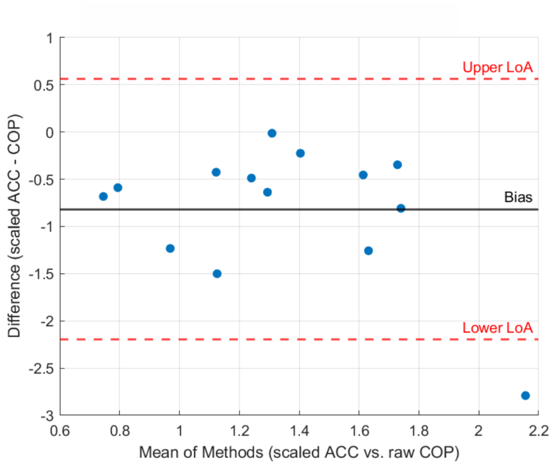
(c) OL-EO



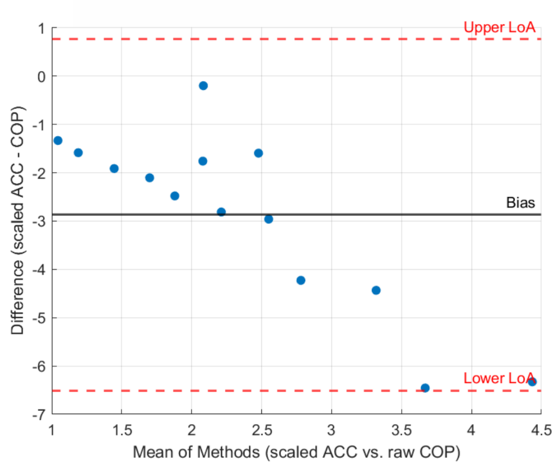
(d) OL-EC

Figure 20: **Agreement Between RMS ACC and RMS COP in T2DM Patients.** Bland-Altman plots for each condition comparing scaled Root Mean Square of Acceleration (RMS ACC) with raw Root Mean Square of Center of Pressure (RMS COP) in the T2DM group. X axis depicts the mean of the two measurement methods and their difference is displayed on y axis. The bias is represented by the black line and the upper and lower limits of agreement (LoA) by the dashed red lines.

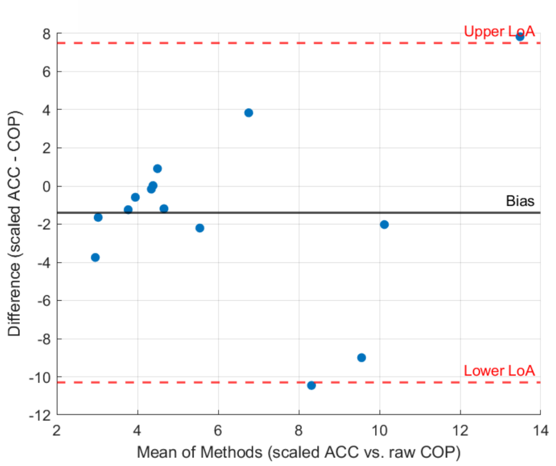
Agreement in MV parameters showed consistent negative bias across all conditions (BL-EO: -0.82; BL-EC: -2.87; OL-EO: -1.40; OL-EC: -3.88), growing in magnitude with increasing task difficulty. LoA were wide for all tasks, particularly in the single-leg conditions (BL-EO: 0.56 to -2.20; BL-EC: 0.77 to -6.51; OL-EO: 7.51 to -10.31; OL-EC: 2.93 TO -10.69) (figures 21d and 21d).



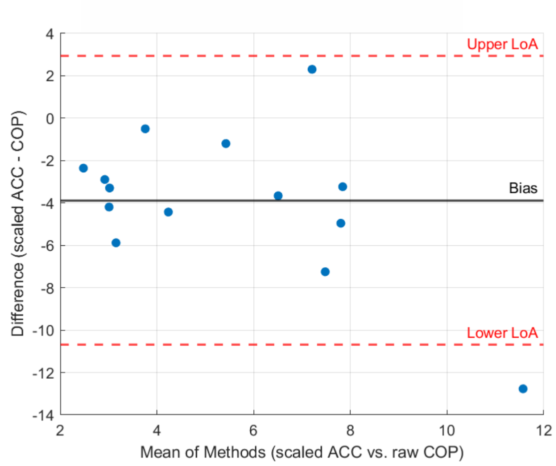
(a) BL-EO



(b) BL-EC



(c) OL-EO

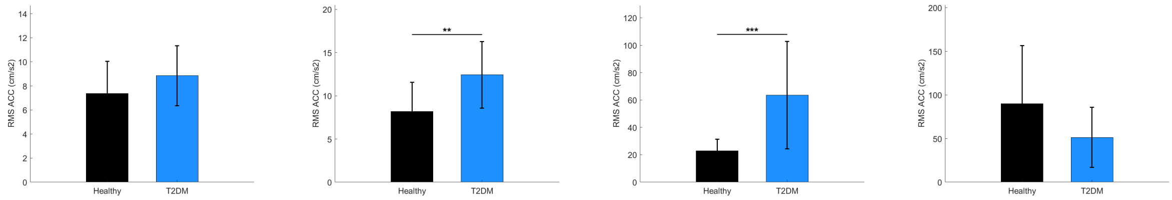


(d) OL-EC

Figure 21: **Agreement Between MV ACC and MV COP in T2DM Patients.** Bland-Altman plots for each condition comparing scaled Mean Velocity of Acceleration (MV ACC) with raw Mean Velocity of Center of Pressure (MV COP) in the T2DM group. The x axis depicts the mean of the two measurement methods, y axis displays the difference between them. The bias is represented by the black line and the upper and lower limits of agreement (LoA) by the dashed red lines.

4.3 Assessment of Balance Parameters in Healthy vs T2DM Groups

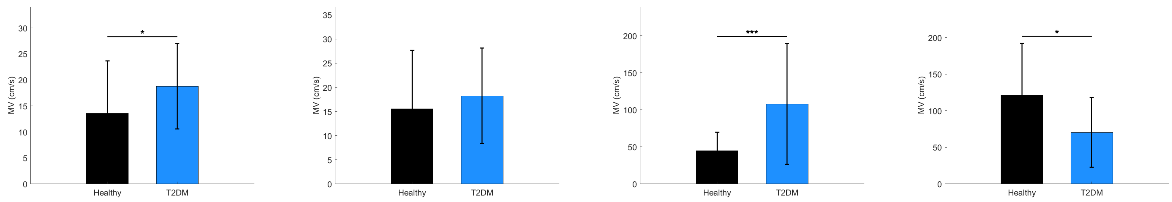
To evaluate whether smartphone-based acceleration measurements could distinguish between healthy and T2DM group, Mann-Whitney U test was performed ($p < 0.05$) (appendix 6).
Although T2DM patients demonstrated higher RMS ACC values in the BL-EO conditions (8.85 ± 2.49 cm/s^2) compared to the healthy group (7.37 ± 2.69 cm/s^2), this difference did not reach statistical significance (U = 86, r = 0.30, p = 0.09) (figure 22a). On the other hand, the difference in BL-EC was statistically significant with T2DM participants showing notably higher values (12.43 ± 3.85 cm/s^2) than healthy participants (8.18 ± 3.37 cm/s^2) (U = 48, r = 0.5, p = 0.002**) (figure 22b). Despite the required support for T2DM group in single leg conditions, a significant difference was also observed in OL-EO condition (U = 18, r = 0.73, p = 0.000***)(figure 22c). However, during the most challenging OL-EC condition (figure 22d), although not significant, healthy participants demonstrated higher RMS ACC values than T2DM patients (U = 82, r = 0.32, p = 0.066).



(a) BL-EO (b) BL-EC (c) OL-EO (d) OL-EC

Figure 22: **Group Comparison of RMS ACC Between Healthy and T2DM Participants.** Comparison of mean and standard deviation Root Mean Square of Acceleration (RMS ACC) values in the healthy (black bar) and T2DM (blue bar) groups during four balance conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC). Asterisks indicate statistically significant differences ($^{**}p < 0.01$, $^{***}p < 0.001$).

The MV ACC measurements revealed a statistically significant difference with medium effect size between healthy (13.54 ± 10.12 cm/s) and T2DM (18.78 ± 8.18 cm/s) groups during the BL-EO condition (U = 76, r = 0.36, p = 0.0396*) (figure23a). In contrast, during the BL-EC condition, no significant difference was observed in MV ACC between T2DM (18.25 ± 9.89 cm/s) and healthy participants (15.55 ± 12.09 cm/s) (U = 107, r = 0.17, p = 0.3530) (figure 23b). However, in OL-EO condition (figure 23c), the difference in MV ACC values reached the highest significance with medium effect (U = 41, r = 0.58, p = 0.001**). The trend reversed in the OL-EC condition, where the healthy group exhibited substantially higher MV ACC values (121.22 ± 70.84 cm/s) compared to the T2DM group (70.38 ± 47.59 cm/s), a difference that was statistically significant (U = 74, r = 0.37, p = 0.033) (figure23d).



(a) BL-EO (b) BL-EC (c) OL-EO (d) OL-EC

Figure 23: **Group Comparison of MV ACC Between Healthy and T2DM Participants.** Comparison of mean and standard deviation Mean Velocity of Acceleration (MV ACC) values in the healthy (black bar) and T2DM (blue bar) groups during four balance conditions: both legs eyes open (BL-EO), both legs eyes closed (BL-EC), one leg eyes open (OL-EO), and one leg eyes closed (OL-EC). Asterisks indicate statistically significant differences ($^{*}p < 0.05$, $^{***}p < 0.001$).

Discussion

The aim of this project was to explore whether smartphone-based postural metrics can reflect the postural impairments typically observed in older adults with T2DM. This project evaluated postural control across four standard balance tasks using smartphone-derived (RMS and MV of acceleration) and force plate-derived (RMS and MV of COP) metrics in both healthy individuals and people with T2DM.

Overall, participants showed greater variability in more challenging balance tasks, suggesting that both measurement devices were sensitive to changes in task demand. The project also found strong correlations between the smartphone and force plate data, especially for RMS parameters. Even with physical support, T2DM patients struggled with single-leg tasks and showed signs of impaired balance even during simpler tasks.

5.1 Smartphone Detects Condition-Specific Changes in Postural Sway

Firstly, demonstrating the condition - sensitivity is essential if smartphones are to be used as alternatives for assessing balance impairments in population such as individuals with T2DM. When comparing postural control between bipedal and single-leg stances, with and without vision input, it was expected for both the smartphone IMU sensor and the force plate to reflect the increasing difficulties of the measured balance tasks.

The findings confirmed that as balance tasks increased in difficulty (e.g., transitioning from bipedal to single-leg stances, and with or without vision), there were significant, measurable changes in postural sway. The simplest condition – standing with both legs and eyes open (BL-EO) - consistently showed the lowest RMS and MV values across both measurement systems in both healthy individuals and T2DM patients.

As anticipated, the values increased when the visual input was removed, which is in accordance with consistent evidence in literature [108], [109], [110]. The increase is due to the vision having a critical role in maintaining postural stability by providing CNS with continuous updates on the position of the body relative to the environment [109].

Standing on both legs creates the largest base of support, making the maintenance of balance easier. Single-leg stance significantly narrows this base, demanding more stability adjustments from the postural control system. The addition of closed eyes further increases this challenge [111]. Therefore, the OL-EC represented the most difficult task in this project and consistently produced the highest RMS and MV values.

However, an exception was observed in the T2DM group's smartphone-derived measurements, where the highest RMS ACC and MV ACC values occurred during OL-EO rather than OL-EC. This divergence from the expected trend was not present in the double-legged stances and therefore could be attributed to both the physical support the patients needed when standing on one leg and the fundamental differences between measurement technologies. Without visual input (OL-EC condition), participants tended to rely more heavily on the support, adopting a more rigid posture, which could have reduced trunk movement and lowered smartphone-based sway values. However, with available visual feedback (OL-EO) they attempted to use balance strategies more actively, which could have generated greater trunk movement that was captured by the IMU sensor, even when force plates measurements remained stable.

This highlights an important distinction between the two measurement systems. While force plates record the forces transmitted through the feet, the IMUs detect movements at the specific body segment where they are placed, which, in this case, was the trunk [112]. The mechanical relevance of this difference is important for understanding balance control.

The human body differentiates between various balance strategies to maintain upright posture. The choice primarily involves ankle and hip strategies, and depends on the magnitude and speed of sway.

Ankle strategies involve small, coordinated movements primarily affecting the ankle joints, and cause the body to act as an inverted pendulum [39]. This movement affects ground reaction forces and can therefore be well-captured, as subtle COP shifts, by force plates [113]. On the other hand, hip strategies involve significant movement at the hip joint and can be effectively recorded by smartphone-embedded IMU sensor. The hip strategies are often triggered by reduced base of support, such as in the single leg conditions, or by increased noise [39]. Furthermore, aging often causes individuals to shift from ankle-based strategy to a more robust hip-based strategy in order to stay upright [114].
However, sensory deficits themselves, whether age-related or due to other factors like injury or disease, directly affect the ability to use the ankle strategy effectively. The instability in T2DM patients can come from multiple sources, such as loss of peripheral sensory information in the feet and consequent switch from ankle to hip-based strategy [115]. Lafond et al. assessed elderly patients with T2DM and diabetic sensory neuropathy during quiet stance on a force plate. They showed that patients with diabetic sensory neuropathy shifted toward hip strategy, especially in the ML direction, as it accounted for over 90% of the recorder COP displacement. Moreover, they demonstrated that after taking out the visual input (eyes closed), the COP displacement increased [116].
The influence of age and the disease could explain why, despite the provided support, T2DM patients may have primarily used larger trunk adjustments in order to remain stable during the challenging conditions. Even though these adjustments were important for maintaining balance, they may have been less detectable as COP shifts on the force plate, since the feet remained relatively stationary, and were rather captured by the smartphone.
Therefore, the smartphone-derived acceleration data could offer valuable insight into the movement patterns used by clinical populations, such as T2DM patients, who may rely more heavily on proximal body segments for stability, due to the loss of lower legs proprioception and consequent reduction of balance responses.

5.2 RMS Parameters Show Consistent Strong Correlation Across Devices

Secondly, in order for the smartphones to be used in balance assessment in T2DM patients, it is essential to determine whether individuals with poor postural stability would be identified by both measurement devices. Therefore, correlation analyses were performed comparing RMS and MV parameters between smartphone IMU and force plate measurements in both healthy controls and T2DM group.
RMS reflects the overall magnitude of postural sway variability [117]. The consistently strong correlation (correlation coefficients ranging from 0.6 to 0.9) could indicate that both smartphone IMU and force plate COP are capturing similar information regarding the magnitude of postural sway, regardless of group or task difficulty. This finding indicates that RMS is a reliable parameter for cross-device postural control assessment, supporting the use of smartphone IMU as a valid alternative to force plates for quantifying sway magnitude. This also aligns with previous research, such as Mancini et al. [118], who similarly demonstrated a strong correlation ($r = 0.74$) between RMS of acceleration and RMS of COP during quiet standing with eyes open in a clinical population. However, while this project focused on direct parameter-to-parameter correlations, other research has explored cross-parameter relationships between IMU and force plate metrics. For example, Hsieh et al. [64] found smartphone-based RMS to be most comparable to COP velocity.
MV is the average rate of movement of body segments during postural sway and reflects the speed of active postural adjustments [119]. The strong correlation only in the most demanding task (OL-EC) suggests that MV is more sensitive to large, rapid postural adjustments, which are more pronounced when balance is challenged the most. In easier tasks, sway velocities are lower and could be influenced by subtle measurement noise or the differences in the sensing principles between the respective devices. This observation is consistent with other studies, such as Hussain SR and Wright WG [120], who demonstrated that correlations for sway area and velocity parameters strengthen as task difficulty increases (progressing from EO-Foam to EC-Foam conditions). Similarly, De Groote et al. [79] reported

that correlations are typically stronger under more challenging compared to easier testing conditions. Furthermore, Hsieh et al. [89] assessed static balance under multiple conditions from BL-EO to OL-EO in people with multiple sclerosis and reported moderate to strong correlation coefficients of RMS (r: 0.38 - 0.92) between smartphone and force plate, also increasing with task difficulty.
Despite careful sensor placement and data processing, noise and fundamental differences in how the devices capture movement (COP vs. trunk acceleration) can have a larger effect when the sway is minimal, further reducing correlation in easy tasks [119]. Another explanation as to why RMS parameters correlated moderate to strongly across all condition as oppose to MV, could be the different computation of the velocities. MV ACC was derived from acceleration signal integration [121], while MV COP involves differentiation of the COP signal [119]. These challenges are also highlighted by previously mentioned Mancini et al. [118], who reported moderate to good correlation for multiple parameters except for MV when comparing COP and ACC parameters.

5.3 Smartphone-Based Measures Reflect Postural Deficits in T2DM Patients.

Thirdly, the project aimed to evaluate how well IMU measurements reflect differences between healthy and T2DM individuals. The smartphone IMU consistently showed greater RMS and MV values in the T2DM group across most conditions, indicating poorer postural control. Specifically, diabetic patients exhibited larger RMS values in the both legs eyes open (BL-EO) condition, with significantly greater values after removing visual input (BL-EC) and reducing the base of support (OL-EO).
A healthy person can maintain their balance even when one of the three balance systems (vision, proprioception, or vestibular function) is compromised, but losing two or more of these systems significantly increases the risk of imbalance and falls [122]. Therefore, in the eyes-open condition (BL-EO), non-significant difference was found between RMS ACC of the healthy and T2DM groups. The T2DM patients could maintain an upright stance by relying on visual and proprioceptive inputs. However, in the eyes-closed condition (BL-EC), the healthy group lost only visual input, while the T2DM group possibly lacked both visual and vestibular input and thus exhibited significant body sway. The sensory information coming from the peripheral nervous system has been proven to be important for maintaining balance. Greater sway was observed in both elderly [123] and diabetic population, in which it is linked to their reduced ability to feel touch and vibration in their legs/feet [124].
These findings are consistent with those of Fernandes et al.[45], who evaluated static balance in 73 participants with and without T2DM using a smartphone positioned at L5. They reported that RMS values were considerably higher in the T2DM group. Specifically, RMS for the T2DM group with eyes open was 18.63 cm/s^2 and 10.79 cm/s^2, compared to 6.18 cm/s^2 and 3.92 cm/s^2 in the control group, in AP and ML directions, respectively. Under eyes-closed conditions, AP RMS was 12.75 cm/^{2} (AP) and 6.86 cm/s^2 (ML) for T2DM versus 10.79 cm/s^2 (AP) and 5.88 cm/s^2 (ML) in controls. In contrast, the RMS values in the present study for T2DM patients were 8.85 cm/s² (BL-EO) and 12.43 cm/s² (BL-EC), falling within a comparable range. Direct comparison of values presents a challenge due to differences in calculations of sway magnitude (separate RMS in AP and ML directions vs resultant RMS). However, both results demonstrate a clear difference between control and T2DM groups, indicating that individuals with T2DM have more difficulties maintaining quiet upright stance. Furthermore, the age-matched controls in Fernandes et al. suggest that the impaired postural control in T2DM group is not solely due to aging, but rather due to the condition itself.

The only instance where the T2DM exhibited lower RMS values than the healthy group was in the last condition (OL-EC). As previously discussed, T2DM patients relied on physical support, especially during this most challenging balance task. Consequently, the patients probably did not use their trunk as much, which lead to the IMU sensor detecting less movement. On the other hand, the

healthy participants used their hips to greater extent, resulting in larger trunk sway that was readily captured by the IMU.
MV followed a similar pattern, demonstrating larger values in the T2DM group than healthy group in all condition except the last one (OL-EC). Significant difference in smartphone-derived MV ACC was already present in the BL-EO condition between groups, which was not the case for RMS ACC. This could be again explained by the differences between the two measured parameters. Where RMS reflects the overall magnitude of sway over time [117], MV captures the speed of postural adjustments, meaning it captures the rapidity of the movement individuals make to correct their balance [119]. Even when overall sway amplitude (RMS) is similar in simple tasks with low sway, T2DM participants may exhibit more frequent or abrupt corrective movements, leading to significantly higher MV ACC in BL-EO condition. Conversely, in challenging conditions like lack of visual input, T2DM participants might have responded to instability not by making faster corrections, but by allowing larger, slower oscillations. This could result in higher sway amplitude but not necessarily translate to a proportional increase in the MV of their movements.

Both the force plate and smartphone IMU detected increased postural sway and instability in the T2DM group, particularly under more challenging conditions (eyes closed, one leg stance). This consistency suggests that both tools are sensitive to group differences in balance performance. The force plate tended to show significant group differences even in the less challenging BL-EO condition, while the IMU detected significant differences only as the task became more difficult (e.g., BL-EC, OL-EO for RMS). This may be due to the force plate's higher sensitivity to subtle shifts in COP, whereas the IMU (placed on the trunk) primarily captures larger, whole-body movements [112]. Similarly to IMU, the BL-EO condition for force plate data also showed that differences in MV values between groups were greater than those in RMS values. This suggest that both measurement devices registered not just the low sway magnitude, but also the potentially more abrupt or frequent adjustments made by T2DM individuals.

These increasing trends in balance parameters are generally supported by other smartphone-based balance studies. For instance, Hussain et al.[120] assessed static balance in healthy adults (aged 20–63 years) under eyes-opened and eyes-closed conditions on both firm and foam surfaces, using a smartphone fixed near L5. They compared velocity and sway area across conditions. The reported sway velocity values (mean ± SD, in cm/s) for the smartphone were: 1.62 ± 0.8, 2.25 ± 1.2, 4.61 ± 4.1, and 7.56 ± 8.4, while the corresponding force plate values were: 1.27 ± 0.9, 1.84 ± 1.2, 3.35 ± 4.5, and 5.87 ± 9.1. The COP velocity values align with those found in this project, particularly for the BL-EO and BL-EC conditions. Although the foam surface in Hussain et al. presented a destabilizing challenge, it may not be as difficult as standing on one leg, which was included in the current protocol.
Notably, the smartphone-derived velocity values reported by Hussain et al. were substantially lower than those observed in this project. This discrepancy can be explained by fundamental difference in how smartphone-derived velocity was calculated. In Hussain et al., sway velocity was defined as total path length divided by trial duration, based on the displacement of either the CoP or the IMU-estimated trajectory. In contrast, the current study computed mean velocity by integrating the acceleration signal from the smartphone IMU placed at the trunk. While the computational approaches differ, both studies observed a progressive increase in sway velocity with rising task difficulty, highlighting the sensitivity of smartphone-based systems in detecting postural changes.
Furthermore, Hsieh et al.[64] also observed growth in both COP velocity and COM RMS as balance task difficulty increased. They assessed static balance in 30 healthy older adults at risk of falling under seven static conditions, including BL-EO and OL-EO. They reported COP velocity values, ranging from 9.996 to 47.951 mm/s in the AP direction and 3.967 to 52.823 mm/s in the ML direction. The smartphone-derived RMS values ranged from 0.077 to 0.870 m/s^2 , and from 0.194 to 0.536 m/s^2 in ML and AP directions, respectively. Despite being similar, the reported values are higher than in this project. Several factors may have influenced the discrepancies, starting with the physical support

required by T2DM participants during single-leg tasks, which likely limited the magnitude of trunk movement. Next, Hsieh et al. study included twice the number of participants, which may have allowed for greater representation of variability in balance responses. Moreover, there was difference in the placement of smartphone. While it was held against chest of participants in Hsieh et al., in the present study, the device was fixed at the lower back (L5 level), which could also influence the recorded magnitude of movement. Lastly, while the present study calculated total RMS of acceleration signal from AP and ML directions, Hsieh et al. reported RMS values separately for each direction. Therefore, the direct numerical comparisons was limited, but the observed progressive increase across conditions is consistent between both works.

5.4 The Need for Accessible Balance Assessment Tools in T2DM Care

Balance impairments and consequent increased fall risk are significant concerns for people with T2DM. Several factors contribute to balance problems in T2DM patients. The severity of diabetic neuropathy alone is a predictor of poorer balance [125]. Other contributing factors include age, depression, cognitive impairment, reduced muscle strength, and an increased reliance on vision to maintain balance due to damaged sensory pathways [126]. Research shows that these postural control problems often precede falls in diabetic patients, making balance a crucial area for intervention [127].

The impact of these balance issues is considerable. Studies consistently show that T2DM patients have more postural control problems compared to healthy individuals. People with T2DM have approximately twice the risk of falling compared to those without diabetes, with fall rates ranging from 19.8% to nearly 40% in older adults with T2DM. When falls do occur, they often lead to serious injuries like fractures and are associated with slower recovery and higher chances of falling again [128]. Moreover, while frailty is often associated with thin, elderly individuals who use walking aids, in T2DM it can actually occur also in younger people who are overweight and have multiple comorbidities. This pattern is becoming more common, as early-onset T2DM (occurring before age 40) increases, and is co-associated with reduced physical fitness and loss of functional muscle mass [129].

There are several important reasons why continuous balance assessment is needed in T2DM, starting with the early detection of balance impairments which are often under-screened and underestimated [125], therefore regular testing could help identify at-risk patients earlier. Second, balance tends to get worse as diabetes complications progress, so ongoing monitoring can help track changes and allow for timely intervention. Finally, exercise and physical therapy have been shown to improve walking, reaction time, and balance in T2DM patients [130], therefore objective balance testing is needed to measure whether these interventions are working effectively. Overall, there is a clear need to develop better ways to help this high-risk group prevent falls and maintain their independence.

This could be accessed and measured through smartphones. For example, the smartphone could be integrated into broader telerehabilitation programs. As diabetes is a complex condition, there are a lot of components required to obtain a proper treatment result, such as regular training, ongoing monitoring, and multiple medication management. However, many patients struggle to achieve their treatment goals due to barriers such as difficulty accessing healthcare centers, changing population needs due to aging and limited public health resources, and maintaining healthcare outside hospital settings, particularly for T2DM patients [131]. Smartphones could serve as a communication tool between patients and healthcare professionals, allowing for remote monitoring of balance improvements and reducing the need for unnecessary clinic visits. This approach would enable exercise interventions and rehabilitation programs to become more personalized and tailored to each patient's specific needs and progress.

Considering the need for accessible and portable balance assessment tools for populations like T2DM patients, it was important to understand how well smartphone sensors compare to established force plates. This is why Bland-Altman analysis was conducted, with a 1/20 scaling of IMU data applied to address the inherent magnitude differences between the two measurement methods. The substantial scaling required reveals that raw acceleration measurements from smartphone IMUs are not directly comparable to force plate COP measurements without mathematical transformation. This suggests that

the two methods measure fundamentally different physical quantities (acceleration vs. COP displacement), meaning that the substitution of one method for another would require consistent application of scaling factors or normalization of data.
While the smartphone IMU may still provide valuable information about postural control, clinicians and researchers cannot directly substitute IMU-derived values for force plate measurements without considering the systematic differences. This is supported by Bisi [132], who stated that, while COP and IMU-based metrics can share similar mathematical formulations, they capture different aspects of postural control, which makes direct comparison between the two methods difficult. However, this doesn't reduce the potential clinical value of smartphone IMU measurements. According to a review by Ghislieri et al.[76], as long as IMUs can extract meaningful information to characterize postural balance, their lack of direct comparability with traditional force plate metrics is not considered a major limitation.

5.5 Limitations

Several major limitations must be acknowledged. First, the lack of age-matched control group represents a significant methodological limitation. Since age independently affects postural control [15], some of the observed group differences may reflect age-related decline rather than diabetes-specific impairments. If age-matched healthy controls had been used, the differences between groups would likely have been smaller. This would have allowed for more accurate isolation of T2DM-specific effects on balance. It would also have provided stronger evidence that the smartphone was sensitive enough to detect these deficits, such as those caused by diabetic neuropathy or impaired vision, which may not be typically present to the same extent in healthy individuals of the same age [32].
Additionally, due to the limited sample size, the statistical power of the study was restricted, possibly preventing detection of smaller but clinically relevant differences.
Next, physical support was required during single-leg stances, limiting direct comparisons between groups. The support was necessary not only because of the narrower base of support that challenges postural control, but also by participants' potential heightened fear of falling. Furthermore, this project used two different force plates between groups. The Biosignalplux force plate for T2DM patients was portable and placed on the hospital floor rather than being ground-mounted. This elevation, even if only by a few centimeters, may have added into psychological fear of patients.

Another important limitation involves user-related factors such as digital literacy and long-term engagement. Despite the widespread availability of smartphones, not all elderly individuals are proficient in their use, which can hinder the adoption of smartphone-based postural assessments in this population [50]. The common barriers in using smartphone applications include lack of awareness of this approach among elderly, lack of technological skills, inability to gain a better understanding or education, and low digital literacy [133]. Participants may struggle to follow instructions within a smartphone application, which could lead to incomplete or inaccurate data collection. Unfamiliarity with technology can cause anxiety or resistance to participate, potentially skewing study results or reducing sample size [134].
Digital fatigue, a physical or mental exhaustion caused by intense use of digital devices, may also pose a challenge, particularly in long-term monitoring scenarios [135]. Even when applications are easy to use, the repetitive nature of balance assessments can lead to reduced motivation or adherence over time. Addressing these challenges requires clear instructions, user-friendly app design, minimal assessment duration, and, where possible, support from caregivers or researchers.
Data privacy and security concerns represent another critical limitation of smartphone-based health assessments. Smartphones often collect or have access to sensitive data, including location information, device identifiers, and health-related information. Therefore, protection-measures to prevent unauthorized access or misuse of personal information have to be implemented by researches or clinicians. Maintaining transparency regarding the collection, storage, and intended use of data has to be a priority.
There are also inherent limitations of smartphone IMU sensors, such as sensor drift or signal noise,

which can cause random variations in the recorded data [136]. These may have influenced the signal accuracy and reliability of the acceleration-based parameters. Additionally, different smartphones can have different sensors quality and calibration, making it challenging to compare results across participants or studies, or to generalize findings.
Lastly, quality control in real-world settings presents a persistent challenge. Although a belt was used in this project to standardize smartphone placement on the lower back, this is not a guarantee in home-based or unsupervised conditions. Other sources of variability include inconsistent standing conditions (e.g., shoes, surface type, posture), differences in how participants start and stop recordings, and potential influence of battery performance on sensor output.

5.6 Future Perspectives

To strengthen the interpretability of results, future research should include age-matched control groups to isolate T2DM-specific effects from age-related balance decline. Moreover, larger cohorts should be included in future studies to extend these findings.
Moreover, while this project used the lower back placement, in order to approximate the COM, exploring the feasibility and validity of alternative placements — such as the front or back pockets of trousers — may further increase usability in daily life.
Beyond methodological refinements, successful implementation in real-world settings will require user education. Patients must receive clear instructions on how to perform the balance assessments consistently — including standardizing foot position, footwear, gaze direction, and body posture — to reduce variability across repeated sessions.
To address the potential issue of technological aversion, future solutions should explore strategies like designing user-friendly interfaces, which also improve adoption rates, especially among older adults [137]. Most importantly, for clinical populations, such as T2DM, it will be essential to educate and demonstrate how the smartphone-based assessment can benefit their daily lives, in order to reduce potential anxiety or reluctance to engage with the technology.
Recent developments in combining IMU data with artificial intelligence also offer promising directions for personalized and adaptive balance monitoring [138]. These advances could enable more accurate fall risk prediction and tailored feedback to users or clinicians. For example, machine learning could be leveraged to personalize balance assessment trajectories in T2DM patients. By learning an individual's baseline performance across a selected set of parameters, AI algorithms could detect trends over time and automatically classify outcomes as improved, worsened, or unchanged. This would reduce the need for manual interpretation and support real-time feedback. In addition, AI systems could adjust task difficulty based on the user's performance history—offering easier postural tasks when needed, or proposing more challenging conditions when the data suggests a plateau, thereby keeping the assessments both safe and sensitive to progress.
Furthermore, machine learning could be used to detect early signs of diabetic neuropathy based on characteristic changes in balance and sway patterns, providing a non-invasive and accessible screening tool for one of the major contributors to fall risk in people with T2DM. In study from Pandey et al. [139], machine learning-based models and COP data from Wii Balance Board, were utilized to categorize individuals as either healthy, diabetic, or neurologically ill. The study reported high accuracy (96-97%) of the models.
This would not only support balance monitoring, but also expand the role of smartphone-based assessments toward early complication detection in diabetes care.
Ultimately, integrating smartphone-based balance assessments into preventive care pathways for T2DM may support earlier detection of functional decline, personalized intervention strategies, and a reduction in diabetes-related fall complications.

Conclusion

This project demonstrated that a smartphone IMU sensor can assess static postural control in individuals with T2DM, showing sensitivity to both task difficulty and group differences. The smartphone successfully distinguished between both-leg and single-leg stances, as well as between eyes-open and eyes-closed conditions. Compared to a force plate, it showed similar directional trends and captured moderate to strong correlations in RMS values, particularly in the most challenging condition (OL-EC), supporting its potential for clinical balance assessment.

Despite these promising results, several limitations must be acknowledged. The smartphone IMU, placed on the lower back, was affected by the physical support required by T2DM patients during single-leg tasks, potentially limiting its ability to reflect true postural demands. Moreover, the observed differences between groups cannot be solely attributed to diabetes, as the healthy control group was younger. The small sample size may have also limited statistical power of this project.

Beyond methodological factors, smartphone-based assessments face user- and device-related limitations. Many older adults lack digital literacy, which can hinder their ability to interact with smartphone applications. Long-term engagement may also be reduced due to reduced motivation, especially during repetitive assessments. Moreover, technical issues such as sensor drift, signal noise, and variability in hardware quality across devices can affect data accuracy and comparability. Privacy concerns around sensitive health and device data must also be addressed through transparent communication and secure data handling.

Despite these challenges, the findings highlight the smartphone's potential as a low-cost, accessible tool for monitoring balance in clinical populations. Future research should prioritize age-matched control groups, explore alternative sensor placements (e.g., pocket-based), and investigate how to ensure usability and sustained engagement among older adults. Longitudinal studies are especially needed to evaluate whether smartphone-based monitoring can reliably track changes over time and support individualized interventions.

Bibliography

[1] M. Z. Banday, A. S. Sameer, and S. Nissar, "Pathophysiology of diabetes: An overview," *Avicenna Journal of Medicine*, vol. 10, p. 174, 10 2020. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7791288/

[2] "Diabetes facts and figures — international diabetes federation." [Online]. Available: https://idf.org/about-diabetes/diabetes-facts-figures/

[3] K. L. et al. Ong, "Global, regional, and national burden of diabetes from 1990 to 2021, with projections of prevalence to 2050: a systematic analysis for the global burden of disease study 2021," 2023. [Online]. Available: https://www.who.int/europe/news-room/fact-sheets/item/diabetes

[4] "Parliamentary question — diabetes care in the eu — e-006356/2020 — european parliament." [Online]. Available: https://www.europarl.europa.eu/doceo/document/E-9-2020-006356_EN.html

[5] H. W. Baynest, "Classification, pathophysiology, diagnosis and management of diabetes mellitus," *Journal of Diabetes Metabolism*, vol. 06, 2015.

[6] P. Farmaki, C. Damaskos, N. Garmpis, A. Garmpi, S. Savvanis, and E. Diamantis, "Complications of the type 2 diabetes mellitus," *Current Cardiology Reviews*, vol. 16, p. 249, 1 2020. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7903505/

[7] E. L. Feldman, B. C. Callaghan, R. Pop-Busui, D. W. Zochodne, D. E. Wright, D. L. Bennett, V. Bril, J. W. Russell, and V. Viswanathan, "Diabetic neuropathy," *Nature reviews. Disease primers*, vol. 5, p. 42, 6 2019. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7096070/

[8] C. W. Hicks and E. Selvin, "Epidemiology of peripheral neuropathy and lower extremity disease in diabetes," *Current diabetes reports*, vol. 19, p. 86, 10 2019. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC6755905/

[9] M. R. Khdour and C. R. M. Khdour, "Treatment of diabetic peripheral neuropathy: a review," *Journal of Pharmacy and Pharmacology*, vol. 72, pp. 863–872, 7 2020. [Online]. Available: https://dx.doi.org/10.1111/jphp.13241

[10] S. J. Brown, J. C. Handsaker, F. L. Bowling, A. J. Boulton, and N. D. Reeves, "Diabetic peripheral neuropathy compromises balance during daily activities," *Diabetes care*, vol. 38, pp. 1116–1122, 6 2015. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/25765355/

[11] "Cost of older adult falls." [Online]. Available: https://stacks.cdc.gov/view/cdc/122747

[12] "Aims network — eurosafe." [Online]. Available: https://www.eurosafe.eu.com/key-actions/older-people/aims-network

[13] "Falls among older adults in the eu-28." [Online]. Available: https://eupha.org/

[14] E. Pijpers, I. Ferreira, R. T. D. jongh, D. J. Deeg, P. Lips, C. D. Stehouwer, and A. C. N. Kruseman, "Older individuals with diabetes have an increased risk of recurrent falls: analysis of potential mediating factors: the longitudinal ageing study amsterdam," *Age and Ageing*, vol. 41, pp. 358–365, 5 2012. [Online]. Available: https://dx.doi.org/10.1093/ageing/afr145

[15] N. Deshpande, E. J. Metter, F. Lauretani, S. Bandinelli, and L. Ferrucci, “Interpreting fear of falling in the elderly: What do we need to consider?” *Journal of geriatric physical therapy (2001)*, vol. 32, p. 91, 2009. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC2954585/

[16] “About older adult fall prevention — older adult fall prevention — cdc.” [Online]. Available: https://www.cdc.gov/falls/about/

[17] A. Cella, A. D. Luca, V. Squeri, S. Parodi, F. Vallone, A. Giorgeschi, B. Senesi, E. Zigoura, K. L. Q. Guerrero, G. Siri, L. D. Michieli, J. Saglia, C. Sanfilippo, and A. Pilotto, “Development and validation of a robotic multifactorial fall-risk predictive model: A one-year prospective study in community-dwelling older adults,” *PLOS ONE*, vol. 15, p. e0234904, 6 2020.

[18] P. Hewston and N. Deshpande, “Falls and balance impairments in older adults with type 2 diabetes: Thinking beyond diabetic peripheral neuropathy,” *Canadian Journal of Diabetes*, vol. 40, pp. 6–9, 2 2016.

[19] M. Duarte and S. M. Freitas, “Revision of posturography based on force plate for balance evaluation,” *Brazilian Journal of Physical Therapy*, vol. 14, pp. 183–192, 2010. [Online]. Available: https://www.scielo.br/j/rbfis/a/hFQTppgw4q3jGBCDKV9fdCH/?lang=en

[20] R. Chiba, K. Takakusaki, J. Ota, A. Yozu, and N. Haga, “Human upright posture control models based on multisensory inputs; in fast and slow dynamics,” *Neuroscience Research*, vol. 104, pp. 96–104, 3 2016.

[21] F. B. Horak, “Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls?” *Age and ageing*, vol. 35 Suppl 2, 9 2006. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/16926210/

[22] J. Massion, “Postural control system,” *Current Opinion in Neurobiology*, vol. 4, pp. 877–887, 12 1994.

[23] A. A. Mahalingasivam, A. K. Jespersen, N. Ejskjaer, D. D. Hougaard, P. Vestergaard, N. H. H. Rasmussen, and J. Røikjer, “The co-existence of peripheral and vestibular neuropathy in diabetes: a cross-sectional study,” *European Archives of Oto-Rhino-Laryngology*, vol. 281, pp. 663–672, 2 2024. [Online]. Available: https://link.springer.com/article/10.1007/s00405-023-08130-6

[24] “In brief: How does our sense of balance work?” 9 2023. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK279394/

[25] D. Purves, G. J. Augustine, D. Fitzpatrick, L. C. Katz, A.-S. LaMantia, J. O. McNamara, and S. M. Williams, “The semicircular canals,” 2001. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK10863/

[26] S. Chaudhary, N. Saywell, and D. Taylor, “The differentiation of self-motion from external motion is a prerequisite for postural control: A narrative review of visual-vestibular interaction,” *Frontiers in Human Neuroscience*, vol. 16, p. 697739, 2 2022. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC8860980/

[27] A. Berencsi, M. Ishihara, and K. Imanaka, “The functional role of central and peripheral vision in the control of posture,” *Human Movement Science*, vol. 24, pp. 689–709, 10 2005.

[28] J. Li, J. Jiang, Y. Zhang, B. Liu, and L. Zhang, “Impairment of vestibular function and balance control in patients with type 2 diabetes,” *Audiology and Neurotology*, vol. 24, pp. 154–160, 8 2019. [Online]. Available: https://dx.doi.org/10.1159/000501291

[29] B. D. Laurence and L. Michel, “The fall in older adults: Physical and cognitive problems,” *Current Aging Science*, vol. 10, 7 2017.

[30] A. V. Schwartz, E. Vittinghoff, D. E. Sellmeyer, K. R. Feingold, N. D. Rekeneire, E. S. Strotmeyer, R. I. Shorr, A. I. Vinik, M. C. Odden, S. W. Park, K. A. Faulkner, and T. B. Harris, "Diabetes-related complications, glycemic control, and falls in older adults," *Diabetes Care*, vol. 31, pp. 391–396, 3 2008. [Online]. Available: https://dx.doi.org/10.2337/dc07-1152

[31] Y. Agrawal, P. Macneilage, B. Thomas, D. M. Merfeld, R. Bermúdez, C. Mc, W. W. Tk, M. Dm, M. Carolina, B. Rey, T. K. Clark, W. Wang, T. Leeder, and Y. Bian, "Vestibular perceptual thresholds increase above the age of 40," *Frontiers in Neurology*, vol. 7, p. 162, 10 2016. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC5046616/

[32] Y. Agrawal, J. P. Carey, C. C. D. Santina, M. C. Schubert, and L. B. Minor, "Disorders of balance and vestibular function in us adults: data from the national health and nutrition examination survey, 2001-2004," *Archives of internal medicine*, vol. 169, pp. 938–944, 5 2009. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/19468085/

[33] ——, "Diabetes, vestibular dysfunction, and falls: analyses from the national health and nutrition examination survey," *Otology neurotology : official publication of the American Otological Society, American Neurotology Society [and] European Academy of Otology and Neurotology*, vol. 31, pp. 1445–1450, 12 2010. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/20856157/

[34] L. J. D'silva, J. Lin, H. Staecker, S. L. Whitney, P. M. Kluding, L. J. D'silva, H. Staecker, S. L. Whitney, and P. M. Kluding, "Impact of diabetic complications on balance and falls: Contribution of the vestibular system," *Physical Therapy*, vol. 96, pp. 400–409, 3 2016. [Online]. Available: https://dx.doi.org/10.2522/ptj.20140604

[35] J. K. Ferris, J. T. Inglis, K. M. Madden, and L. A. Boyd, "Brain and body: A review of central nervous system contributions to movement impairments in diabetes," *Diabetes*, vol. 69, pp. 3–11, 1 2020. [Online]. Available: https://dx.doi.org/10.2337/db19-0321

[36] R. J. Peterka, "Sensory integration for human balance control," *Handbook of clinical neurology*, vol. 159, pp. 27–42, 1 2018. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/30482320/

[37] J. C. Xu, A. P. Silvano, A. Keller, S. Krašna, R. Thomson, C. Klug, and A. Linder, "Identifying and characterizing types of balance recovery strategies among females and males to prevent injuries in free-standing public transport passengers," *Frontiers in Bioengineering and Biotechnology*, vol. 9, p. 670498, 7 2021. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC8287834/

[38] Y. Kanamiya, S. Ota, and D. Sato, "Ankle and hip balance control strategies with transitions," in *2010 IEEE International Conference on Robotics and Automation*. IEEE, 5 2010, pp. 3446–3451.

[39] G. M. Blenkinsop, M. T. Pain, and M. J. Hiley, "Balance control strategies during perturbed and unperturbed balance in standing and handstand," *Royal Society Open Science*, vol. 4, p. 161018, 2017. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC5541526/

[40] M. C. Kilby, S. M. Slobounov, and K. M. Newell, "Aging and the recovery of postural stability from taking a step," *Gait Posture*, vol. 40, pp. 701–706, 9 2014.

[41] J. Howcroft, E. D. Lemaire, J. Kofman, and W. E. McIlroy, "Elderly fall risk prediction using static posturography," *PLOS ONE*, vol. 12, p. e0172398, 2 2017.

[42] A. Wiśniowska-Szurlej, A. Ćwirlej Sozańska, A. Wilmowska-Pietruszyńska, and B. Sozański, "The use of static posturography cut-off scores to identify the risk of falling in older adults." *International journal of environmental research and public health*, vol. 19, 5 2022.

[43] M. Mancini and F. B. Horak, "The relevance of clinical balance assessment tools to differentiate balance deficits." *European journal of physical and rehabilitation medicine*, vol. 46, pp. 239–48, 6 2010.

[44] H. B. Nakagawa, J. R. Ferraresi, M. G. Prata, and M. E. Scheicher, "Postural balance and functional independence of elderly people according to gender and age: cross-sectional study," *Sao Paulo Medical Journal*, vol. 135, pp. 260–265, 5 2017. [Online]. Available: https://www.scielo.br/j/spmj/a/mb5fVrsDJcp7rGWC4wKWwNr/?lang=en

[45] T. F. FERNANDES, M. I. T. VOLPE, F. P. PENA, E. G. R. SANTOS, G. H. L. PINTO, A. BELGAMO, A. A. C. E. SILVA, A. S. CABRAL, B. CALLEGARI, and G. S. SOUZA, "Smartphone-based evaluation of static balance and mobility in type 2 diabetes," *Anais da Academia Brasileira de Ciências*, vol. 96, 2024.

[46] C.-Y. Hsieh, H.-Y. Huang, K.-C. Liu, K.-H. Chen, S. J.-P. Hsu, and C.-T. Chan, "Subtask segmentation of timed up and go test for mobility assessment of perioperative total knee arthroplasty," *Sensors*, vol. 20, p. 6302, 11 2020.

[47] A. Marques, S. Almeida, J. Carvalho, J. Cruz, A. Oliveira, and C. Jácome, "Reliability, validity, and ability to identify fall status of the balance evaluation systems test, mini–balance evaluation systems test, and brief–balance evaluation systems test in older people living in the community," *Archives of Physical Medicine and Rehabilitation*, vol. 97, pp. 2166–2173.e1, 12 2016.

[48] S. R. Lord, H. B. Menz, and A. Tiedemann, "A physiological profile approach to falls risk assessment and prevention," *Physical Therapy*, vol. 83, pp. 237–252, 3 2003. [Online]. Available: https://dx.doi.org/10.1093/ptj/83.3.237

[49] L. Ferrari, G. Bochicchio, A. Bottari, A. Scarton, F. Lucertini, and S. Pogliaghi, "Construct validity of a wearable inertial measurement unit (imu) in measuring postural sway and the effect of visual deprivation in healthy older adults." *Biosensors*, vol. 14, 11 2024.

[50] K. L. Roeing, K. L. Hsieh, and J. J. Sosnoff, "A systematic review of balance and fall risk assessments with mobile phone technology," *Archives of Gerontology and Geriatrics*, vol. 73, pp. 222–226, 11 2017.

[51] J. E. Visser, M. G. Carpenter, H. van der Kooij, and B. R. Bloem, "The clinical utility of posturography," *Clinical Neurophysiology*, vol. 119, pp. 2424–2436, 11 2008.

[52] F. Quijoux, A. Nicolaï, I. Chairi, I. Bargiotas, D. Ricard, A. Yelnik, L. Oudre, F. Bertin-Hugault, P.-P. Vidal, N. Vayatis, S. Buffat, and J. Audiffren, "A review of center of pressure (cop) variables to quantify standing balance in elderly people: Algorithms and open-access code." *Physiological reports*, vol. 9, p. e15067, 11 2021.

[53] M. G. Silva, P. V. S. Moreira, and H. M. Rocha, "Development of a low cost force platform for biomechanical parameters analysis," *Research on Biomedical Engineering*, vol. 33, pp. 259–268, 9 2017.

[54] B. Chen, P. Liu, F. Xiao, Z. Liu, and Y. Wang, "Review of the upright balance assessment based on the force plate," *International Journal of Environmental Research and Public Health*, vol. 18, p. 2696, 3 2021.

[55] S. B. Richmond, K. D. Dames, D. J. Goble, and B. W. Fling, "Leveling the playing field: Evaluation of a portable instrument for quantifying balance performance," *Journal of Biomechanics*, vol. 75, pp. 102–107, 6 2018.

[56] V. Mylonas, C. Chalitsios, and T. Nikodelis, “Validation of a portable wireless force platform system to measure ground reaction forces during various tasks.” *International journal of sports physical therapy*, vol. 18, pp. 1283–1289, 2023.

[57] R. J. Mobbs, J. Perring, S. M. Raj, M. Maharaj, N. K. M. Yoong, L. W. Sy, R. D. Fonseka, P. Natarajan, and W. J. Choy, “Gait metrics analysis utilizing single-point inertial measurement units: a systematic review.” *mHealth*, vol. 8, p. 9, 2022.

[58] S. Morrison, R. Simmons, S. R. Colberg, H. K. Parson, and A. I. Vinik, “Supervised balance training and wii fit–based exercises lower falls risk in older adults with type 2 diabetes,” *Journal of the American Medical Directors Association*, vol. 19, pp. 185.e7–185.e13, 2 2018.

[59] G. Severini, S. Straudi, C. Pavarelli, M. D. Roit, C. Martinuzzi, L. D. M. Pizzongolo, and N. Basaglia, “Use of nintendo wii balance board for posturographic analysis of multiple sclerosis patients with minimal balance impairment,” *Journal of NeuroEngineering and Rehabilitation*, vol. 14, p. 19, 12 2017.

[60] D. J. Geerse, B. H. Coolen, and M. Roerdink, “Kinematic validation of a multi-kinect v2 instrumented 10-meter walkway for quantitative gait assessments,” *PLOS ONE*, vol. 10, p. e0139913, 10 2015.

[61] J. Bertram, T. Krüger, H. M. Röhling, A. Jelusic, S. Mansow-Model, R. Schniepp, M. Wuehr, and K. Otte, “Accuracy and repeatability of the microsoft azure kinect for clinical measurement of motor function,” *PLOS ONE*, vol. 18, p. e0279697, 1 2023.

[62] A. Bawa, K. Banitsas, and M. Abbod, “A review on the use of microsoft kinect for gait abnormality and postural disorder assessment,” *Journal of Healthcare Engineering*, vol. 2021, pp. 1–19, 11 2021.

[63] J. Howcroft, J. Kofman, and E. D. Lemaire, “Review of fall risk assessment in geriatric populations using inertial sensors.” *Journal of neuroengineering and rehabilitation*, vol. 10, p. 91, 8 2013.

[64] K. L. Hsieh, K. L. Roach, D. A. Wajda, and J. J. Sosnoff, “Smartphone technology can measure postural stability and discriminate fall risk in older adults,” *Gait Posture*, vol. 67, pp. 160–165, 1 2019.

[65] M. H. Pham, M. Elshehabi, L. Haertner, S. D. Din, K. Srulijes, T. Heger, M. Synofzik, M. A. Hobert, G. S. Faber, C. Hansen, D. Salkovic, J. J. Ferreira, D. Berg, Álvaro Sanchez-Ferro, J. H. van Dieën, C. Becker, L. Rochester, G. Schmidt, and W. Maetzler, “Validation of a step detection algorithm during straight walking and turning in patients with parkinson’s disease and older adults using an inertial measurement unit at the lower back,” *Frontiers in Neurology*, vol. 8, 9 2017.

[66] E. A. Keshner, A. I. Mallinson, N. S. Longridge, S. Sinno, H. Petersen, and P. Perrin, “Evolution of postural control assessment: From dynamic posturography to virtual reality.” *Frontiers in neurology*, vol. 13, p. 1054346, 2022.

[67] E. A. Keshner and A. Lamontagne, “The untapped potential of virtual reality in rehabilitation of balance and gait in neurological disorders,” *Frontiers in Virtual Reality*, vol. 2, 3 2021.

[68] C.-C. Huang, H.-H. Hung, F.-S. Jaw, and Y.-H. Young, “Comparison of the wii balance board system and foam posturography system in assessing postural balance,” *Ear Hearing*, vol. 43, pp. 1800–1806, 11 2022.

[69] M. V. Matamala, C. Tapia, F. S. Sagüez, and J. Guerrero-Henriquez, “Postural performance assessment in aging people with diabetes and diabetic peripheral neuropathy using a wii balance board,” *Disability and Rehabilitation*, vol. 45, pp. 1202–1207, 3 2023.

[70] M. Patel, A. Pavic, and V. A. Goodwin, "Wearable inertial sensors to measure gait and posture characteristic differences in older adult fallers and non-fallers: A scoping review," *Gait Posture*, vol. 76, pp. 110–121, 2 2020.

[71] R. D. Fazio, V. M. Mastronardi, M. D. Vittorio, and P. Visconti, "Wearable sensors and smart devices to monitor rehabilitation parameters and sports performance: An overview." *Sensors (Basel, Switzerland)*, vol. 23, 2 2023.

[72] E. Bergamini, M. Iosa, V. Belluscio, G. Morone, M. Tramontano, and G. Vannozzi, "Multi-sensor assessment of dynamic balance during gait in patients with subacute stroke," *Journal of Biomechanics*, vol. 61, pp. 208–215, 8 2017.

[73] C. Moreau, T. Rouaud, D. Grabli, I. Benatru, P. Remy, A.-R. Marques, S. Drapier, L.-L. Mariani, E. Roze, D. Devos, G. Dupont, M. Bereau, and M. Fabbri, "Overview on wearable sensors for the management of parkinson's disease," *npj Parkinson's Disease*, vol. 9, p. 153, 11 2023.

[74] X. Huang, Y. Xue, S. Ren, and F. Wang, "Sensor-based wearable systems for monitoring human motion and posture: A review," *Sensors*, vol. 23, p. 9047, 11 2023.

[75] J. F. Hafer, R. Vitali, R. Gurchiek, C. Curtze, P. Shull, and S. M. Cain, "Challenges and advances in the use of wearable sensors for lower extremity biomechanics." *Journal of biomechanics*, vol. 157, p. 111714, 8 2023.

[76] M. Ghislieri, L. Gastaldi, S. Pastorelli, S. Tadano, and V. Agostini, "Wearable inertial sensors to assess standing balance: A systematic review," *Sensors*, vol. 19, p. 4075, 9 2019.

[77] N. Baker, C. Gough, and S. J. Gordon, "Inertial sensor reliability and validity for static and dynamic balance in healthy adults: A systematic review," *Sensors*, vol. 21, p. 5167, 7 2021.

[78] H. Zhou, F. Al-Ali, H. Rahemi, N. Kulkarni, A. Hamad, R. Ibrahim, T. K. Talal, and B. Najafi, "Hemodialysis impact on motor function beyond aging and diabetes—objectively assessing gait and balance by wearable technology," *Sensors*, vol. 18, p. 3939, 11 2018.

[79] F. D. Groote, S. Vandevyvere, F. Vanhevel, and J. J. O. de Xivry, "Validation of a smartphone embedded inertial measurement unit for measuring postural stability in older adults," *Gait & Posture*, vol. 84, pp. 17–23, 2 2021.

[80] M. Nouredanesh and J. Tung, "Machine learning based detection of compensatory balance responses to lateral perturbation using wearable sensors," in *2015 IEEE Biomedical Circuits and Systems Conference (BioCAS)*. IEEE, 10 2015, pp. 1–4.

[81] P. Liuzzi, I. Carpinella, D. Anastasi, E. Gervasoni, T. Lencioni, R. Bertoni, M. C. Carrozza, D. Cattaneo, M. Ferrarin, and A. Mannini, "Machine learning based estimation of dynamic balance and gait adaptability in persons with neurological diseases using inertial sensors," *Scientific Reports*, vol. 13, p. 8640, 5 2023.

[82] Eurostat, "Trust, security and privacy - smartphones (2020 onwards)," 6 2024. [Online]. Available: https://ec.europa.eu/eurostat/databrowser/view/ISOC_CISCI_SP20__custom_3858321/default/table?lang=en

[83] A. G. Bikou, E. Deligianni, F. Dermiki-Gkana, N. Liappas, J. G. Teriús-Padrón, M. E. B. Jaunsarás, M. F. Cabrera-Umpiérrez, and C. Kontogiorgis, "Improving participant recruitment in clinical trials: Comparative analysis of innovative digital platforms," *J Med Internet Res 2024;26:e60504 https://www.jmir.org/2024/1/e60504*, vol. 26, p. e60504, 12 2024. [Online]. Available: https://www.jmir.org/2024/1/e60504

[84] G. M. Harari, N. D. Lane, R. Wang, B. S. Crosier, A. T. Campbell, and S. D. Gosling, "Using smartphones to collect behavioral data in psychological science: Opportunities, practical considerations, and challenges," *Perspectives on psychological science : a journal of the Association for Psychological Science*, vol. 11, p. 838, 11 2016. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC5572675/

[85] S. X. Li, R. Halabi, R. Selvarajan, M. Woerner, I. G. Fillipo, S. Banerjee, B. Mosser, F. Jain, P. Areán, and A. Pratap, "Recruitment and retention in remote research: Learnings from a large, decentralized real-world study," *JMIR Form Res 2022;6(11):e40765 https://formative.jmir.org/2022/11/e40765*, vol. 6, p. e40765, 11 2022. [Online]. Available: https://formative.jmir.org/2022/11/e40765

[86] "Tal og statistik for digitaliseringsstyrelsens produkter." [Online]. Available: https://digst.dk/tal-og-statistik/

[87] N. L. Geller, D. Y. Kim, and X. Tian, "Smart technology in lung disease clinical trials," *Chest*, vol. 149, pp. 22–26, 1 2016.

[88] A. P. Jeremy, R. Z. Amick, T. Thummar, and M. E. Rogers, "Validation of measures from the smartphone sway balance application: A pilot study," *International Journal of Sports Physical Therapy*, vol. 9, p. 135, 4 2014. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC4004118/

[89] K. L. Hsieh and J. J. Sosnoff, "Smartphone accelerometry to assess postural control in individuals with multiple sclerosis," *Gait Posture*, vol. 84, pp. 114–119, 2 2021.

[90] C. K. Rhea, M. Yamada, N. A. Kuznetsov, J. T. Jakiela, C. T. LoJacono, S. E. Ross, F. J. Haran, J. M. Bailie, and W. G. Wright, "Neuromotor changes in participants with a concussion history can be detected with a custom smartphone app," *PLOS ONE*, vol. 17, p. e0278994, 12 2022.

[91] A. A. da Costa Moraes, M. B. Duarte, E. V. Ferreira, G. C. da Silva Almeida, E. G. da Rocha Santos, G. H. L. Pinto, P. R. de Oliveira, C. F. Amorim, A. dos Santos Cabral, A. de Athayde Costa e Silva, G. S. Souza, and B. Callegari, "Validity and reliability of smartphone app for evaluating postural adjustments during step initiation," *Sensors*, vol. 22, p. 2935, 4 2022.

[92] J. H. Chien, D. Torres-Russotto, Z. Wang, C. Gui, D. Whitney, and K. C. Siu, "The use of smartphone in measuring stance and gait patterns in patients with orthostatic tremor," *PLOS ONE*, vol. 14, p. e0220012, 7 2019. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0220012

[93] C. Lee, J. Ahn, and B.-C. Lee, "A systematic review of the long-term effects of using smartphone- and tablet-based rehabilitation technology for balance and gait training and exercise programs," *Bioengineering*, vol. 10, p. 1142, 9 2023.

[94] R. Zhao, L. Cheng, Q. Zheng, Y. Lv, Y. M. Wang, M. Ni, P. Ren, Z. Feng, Q. Ji, and G. Zhang, "A smartphone application-based remote rehabilitation system for post-total knee arthroplasty rehabilitation: A randomized controlled trial," *The Journal of Arthroplasty*, vol. 39, pp. 575–581.e8, 3 2024.

[95] S. J. Ozinga, A. G. Machado, M. M. Koop, A. B. Rosenfeldt, and J. L. Alberts, "Objective assessment of postural stability in parkinson's disease using mobile technology," *Movement Disorders*, vol. 30, pp. 1214–1221, 8 2015. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1002/mds.26214https://onlinelibrary.wiley.com/doi/abs/10.1002/mds.26214https://movementdisorders.onlinelibrary.wiley.com/doi/10.1002/mds.26214

[96] S. J. Ozinga and J. L. Alberts, "Quantification of postural stability in older adults using mobile technology," *Experimental Brain Research*, vol. 232, pp. 3861–3872, 11 2014. [Online]. Available: https://link.springer.com/article/10.1007/s00221-014-4069-8

[97] A. Cerrito, L. Bichsel, L. Radlinger, and S. Schmid, "Reliability and validity of a smartphone-based application for the quantification of the sit-to-stand movement in healthy seniors," *Gait Posture*, vol. 41, pp. 409–413, 2 2015.

[98] L. Borzì, S. Fornara, F. Amato, G. Olmo, C. A. Artusi, and L. Lopiano, "Smartphone-based evaluation of postural stability in parkinson's disease patients during quiet stance," *Electronics*, vol. 9, p. 919, 6 2020.

[99] Y.-R. Hou, Y.-L. Chiu, S.-L. Chiang, H.-Y. Chen, and W.-H. Sung, "Development of a smartphone-based balance assessment system for subjects with stroke," *Sensors*, vol. 20, p. 88, 12 2019.

[100] R. Daryabeygi-Khotbehsara, S. M. S. Islam, D. W. Dunstan, M. Abdelrazek, B. Markides, T. Pham, and R. Maddison, "Development of an android mobile application for reducing sitting time and increasing walking time in people with type 2 diabetes," *Electronics*, vol. 11, p. 3011, 9 2022.

[101] D. P. Bailey, L. H. Mugridge, F. Dong, X. Zhang, and A. M. Chater, "Randomised controlled feasibility study of the myhealthavatar-diabetes smartphone app for reducing prolonged sitting time in type 2 diabetes mellitus," *International Journal of Environmental Research and Public Health*, vol. 17, p. 4414, 6 2020.

[102] L. S. Valentiner, M. Ried-Larsen, K. Karstoft, C. F. Brinkløv, C. Brøns, R. O. Nielsen, R. Christensen, J. S. Nielsen, A. A. Vaag, B. K. Pedersen, and H. Langberg, "Long-term effect of smartphone-delivered interval walking training on physical activity in patients with type 2 diabetes: protocol for a parallel group single-blinded randomised controlled trial," *BMJ Open*, vol. 7, p. e014036, 4 2017.

[103] "Mountable force plate — biomechanics measurement systems — bms400600." [Online]. Available: https://www.amti.biz/product/bms400600/

[104] "Plux biosignals — force platform." [Online]. Available: https://www.pluxbiosignals.com/products/force-platform?_pos=1&_sid=3b40cf0d1&_ss=r

[105] M. M. Mukaka, "A guide to appropriate use of correlation coefficient in medical research," *Malawi Medical Journal : The Journal of Medical Association of Malawi*, vol. 24, p. 69, 2012. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC3576830/

[106] G. M. Sullivan and R. Feinn, "Using effect size—or why the p value is not enough," *Journal of Graduate Medical Education*, vol. 4, p. 279, 9 2012. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC3444174/

[107] M. M. Mukaka, "Statistics corner: A guide to appropriate use of correlation coefficient in medical research." *Malawi medical journal : the journal of Medical Association of Malawi*, vol. 24, pp. 69–71, 9 2012.

[108] Y. Tamaru and A. Matsugi, "Eye position shifts body sway under foot dominance bias in the absence of visual feedback," *Frontiers in Neurology*, vol. 13, p. 835450, 3 2022. [Online]. Available: www.frontiersin.org

[109] S. R. Lord and H. B. Menz, "Visual contributions to postural stability in older adults," *Gerontology*, vol. 46, pp. 306–310, 2000. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/11044784/

[110] T. Chen, Y. Fan, X. Zhuang, D. Feng, Y. Chen, P. Chan, and Y. Du, "Postural sway in patients with early parkinson's disease performing cognitive tasks while standing," *Neurological Research*, vol. 40, pp. 491–498, 6 2018.

[111] R. M. Palmieri, C. D. Ingersoll, M. B. Stone, and B. A. Krause, "Center-of-pressure parameters used in the assessment of postural control," *Journal of Sport Rehabilitation*, vol. 11, pp. 51–66, 2 2002.

[112] N. R. Heebner, J. S. Akins, S. M. Lephart, and T. C. Sell, "Reliability and validity of an accelerometry based measure of static and dynamic postural stability in healthy and active individuals," *Gait Posture*, vol. 41, pp. 535–539, 2 2015.

[113] J. Z. Lin, Y. A. Lin, W. H. Tai, and C. Y. Chen, "Influence of landing in neuromuscular control and ground reaction force with ankle instability: A narrative review," *Bioengineering 2022, Vol. 9, Page 68*, vol. 9, p. 68, 2 2022. [Online]. Available: https://www.mdpi.com/2306-5354/9/2/68/htmhttps://www.mdpi.com/2306-5354/9/2/68

[114] M. Asghari, K. Elali, and N. Toosizadeh, "The effect of age on ankle versus hip proprioceptive contribution in balance recovery: application of vibratory stimulation for altering proprioceptive performance." *Biomedical engineering letters*, vol. 15, pp. 337–347, 3 2025.

[115] H. Salsabili, F. Bahrpeyma, B. Forogh, and S. Rajabali, "Dynamic stability training improves standing balance control in neuropathic patients with type 2 diabetes," *Journal of Rehabilitation Research and Development*, vol. 48, 2011.

[116] D. Lafond, H. Corriveau, and F. Prince, "Postural control mechanisms during quiet standing in patients with diabetic sensory neuropathy," *Diabetes Care*, vol. 27, 2004.

[117] M. Mancini, F. B. Horak, C. Zampieri, P. Carlson-Kuhta, J. G. Nutt, and L. Chiari, "Trunk accelerometry reveals postural instability in untreated parkinson's disease," *Parkinsonism related disorders*, vol. 17, p. 557, 8 2011. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC5327861/

[118] M. Mancini, A. Salarian, P. Carlson-Kuhta, C. Zampieri, L. King, L. Chiari, and F. B. Horak, "Isway: a sensitive, valid and reliable measure of postural control," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, p. 59, 2012.

[119] F. Quijoux, A. Nicolaï, I. Chairi, I. Bargiotas, D. Ricard, A. Yelnik, L. Oudre, F. Bertin-Hugault, P. P. Vidal, N. Vayatis, S. Buffat, and J. Audiffren, "A review of center of pressure (cop) variables to quantify standing balance in elderly people: Algorithms and open-access code*," *Physiological Reports*, vol. 9, p. e15067, 11 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.14814/phy2.15067https://onlinelibrary.wiley.com/doi/abs/10.14814/phy2.15067https://physoc.onlinelibrary.wiley.com/doi/10.14814/phy2.15067

[120] S. R. Hussain and W. G. Wright, "The development and validation of a novel smartphone application to detect postural instability," *Sensors*, vol. 25, p. 1505, 2 2025.

[121] X. Kong, W. Yang, H. Luo, and B. Li, "Application of stabilized numerical integration method in acceleration sensor data processing," *IEEE Sensors Journal*, vol. 21, pp. 8194–8203, 3 2021.

[122] K. C. Ting, Y. C. Lin, C. T. Chan, T. Y. Tu, C. C. Shih, K. C. Liu, and Y. Tsao, "Inertial measurement unit-based romberg test for assessing adults with vestibular hypofunction," *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 12, p. 245, 2023. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC10776102/

[123] S. R. Lord, R. D. Clark, and I. W. Webster, "Postural stability and associated physiological factors in a population of aged persons," *Journal of Gerontology: MEDICAL SCIENCES*, vol. 46, pp. 69–76, 1991. [Online]. Available: https://academic.oup.com/geronj/article/46/3/M69/625924

[124] S. R. Lord, G. A. Caplan, R. Colagiuri, S. Colagiuri, and J. A. Ward, "Sensori-motor function in older persons with diabetes," *Diabetic medicine : a journal of the British Diabetic Association*, vol. 10, pp. 614–618, 1993. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/8403821/

[125] B. Timar, R. Timar, L. Gaiță, C. Oancea, C. Levai, and D. Lungeanu, "The impact of diabetic neuropathy on balance and on the risk of falls in patients with type 2 diabetes mellitus: A cross-sectional study," *PLOS ONE*, vol. 11, p. e0154654, 4 2016. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0154654

[126] L. Yin, J. Qin, Y. Chen, J. Xie, C. Hong, J. Huang, Y. Xu, Z. Liu, and J. Tao, "Impact of body mass index on static postural control in adults with and without diabetes: A cross-sectional study," *Frontiers in Endocrinology*, vol. 12, p. 768185, 12 2021. [Online]. Available: www.frontiersin.org

[127] J. D. Pozo-Cruz, R. M. Alfonso-Rosa, J. L. Ugia, J. G. McVeigh, B. D. Pozo-Cruz, and B. Sañudo, "A primary care–based randomized controlled trial of 12-week whole-body vibration for balance improvement in type 2 diabetes mellitus," *Archives of Physical Medicine and Rehabilitation*, vol. 94, pp. 2112–2118, 11 2013.

[128] C. L. Lin, H. C. Wu, N. C. Yu, Y. C. Liu, I. Y. Chiu, and W. C. Chien, "Risk factors for falls in older adults with type 2 diabetes: A cross-sectional study," *Medicine*, vol. 103, p. e40895, 12 2024. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC11651476/

[129] E. Ahmad, J. A. Sargeant, T. Yates, D. R. Webb, and M. J. Davies, "Type 2 diabetes and impaired physical function: A growing problem," *Diabetology 2022, Vol. 3, Pages 30-45*, vol. 3, pp. 30–45, 1 2022. [Online]. Available: https://www.mdpi.com/2673-4540/3/1/3/htmhttps://www.mdpi.com/2673-4540/3/1/3

[130] T. Lopatin, K. Sakyi, B. Kendall, G. Grunberger, and J. Haworth, "Standing balance impairment in persons with type 2 diabetes is predicted by peripheral neuropathy and vestibulopathy," *Primary care diabetes*, vol. 19, 2 2025. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/39709234/

[131] N. Duruturk, "Telerehabilitation intervention for type 2 diabetes," *World Journal of Diabetes*, vol. 11, p. 218, 6 2020. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC7284018/

[132] M. C. Bisi and R. Stagni, "Is imu- alternative to grf-based posturography? a comparative assessment on young healthy adults," *Journal of Biomechanics*, vol. 185, p. 112687, 5 2025.

[133] R. Jiao, "Is there a barrier between seniors and smartphone use in the internet age? a study of digital disconnection among older adults," *SHS Web of Conferences*, vol. 155, p. 03010, 2023. [Online]. Available: https://www.shs-conferences.org/articles/shsconf/abs/2023/04/shsconf_sdmc2022_03010/shsconf_sdmc2022_03010.html

[134] Y. Farag, G. Narra, D. Balasubramaniam, and K. M. Boyd, "Improving the digital literacy and social participation of older adults: an inclusive platform that fosters intergenerational learning," *International Conference on Information and Communication Technologies for Ageing Well and e-Health, ICT4AWE - Proceedings*, pp. 47–58, 4 2024. [Online]. Available: https://research-portal.st-andrews.ac.uk/en/publications/improving-the-digital-literacy-and-social-participation-of-older-

[135] M. Rashadh, M. Scholar, and K. Murugan, "A study on reducing digital fatigue in remote work," *International Journal of Foreign Trade and International Business*, vol. 6, pp. 153–159, 7 2024. [Online]. Available: https://www.foreigntradejournal.com/archives/2024.v6.i2.B.130

[136] Y. Nkizi and O. Thamsuwan, "Fall risk assessment in active elderly through the use of inertial measurement units: Determining the right postural balance variables and sensor locations," *Applied Sciences 2024, Vol. 14, Page 11312*, vol. 14, p. 11312, 12 2024. [Online]. Available: https://www.mdpi.com/2076-3417/14/23/11312/htmhttps://www.mdpi.com/2076-3417/14/23/11312

[137] N. A. Ahmad, A. F. M. Ludin, S. Shahar, S. A. M. Noah, and N. M. Tohit, "Willingness, perceived barriers and motivators in adopting mobile applications for health-related interventions among older adults: a scoping review," *BMJ Open*, vol. 12, p. e054561, 3 2022. [Online]. Available: https://pmc.ncbi.nlm.nih.gov/articles/PMC8915330/

[138] S. A. Ahmadi, G. Vivar, J. Frei, S. Nowoshilow, S. Bardins, T. Brandt, and S. Krafczyk, "Towards computerized diagnosis of neurological stance disorders: data mining and machine learning of posturography and sway," *Journal of Neurology*, vol. 266, pp. 108–117, 9 2019. [Online]. Available: https://link.springer.com/article/10.1007/s00415-019-09458-y

[139] S. R. Pandey, M. M. Oghaz, and J. G. Varghese, "Decoding diabetic neuropathy: Tap into postural sway for optimal feature detection based on machine learning approach," *7th International Conference on Inventive Computation Technologies, ICICT 2024*, pp. 1104–1111, 2024.

Appendix

Table 1: **Descriptive statistics for acceleration (ACC) and center of pressure (COP) parameters across four balance conditions in healthy participants.** Values are presented as mean ± standard deviation (SD), 95% confidence interval lower bound (95% CI L), 95% confidence interval upper bound (95% CI U), median, and interquartile range (Q3–Q1). RMS ACC = Root Mean Square of Acceleration (cm/s^2), RMS COP = Root Mean Square of Center of Pressure (cm), MV ACC = Mean Velocity of Acceleration (cm/s), MV COP = Mean Velocity of Center of Pressure (cm/s). BL-EO = Both Legs Eyes Open, BL-EC = Both Legs Eyes Closed, OL-EO = One Leg Eyes Open, OL-EC = One Leg Eyes Closed. Normality of the parameters is denoted by ✓.

Parameter	Condition	Mean	SD	95% CI L	95% CI U	Median	(Q3 - Q1)
RMS ACC	BL-EO	7.37	2.69	6.16	8.57	6.93	(8.23 - 5.68)
	BL-EC	8.18	3.37	6.67	9.70	7.08	(9.26 - 6.19)
	OL-EO ✓	22.98	8.35	19.22	26.73	19.66	(28.85 - 16.38)
	OL-EC	90.08	66.49	60.18	119.97	63.64	(120.35 - 38.13)
RMS COP	BL-EO ✓	0.45	0.16	0.38	0.52	0.42	(0.49 - 0.37)
	BL-EC	0.60	0.24	0.49	0.71	0.53	(0.69 - 0.44)
	OL-EO ✓	1.05	0.20	0.96	1.14	1.01	(1.14 - 0.91)
	OL-EC	3.35	2.53	2.21	4.49	2.52	(3.59 - 1.67)
MV ACC	BL-EO	13.54	10.12	8.99	18.09	10.21	(15.39 - 7.28)
	BL-EC	15.55	12.09	10.12	20.99	13.92	(16.80 - 10.17)
	OL-EO	44.63	25.96	33.27	55.98	34.38	(56.17 - 26.42)
	OL-EC ✓	121.22	70.84	89.37	153.08	111.51	(166.75 - 59.46)
MV COP	BL-EO ✓	0.99	0.26	0.87	1.11	0.95	(1.15 - 0.80)
	BL-EC ✓	1.33	0.46	1.12	1.54	1.25	(1.78 - 1.02)
	OL-EO	4.31	1.25	3.74	4.87	3.84	(4.70 - 3.47)
	OL-EC	14.03	9.24	9.88	18.19	10.77	(15.23 - 8.81)

Table 2: **Descriptive statistics for acceleration (ACC) and center of pressure (COP) parameters across four balance conditions in T2DM patients.** Values are presented as mean ± standard deviation (SD), 95% confidence interval lower bound (95% CI L), 95% confidence interval upper bound (95% CI U), median, and interquartile range (Q3–Q1).MV ACC = Mean Velocity of Acceleration (cm/s), MV COP = Mean Velocity of Center of Pressure (cm/s), RMS ACC = Root Mean Square of Acceleration (cm/s^2), RMS COP = Root Mean Square of Center of Pressure (cm). Normality of the parameters is denoted by ✓.

Parameter	**Condition**	**Mean**	**SD**	**95% CI L**	**95% CI U**	**Median**	**(Q3 - Q1)**
RMS ACC	BL-EO ✓	8.85	2.49	7.54	10.15	8.90	(11.79 - 6.37)
	BL-EC ✓	12.43	3.85	10.41	14.45	12.67	(15.98 - 9.12)
	OL-EO	63.55	39.27	42.98	84.12	44.12	(95.25 - 37.51)
	OL-EC	51.27	34.48	33.21	69.33	39.79	(65.80 - 23.09)
RMS COP	BL-EO ✓	0.61	0.19	0.51	0.70	0.56	(0.73 - 0.45)
	BL-EC ✓	0.96	0.27	0.81	1.10	0.86	(1.16 - 0.83)
	OL-EO ✓	1.33	0.51	1.06	1.59	1.13	(1.63 - 0.96)
	OL-EC	1.62	0.71	1.25	1.99	1.50	(1.88 - 1.04)
MV ACC	BL-EO ✓	18.78	8.18	14.50	23.07	19.72	(26.05 - 9.99)
	BL-EC ✓	18.25	9.89	13.07	23.43	14.72	(24.01 - 9.79)
	OL-EO	107.92	81.54	65.21	150.64	86.61	(101.13 - 62.99)
	OL-EC ✓	70.38	47.59	45.45	95.31	73.65	(103.71 - 27.48)
MV COP	BL-EO	1.76	0.63	1.43	2.09	1.60	(1.90 - 1.34)
	BL-EC ✓	3.78	1.82	2.83	4.74	3.20	(4.89 - 2.40)
	OL-EO	6.80	3.67	4.88	8.72	4.83	(9.57 - 4.37)
	OL-EC	7.40	3.85	5.38	9.41	6.07	(9.46 - 4.67)

Table 3: **Friedman test results for root mean square (RMS) and mean velocity (MV) parameters across all balance conditions for healthy and T2DM groups.** Test statistics (χ^2) and corresponding p-values are reported for both acceleration (ACC) and center of pressure (COP) measures. ***$p < 0.05$

(a) Healthy

Parameter	χ^2	p-value
MV ACC	39.69	0.00***
MV COP	52.83	0.00***
RMS ACC	48.35	0.00***
RMS COP	49.93	0.00***

(b) T2DM

Parameter	χ^2	p-value
MV ACC	17.40	0.00***
MV COP	31.97	0.00***
RMS ACC	36.09	0.00***
RMS COP	23.83	0.00***

Table 4: **Post-hoc Wilcoxon signed-rank test results with Bonferroni correction** ($\alpha = 0.0083$) **for all condition pairs and parameters in the T2DM group.** Each condition is coded as follows: 1 (BL-EO), 2 (BL-EC), 3 (OL-EO), 4 (OL-EC). Reported values include p-values, Bonferroni-adjusted significance, and effect sizes. Significant comparisons are denoted with asterisks.

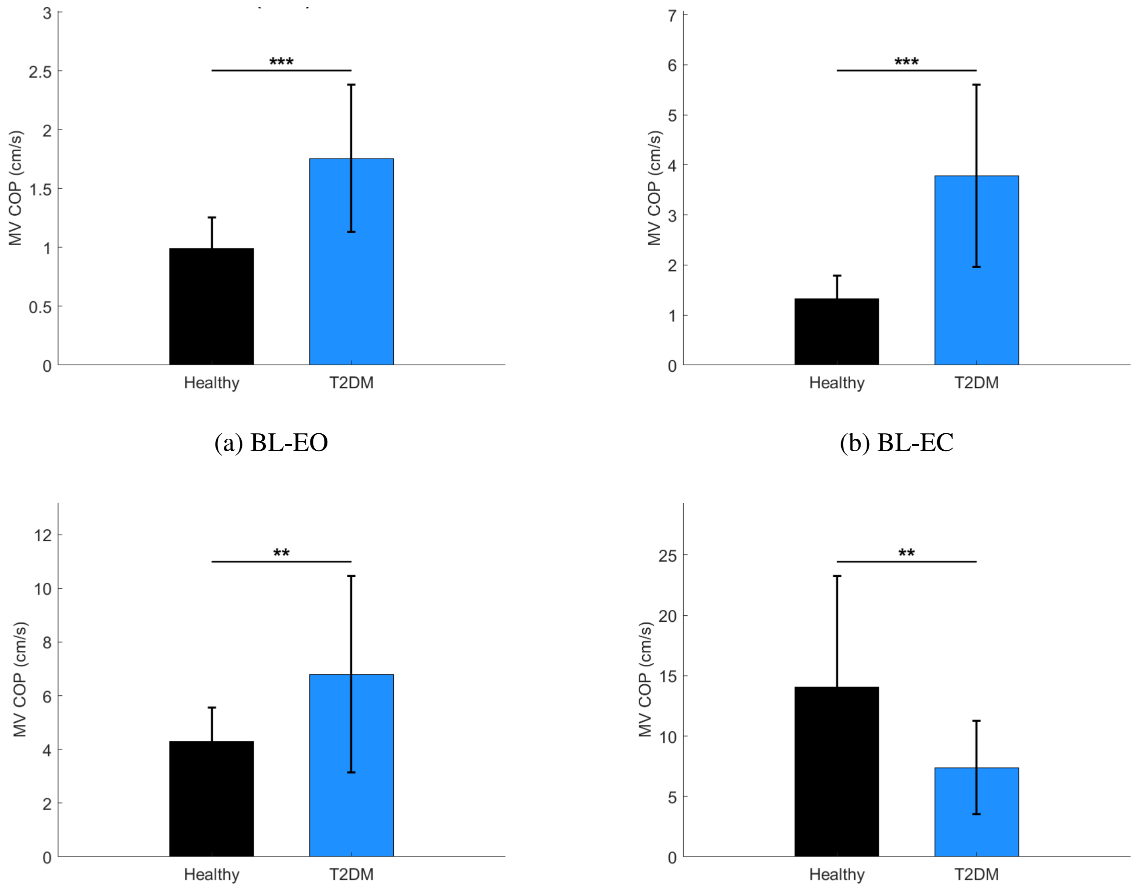
Parameter	Condition Comparison	p-value	Significant (Bonf.)	Effect Size
RMS ACC	1 vs 2	0.002*	TRUE	0.55
	1 vs 3	0.000*	TRUE	0.62
	1 vs 4	0.000*	TRUE	0.62
	2 vs 3	0.000*	TRUE	0.62
	2 vs 4	0.000*	TRUE	0.62
	3 vs 4	0.135	FALSE	0.29
RMS COP	1 vs 2	0.000*	TRUE	0.60
	1 vs 3	0.000*	TRUE	0.61
	1 vs 4	0.000*	TRUE	0.62
	2 vs 3	0.030	FALSE	0.41
	2 vs 4	0.020	FALSE	0.43
	3 vs 4	0.020	FALSE	0.43
MV ACC	1 vs 2	1.000	FALSE	0.01
	1 vs 3	0.000*	TRUE	0.62
	1 vs 4	0.009	FALSE	0.48
	2 vs 3	0.000*	TRUE	0.61
	2 vs 4	0.007*	TRUE	0.49
	3 vs 4	0.268	FALSE	0.22
MV COP	1 vs 2	0.000*	TRUE	0.62
	1 vs 3	0.000*	TRUE	0.62
	1 vs 4	0.000*	TRUE	0.62
	2 vs 3	0.005*	TRUE	0.50
	2 vs 4	0.002*	TRUE	0.55
	3 vs 4	0.358	FALSE	0.18

Table 5: **Post-hoc Wilcoxon signed-rank test results with Bonferroni correction** ($\alpha = 0.0083$) **for all condition pairs and parameters in the healthy group.** Each condition is coded as follows: 1 (BL-EO), 2 (BL-EC), 3 (OL-EO), 4 (OL-EC). Reported values include p-values, Bonferroni-adjusted significance, and effect sizes. Significant comparisons are denoted with asterisks.

Parameter	Condition Comparison	p-value	Significant (Bonf.)	Effect Size
RMS ACC	1 vs 2	0.520	FALSE	0.10
	1 vs 3	0.000*	TRUE	0.62
	1 vs 4	0.000*	TRUE	0.62
	2 vs 3	0.000*	TRUE	0.57
	2 vs 4	0.000*	TRUE	0.61
	3 vs 4	0.000*	TRUE	0.59
RMS COP	1 vs 2	0.016	FALSE	0.39
	1 vs 3	0.000*	TRUE	0.62
	1 vs 4	0.000*	TRUE	0.62
	2 vs 3	0.000*	TRUE	0.59
	2 vs 4	0.000*	TRUE	0.62
	3 vs 4	0.000*	TRUE	0.61
MV ACC	1 vs 2	0.494	FALSE	0.11
	1 vs 3	0.000*	TRUE	0.58
	1 vs 4	0.000*	TRUE	0.62
	2 vs 3	0.001*	TRUE	0.55
	2 vs 4	0.000*	TRUE	0.61
	3 vs 4	0.001*	TRUE	0.55
MV COP	1 vs 2	0.009	FALSE	0.42
	1 vs 3	0.000*	TRUE	0.62
	1 vs 4	0.000*	TRUE	0.62
	2 vs 3	0.000*	TRUE	0.61
	2 vs 4	0.000*	TRUE	0.62
	3 vs 4	0.000*	TRUE	0.61

Table 6: **Mann–Whitney U test results comparing postural control parameters between healthy and T2DM participants across four balance conditions.** Reported values include the U statistic, effect size (r), and corresponding p-values. Significant p-values are marked with asterisks: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Effect size is interpreted as small ($r \geq 0.1$), medium ($r \geq 0.3$), and large ($r \geq 0.5$).

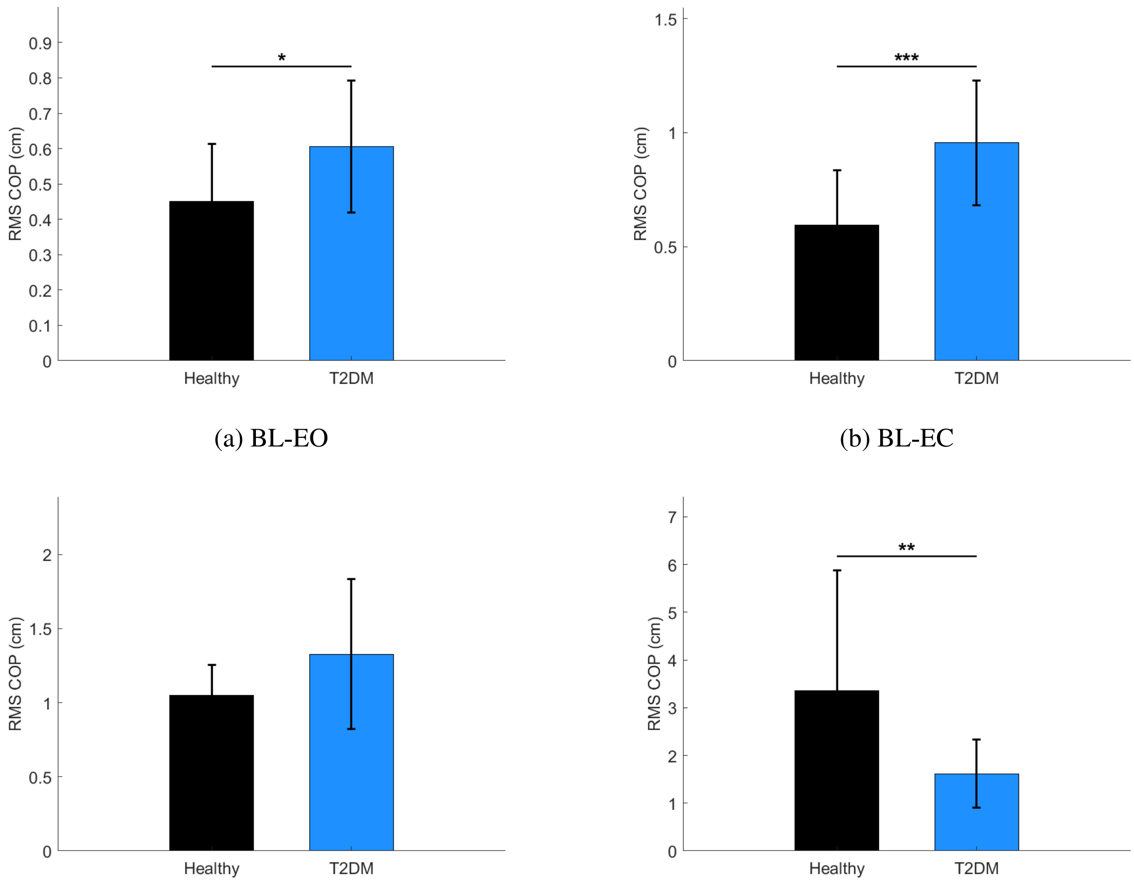
Condition	Parameter	U statistic	Effect size	p-value
BL-EO	RMS ACC	86	0.30	0.090
	RMS COP	66	0.43	0.015*
	MV ACC	76	0.36	0.040*
	MV COP	22	0.70	0.000***
BL-EC	RMS ACC	48	0.54	0.002**
	RMS COP	36	0.62	0.000***
	MV ACC	107	0.17	0.353
	MV COP	7	0.80	0.000***
OL-EO	RMS ACC	18	0.73	0.000***
	RMS COP	94	0.25	0.161
	MV ACC	41	0.58	0.001**
	MV COP	50	0.48	0.007**
OL-EC	RMS ACC	82	0.32	0.066
	RMS COP	53	0.51	0.004**
	MV ACC	74	0.37	0.033*
	MV COP	52	0.51	0.003**



(a) BL-EO (b) BL-EC

(c) OL-EO (d) OL-EC

Figure 24: **Comparison of Mean Velocity of Center of Pressure (MV COP, cm/s) between healthy and T2DM groups across four balance conditions.** (a) Both Legs Eyes Open (BL-EO), (b) Both Legs Eyes Closed (BL-EC), (c) One Leg Eyes Open (OL-EO), and (d) One Leg Eyes Closed (OL-EC). Asterisks indicate statistical significance based on Mann–Whitney U test: $^{**}p < 0.01$, $^{***}p < 0.001$. Error bars represent standard deviation.



(a) BL-EO (b) BL-EC

(c) OL-EO (d) OL-EC

Figure 25: **Comparison of Root Mean Square of COP (RMS COP, cm) between healthy and T2DM groups across four balance conditions.** (a) Both Legs Eyes Open (BL-EO), (b) Both Legs Eyes Closed (BL-EC), (c) One Leg Eyes Open (OL-EO), and (d) One Leg Eyes Closed (OL-EC). Asterisks indicate statistical significance based on Mann–Whitney U test:$*p < 0.05$ $**p < 0.01$, $***p < 0.001$. Error bars represent standard deviation.

Table 7: **Bias and limits of agreement (LoA) between scaled accelerometer and raw COP values for each balance condition and parameter in the T2DM group (scaling factor = 20).** Values are reported in scaled units. Bias is presented with its 95% confidence interval in parentheses, along with the upper and lower limits of agreement.

Parameter	Condition	Bias	Upper LoA	Lower LoA
RMS	BL-EO	-0.16(–0.23 to –0.10)	0.09(–0.03 to 0.21)	-0.42(–0.53 to –0.30)
	BL-EC	-0.33(–0.42 to –0.25)	0.00(–0.16 to –0.15)	-0.67(–0.82 to –0.51)
	OL-EO	1.85(1.02 to 2.68)	4.94(3.51 to 6.37)	-1.24(–2.67 to 0.19)
	OL-EC	0.94(0.34 to 1.55)	3.21(2.16 to 4.26)	-1.32(–2.37 to –0.27)
MV	BL-EO	-0.82(–1.19 to –0.45)	0.56(–0.08 to 1.20)	-2.20(–2.84 to –1.56)
	BL-EC	-2.87(–3.84 to –1.90)	0.77(–0.92 to 2.45)	-6.51(–8.19 to –4.82)
	OL-EO	-1.40(–3.78 to –0.98)	7.51(3.38 to 11.63)	-10.31(–14.44 to –6.19)
	OL-EC	-3.88(–5.70 to –2.06)	2.93(–0.22 to 6.08)	-10.69(–13.84 to –7.54)

Table 8: **Bias and limits of agreement (LoA) between scaled accelerometer and raw COP values for each balance condition and parameter in the healthy group (scaling factor = 20).** Values are reported in scaled units. Bias is presented with its 95% confidence interval in parentheses, along with the upper and lower limits of agreement.

Parameter	Condition	Bias	Upper LoA	Lower LoA
RMS	BL-EO	-0.08(–0.16 to –0.01)	0.24(0.11 to 0.37)	-0.40(–0.53 to –0.28)
	BL-EC	-0.19(–0.29 to –0.09)	0.26(0.08 to 0.43)	-0.63(–0.81 to –0.45)
	OL-EO	0.10(–0.05 to 0.25)	0.74(0.48 to 0.99)	-0.54(–0.79 to –0.28)
	OL-EC	1.15(0.50 to 1.81)	3.99(2.87 to 5.12)	-1.69(–2.82 to –0.56)
MV	BL-EO	-0.31(–0.57 to –0.05)	0.82(0.37 to 1.27)	-1.45(–1.90 to –1.00)
	BL-EC	-0.55(–0.84 to –0.27)	0.69(0.19 to 1.18)	-1.80(–2.29 to –1.30)
	OL-EO	-2.08(–2.71 to –1.45)	0.67(–0.42 to 1.76)	-4.82(–5.91 to –3.73)
	OL-EC	-7.97(–11.53 to –4.42)	7.52(1.37 to 13.68)	-23.47(–29.62 to –17.31)