

MOBILE MOTION ANALYSIS

PhD. Thesis

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***“Education is the most powerful
weapon we can use to change the
world.”***

Nelson Mandela

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1. LIST OF ABBREVIATIONS

AP — Anterior–Posterior

BW — Body Weight

CF — Centroidal Frequency

CI — Confidence Interval

CENTRAL — Cochrane Central Register of Controlled Trials

COP — Center of Pressure

CTSIB — Clinical Test of Sensory Interaction on Balance

F50 — Median Power Frequency (frequency below which 50% of spectral power is contained)

F95 — 95% Power Frequency (frequency below which 95% of spectral power is contained)

FD — Frequency Dispersion

GRF — Ground Reaction Force

ICC — Intraclass Correlation Coefficient

IMU — Inertial Measurement Unit

LSTM — Long Short-Term Memory

MF — Mean Frequency

ML — Mediolateral

MPF — Mean Power Frequency

MV — Mean Velocity

NPL — Normalized Path Length

OMC — Optical Motion Capture

P2P — Peak-to-Peak

PD — Parkinson's Disease

PRISMA — Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PROSPERO — International Prospective Register of Systematic Reviews

PWR — Power

QUADAS-2 — Quality Assessment of Diagnostic Accuracy Studies 2

RMS — Root Mean Square

RMSE — Root Mean Square Error

RoM — Range of Motion

SD — Standard Deviation

SE — Standard Error

SOT — Sensory Organization Test

TP — Total Power

TR — Trunk Rotation

2. STUDENT PROFILE

2.1 Vision, mission, and specific goals

My vision is to make objective motion assessment more accessible beyond specialised laboratories, thereby supporting more personalised and evidence-based care for people with musculoskeletal and neurological disorders. My mission is to evaluate mobile motion-analysis technologies and determine the clinical situations in which they can be used reliably. By clarifying both their capabilities



and their limitations, I aim to support the responsible translation of wearable sensor technology into clinical practice. The specific goals of my doctoral research were, first, to assess the concurrent validity of wearable inertial measurement units for measuring sagittal-plane lower-limb range of motion and estimating ground reaction forces during walking; and second, to evaluate the concurrent validity of wearable inertial sensors for measuring postural sway during quiet standing compared with laboratory reference systems.

2.2 Scientometrics

Number of all publications	4
Cumulative IF	18
Average IF/publication	4.5
Ranking (SCImago)	Q1:3 , D1:1
Number of publications related to the subject of the thesis	2
Cumulative IF	8.7

Average IF/publication	4.35
Ranking (SCImago)	Q1:2
Number of citations (Google Scholar)	17
Number of citations (MTMT, independent)	9
H-index	2

2.3. Future plans

The next step in my career is to pursue advanced international fellowship training in paediatric orthopaedics. This will allow me to develop my skills further in diagnosing and treating paediatric musculoskeletal conditions, as well as in using wearable inertial measurement units (IMUs) for motion analysis. After that, I plan to pursue additional international surgical training opportunities in paediatric orthopaedics before returning to West Kazakhstan State Medical University.

In the longer term, I would like to establish a dedicated motion analysis research unit and help strengthen the academic orthopaedic program at my home institution. I also plan to continue my scientific work by supervising junior researchers and PhD students and by developing prospective studies on IMU-based gait assessment as a non-invasive tool for measuring functional impairment, especially in underserved populations in Kazakhstan.

I plan to expand my international collaborative network, obtain competitive postdoctoral funding, and continue contributing to orthopaedic research through teaching, mentorship, and publication.

3. SUMMARY OF THE THESIS

This thesis summarises two systematic reviews and meta-analyses evaluating the concurrent validity of wearable inertial sensors for the objective assessment of human movement and postural control.

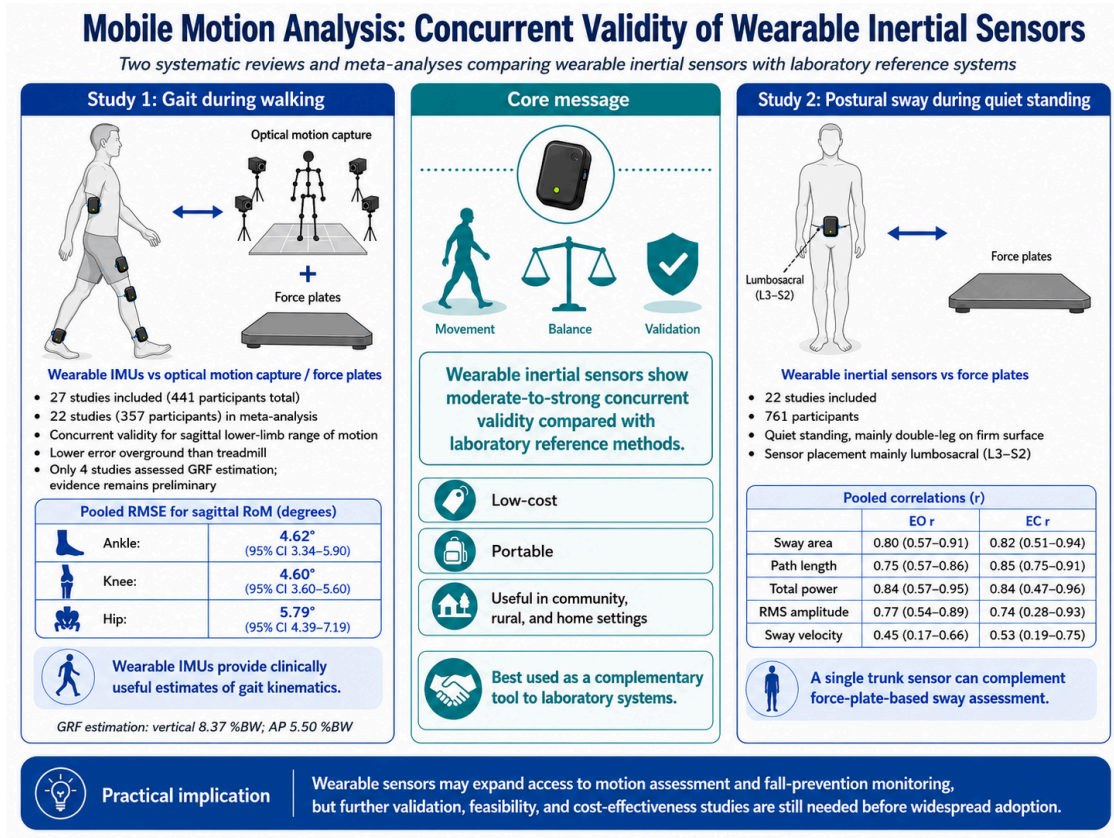
Study I examined the validity of wearable inertial measurement units for measuring sagittal-plane lower-limb range of motion during walking and for estimating ground reaction forces. The systematic review included 27 studies involving 441 participants, of which 22 studies with 357 participants could be used in the meta-analysis. Wearable IMUs showed acceptable concurrent validity for ankle and knee range of motion, with pooled root mean square errors of 4.62° and 4.60° , respectively. The error was greater at the hip and exceeded the commonly used 5° threshold, particularly during treadmill walking. Only four studies assessed the ability of wearable IMU devices to estimate the ground reaction forces and should therefore be regarded as preliminary. These findings suggest that wearable IMUs may support assessment of distal lower-limb kinematics, while hip measurements and ground reaction force estimation require further methodological development and validation.

Study II assessed the concurrent validity of wearable inertial sensors and consumer devices for measuring postural sway during quiet standing. Twenty-two studies involving 761 participants were included. Moderate-to-strong correlations with laboratory reference systems were found for sway area, path length, total power, root mean square amplitude, and sway range. Results also indicated lower values of correlation for sway velocity when comparing inertial sensors to established laboratory reference systems. Most frequently, inertial sensors were placed on or near the lumbar sacrum spine. However, there was considerable variability in the assessment results due to differences across participant populations, types of devices used to record data, placement of inertial sensors, testing protocols, sampling rates, and data processing methods.

Taken together, the two studies indicate that wearable inertial sensors perform most favorably for ankle and knee kinematics during walking and for several principal measures of postural sway during quiet standing. Performance was less consistent for hip kinematics, ground reaction force estimation, and sway velocity. Current evidence

therefore supports the use of wearable inertial sensors as practical complementary tools rather than direct replacements for optical motion-capture systems and force plates. The findings also identify priorities for future research and application of this technique: standardization, clinical validation, and real-world implementation.

4. GRAPHICAL ABSTRACT



5. INTRODUCTION

5.1 The Clinical Relevance of Quantifying Human Movement and Postural Control

Posture and movement are basic functions of daily living, and a person's ability to perform them is an essential determinant of independence and quality of life. For many clinical disciplines (orthopaedics, neurology, paediatrics, gerontology, etc.), objectively measuring gait and balance is essential for early detection of dysfunction, fall prevention, and evaluation of the success of rehabilitation programs (1, 2). Traditional clinical assessments (i.e., observational rating scales) have been widely accepted; however, they have several limitations, including reduced sensitivity to detect small biomechanical changes and to monitor long-term functional changes (2, 3). Therefore, there is a need for a clinically relevant tool that objectively and precisely measures movement in clinical practice settings.

5.2 The Translation Gap: Laboratory Standards vs Clinical Practice

To obtain high-resolution data on joint kinematics, center of pressure (COP) and postural sway metrics, researchers typically rely on optical motion capture (OMC) and laboratory-grade force plates as the primary reference standards.(3, 4) However, OMC and laboratory force plates have two significant drawbacks for widespread use: 1) They are expensive, and 2) they require specialized equipment and cannot easily be moved to other locations. As a result, a large translation gap exists between what can be measured in a laboratory setting and what can be measured in community-based clinics, patients' homes, and resource-poor settings.

5.3 Portable Wearable Motion Sensors Provide A Low-Cost Alternative

Wearable inertial measurement units (IMUs) represent a technology that may help close the translation gap mentioned above. IMUs are wearable devices that can estimate dynamic gait kinematics (sagittal-plane joint RoM) and static postural stability (postural sway)(4, 5). In most cases, IMUs include accelerometers and gyroscopes, while some systems also contain a magnetometer (3-5). Sensor-fusion algorithms combine signals from these sensors to estimate the orientation and movement of body segments. However, several factors may cause the measured values to deviate from the true values, including sensor placement, sensor-to-segment alignment, calibration procedures, sampling frequency, soft-tissue artefacts, magnetic interference, and differences in

data-processing methods(3-5). For this reason, before using IMU-derived measurements in a clinical context, they should be validated with respect to established reference systems available in the laboratory.

The literature on the concurrent validity of wearable motion sensors is heterogeneous. Studies differ in sensor hardware and placement, calibration procedures, task protocols, sampling frequency, and data-processing methods. To inform the use of IMUs in clinical settings, and to establish standards for the application of IMUs, the goal of this thesis is to summarize the existing evidence regarding the concurrent validity of IMUs for assessing different levels of function including static postural control and dynamic movement. This will allow clinicians to implement objective, portable movement assessment into clinical practice.

6. OBJECTIVES

6.1 Study I

The goal of this study was to assess the concurrent validity of data collected from wearable IMUs compared to data from laboratory reference systems (OMC, force plates) for measuring sagittal-plane lower-limb (ankle, knee, hip) RoM during walking. In addition, it measured how well IMU-based measurements estimate GRFs (vertical, anterior-posterior (AP)) during walking. Lastly, it explored whether differences in concurrent validity are due to walking type (overground vs treadmill) or to other methodological issues across studies.

6.2 Study II

Our objective was to assess the concurrent validity of measurements obtained from wearable inertial sensors for assessing postural stability. We examined the validity of commonly reported postural sway parameters, including sway area, path length, root mean square (RMS) amplitude, total power, sway velocity, and sway range, under eyes-open and eyes-closed conditions. Finally, we aimed to identify which parameters showed the strongest correlations between force-platform-derived and inertial-sensor-derived measures.

7. METHODS

7.1. Study I

7.1.1. Methodology and protocol

We conducted a systematic review and meta-analysis to evaluate the concurrent validity of wearable IMUs in gait assessment. We adhered to the PRISMA 2020 framework and followed established systematic review methodologies (6, 7). This review protocol was also registered in PROSPERO (ID: CRD42023492248) before the review took place.

Our main objective was to compile evidence comparing gait data from IMUs to gold-standard laboratory systems. Specifically, we examined studies that used OMC to measure lower-limb sagittal-plane RoM and force plates to measure GRFs.

7.1.2. Eligibility Criteria

Studies were eligible if they included ambulatory human participants of any age or health status, and assessed walking gait using IMUs to measure sagittal-plane lower-limb RoM or to estimate vertical and AP GRFs. Included studies were required to use a gold-standard comparator, specifically 3D optical motion capture systems or force plates. Data had to be collected concurrently with the two methods.. The primary outcomes were RMSE values for ankle, knee, and hip sagittal-plane RoM (degrees°) and for vertical and AP GRFs expressed as a percentage of body weight (%BW). Both observational and randomized study designs were eligible.

7.1.3. Information Sources and Search Strategy

In line with PRISMA principles, databases were searched on 10 December 2023 and updated on 26 August 2025 in PubMed, Embase, Web of Science, and CENTRAL. Search terms covered inertial sensors, gait, and biomechanics, and required comparison with a gold-standard system (3D optical motion capture and/or force plates). The main Boolean string was: ("IMU" OR ("inertial" AND "measurement" AND "unit") OR inertia* OR acceler* OR "sensor" OR gyroscop* OR magnetomet*) AND ("capture" OR "analysis" OR "treadmill" OR ("force" AND "plate")) AND (biomechanic* OR kinematic* OR kinetic* OR "force" OR load* OR "moment" OR torque* OR "power") AND ("gait" OR "locomotion" OR ambula* OR walk* OR "run" OR "running" OR "jog" OR "jogging"). No limits were set for language, year, or participant

characteristics; results were restricted to human studies. Reference lists and citing articles were also screened.

7.1.4. Study Selection and Data Extraction

All records from the searches were first stored in EndNote 20 and then uploaded to Rayyan (QCRI)(8). Duplicates were removed before screening. Two reviewers screened titles and abstracts, followed by full-text assessment. Any differences were handled through discussion; when needed, a third reviewer helped to reach a final decision. Inter-rater agreement was reported using Cohen's kappa (9).

Two reviewers independently extracted data using a predefined Excel spreadsheet, including basic study characteristics (authors, publication year, and sample size) and details of the IMU configuration, including the IMU device or model, sampling rate, fusion or filtering technique, calibration methodology, sensor placement, reference system, measured outcomes (ankle, knee, and hip sagittal-plane RoM and vertical and AP GRFs), and statistical results. Only studies reporting RMSE with mean $\pm$ SD were included in the meta-analysis, as RMSE directly quantifies deviation from the reference and assigns greater weight to larger errors (10).

7.1.5. Risk of Bias Assessment

Risk of bias was evaluated with QUADAS-2, which is suited to accuracy/validation questions like ours, where the focus is on how closely IMU outcomes match reference-standard measurements (11). The assessment covered the four QUADAS-2 domains: patient selection, index test (IMU assessment), reference standard, and flow and timing, as these domains fit the methodological design of the included validation studies.

7.1.6. Data Synthesis and Analysis

Due to anticipated study-to-study heterogeneity as a result of different sensor configurations and processing pipelines for IMUs, we performed random-effects meta-analysis with the Hartung-Knapp adjustment (12, 13) and restricted maximum likelihood estimation of τ^2 with Q-profile confidence intervals (14, 15). The main outcome was the mean RMSE for joint RoM and GRF estimates, pooled using inverse-variance weighting and reported with 95% CIs; when needed, SDs were taken from the papers or derived from CIs/SEs (15). We used Cochran's Q-test ($\alpha = 0.05$) to

evaluate subgroup differences (15) and calculated heterogeneity among studies using the I^2 statistic (16). When at least 10 studies were included in the analysis, we also examined small-study effects by creating funnel plots and performing Egger's test ($p < 0.10$) (15). Finally, we ran influence diagnostics to identify potential outliers (15), and all analyses were performed in R (17) using the meta and dmetar packages (18).

7.2 Study II

7.2.1. Methodology and Protocol

The systematic review and meta-analysis of this study used the PRISMA guidelines and Cochrane methodological recommendations to evaluate the concurrent validity of wearable inertial sensors and smartphone-based tools for assessing postural sway during quiet standing (6, 7). The protocol for this systematic review and meta-analysis was pre-registered in PROSPERO (ID: CRD42024596870) prior to initiating the review process.

7.2.2. Eligibility Criteria

Studies were included when they investigated quiet-standing postural sway in ambulatory participants from any age group or clinical population. The inertial-sensor measurements had to be collected at the same time as force-plate data. Eligible devices included IMUs, accelerometers, and sensors built into smartphones or tablets. Eligible outcomes were sway area, path length, sway range, RMS amplitude, sway velocity, and total power. Both observational and randomized controlled studies were accepted.

7.2.3. Information Sources and Search Strategy

PubMed, Embase, and Cochrane Central were searched on 2 October 2024. The main search string was: (IMU OR Accelerometer* OR “Force plate”) AND (“Balance” OR “Stability” OR “Equilibrium” OR “Sway” OR Postur*). Searches were not limited by publication date or language to ensure that as many relevant studies as possible were identified.

7.2.4. Study Selection and Data Extraction

First, search results were imported into EndNote 20 and Rayyan (QCRI) (8). Then, the two reviewers reviewed titles, abstracts and full-text articles independently. Any discrepancies among reviewers were addressed through discussion or consulting a third reviewer. A measure of inter-rater agreement was obtained by utilizing Cohen's Kappa

(9). For data extraction, two independent reviewers used a predefined table to extract relevant data from the studies they evaluated, including study design, participant demographics, type and placement of the sensor, reference system, postural sway parameters, and reported validity and reliability statistics, including Pearson's r , Spearman's ρ , and intraclass correlation coefficients.

7.2.5. Risk of Bias and Quality of Evidence Assessment

Each reviewer independently appraised the methodological quality of included studies using a modified 12-item checklist based on the Critical Appraisal of Study Design for Psychometric Articles (19). Scores were expressed as percentages and used to classify each study as high, moderate, low, or very low quality. The van Tulder framework was then applied to determine the overall strength of evidence across the body of literature (20).

7.2.6. Data Synthesis and Analysis

We pooled the correlations between sway parameters obtained from inertial sensors and those derived from force plates using a random-effects meta-analysis. Fisher's z -transformation was applied before pooling, and inverse-variance weighting was used for the analysis in R (21, 22). Heterogeneity was quantified with τ^2 and I^2 (16). As ICC models and reporting varied considerably across studies, ICCs were not meta-analyzed; instead, sample-size-weighted mean ICCs and observed ranges were summarized descriptively (23).

8. RESULTS

8.1. Concurrent validity of wearable IMUs for sagittal plane lower-limb range of motion during walking and estimated ground reaction forces: a systematic review and meta-analysis

8.1.1. Study Search and Selection

A total of 19,580 records were identified in the updated search. After removing 15,186 duplicate/overlapping records, 4,394 unique records remained for screening. Following title–abstract screening and full-text review, 27 studies were included in the systematic review, of which 22 contributed to the meta-analysis. Inter-rater agreement was very high for both title–abstract screening ($\kappa = 0.90$) and full-text selection ($\kappa = 0.97$). The selection process is shown in the PRISMA flowchart (Figure 1), and study characteristics are summarized in Table 1.

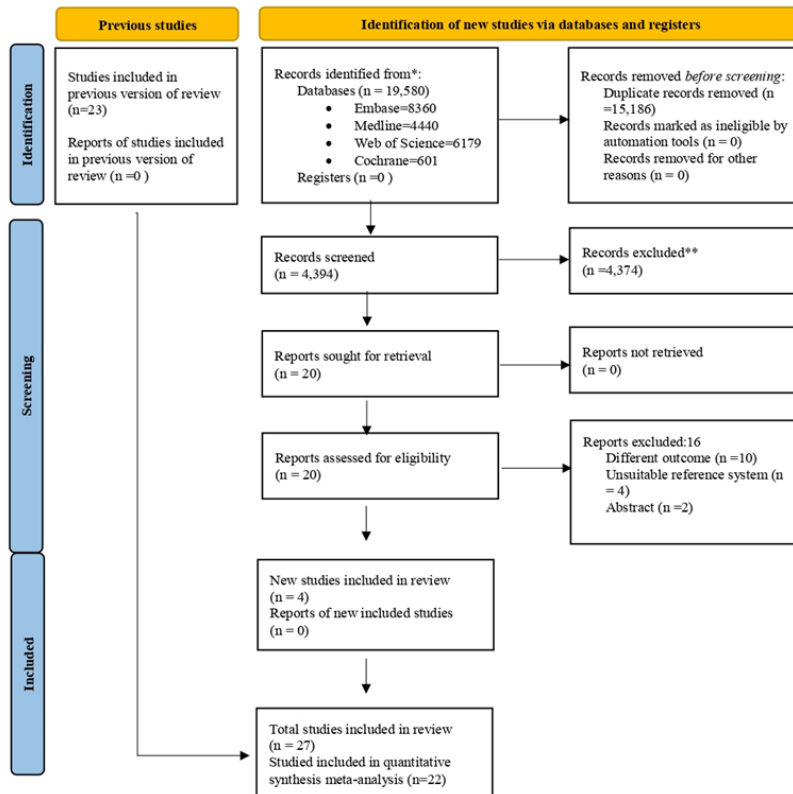


Figure 1. PRISMA 2020 flowchart representing the study selection process

Table 1. Basic characteristics of included studies included in Study I

Name of Author and Year	Population (n, age)	IMU Device (Hz) (n)	Sensor Placement	Data fusion algorithm/filter	Calibration methods	Reference system	Measured joints	Type of activity
H.Saito et al., 2011 (24)	3, 22.3 $\pm$ 0.6	WAA-006 (100 Hz) (7)	Shoes, shanks, thighs, lumbar	Kalman filter	N/A	Optotrak	hip, knee, and ankle joints	Overground walking
L.Kun et al., 2012 (25)	5, 25 $\pm$ 3	IMUs MM-2860, MAG ³ (100 Hz) (5)	Hip, bilateral thighs and shanks (lateral)	Physical and virtual sensor difference	Anatomical calibration	NAC Hi-Dcam II	knee and hip joints	Treadmill walking (straight line)
S.Tadano et al., 2013 (26)	5, 23.8 $\pm$ 1.9	WAA-006 Wireless (500 Hz) (7)	Pelvis, bilateral thighs, shanks, feet.	Quaternion orientation + 4th-order Butterworth filter	Static anatomical calibration	DIPP-Motion Pro	hip, knee, and ankle joints	Overground walking

C.Nüesch et al., 2017 (27)	20, 27.4 $\pm$ 8.3	RehaGait (400 Hz) (7)	Sacrum and bilaterally on the lateral thigh, lateral shank, and lateral foot	N/A	Static calibration	Vicon Motion Systems	hip, knee, and ankle joints	Treadmill walking
L.Adamowicz et al., 2019 (28)	20, 22.9 $\pm$ 5.4	Opal v2 APDM (128 Hz) (8)	Feet, shanks, thighs, lumbar, and sternum	Novel Kalman filter	Static+functional calibration	Vicon Motion Systems	hip joints	Treadmill walking
E.Dorschky et al., 2019 (29)	10, 27.1 $\pm$ 2.6	IMUs (Portables) (1000 Hz) (7)	Lower back, bilateral thigh, lateral shank, and upper midfoot	Optimal control fusion	Functional calibration	Vicon Motion Systems	hip, knee, and ankle joints	Overground walking
M.Nazarahari et al., 2019 (30)	10, 24 $\pm$ 3	Xsens MTw IMUs (100 Hz) (4)	Pelvis, thigh, shank, and foot	N/A	Functional calibration	Vicon Motion Systems	hip, knee, and ankle joints	Overground walking (functional tasks)

A.Karatsidis et al., 2019 (31)	11, 31.0 $\pm$ 7.2	Xsens MVN Link (240 Hz) (17)	Head, sternum, pelvis, upper legs, lower legs, feet, shoulders, upper arms, forearms, and hands	N/A	Static calibration.	Oqus 300 series, Qualisys	hip, knee, and ankle joints	Overground walking
M.Refai et al., 2020 (32)	8, 26.7 $\pm$ 3.8	Xsens MTw IMUs (100 Hz) (3)	Sacrum, bilateral midfoot	Extended Kalman filter	Static calibration	ForceShoe	GRFs	Overground walking
X.Robert-Lachaine et al., 2020 (33)	24, 24.8 $\pm$ 2.3	IMUs Xsens (100 Hz) (2)	Thigh and shank	N/A	Static calibration	Polaris Spectra	knee joints	Treadmill walking
L.Vargas-Valencia et al., 2021 (34)	12, 23.08 $\pm$ 2.3	IMU BNO055 (100 Hz) (2)	Thigh and shank	Multiplicative extended Kalman filter	Static + Device calibration	Vantage V5-Wide, Vicon	knee joints	Overground walking

J.Sung et al., 2021(35)	30, 23.5 ± 2.5	eCEN Eburnean (23 Hz) (1)	Lateral shank	LSTM neural network+4th-order Butterworth filter	N/A	MoCap	hip, knee, and ankle joints	Overground walking
C.Bailey et al., 2021 (36)	14, 23.5±3.9	Xsens Dot (60 Hz) (8)	Feet, shanks, thighs, pelvis, trunk	Magnetometer-free algorithm	Static calibration	Vicon Motion Systems	hip, knee, and ankle joints	Treadmill walking
L.Sy et al, 2021 (37)	9, 24.6±3.9	Xsens Awinda (100 Hz) (3)	Pelvis and bilateral ankles	Kalman filter	Anatomical calibration	Vicon Motion Systems	knee and hip joints	Overground walking (complex task)
V.Bessone et al., 2022 (38)	14, 29 ± 5	IMU-system aktos-t (143 Hz) (16)	Feet, shanks, thighs, pelvis, C7 vertebra, chest, forearms, upper arms, hands, and head	iSen 3.08+ 2nd order Butterworth	Static calibration + Reference-by-Global (T-pose)	Vicon Motion Systems	major joints in both the upper and lower body.	Repetitive overground walking

E. Piche et al., 2022 (39)	22, 26± 5.4	iSen IMUs (100 Hz) (11)	On the feet (rearfoot and forefoot), shanks, thighs, pelvis, chest, and back	N/A	Static calibration	OptiTrack MOCAP	hip, knee, and ankle joints	Treadmill walking
Z.Shuai et al., 2022 (40)	20, 25.2 ± 2.8	Perception Neuron (100 Hz) (7)	Sacrum, bilateral thighs, shanks, and dorsal feet.	Kalman filter	A and S pose	OptiTrack system	hip, knee, and ankle joints	Overground walking (functional tasks)

CZY.Choo et al., 2022 (41)	10, 26 ± 2	Perception Neuron (N/A) (17)	Sensors were placed on the head, sternum, thoracic spine, pelvis, both upper arms, forearms, thighs, shanks, and feet	N/A	A-pose, T-pose, S-pose	Vicon Motion Systems	hip, knee, and ankle joints	Overground walking
G.Patel et al., 2022 (42)	15, 20.07 ± 3.4	iSens system (100 Hz) (2)	Thigh and shank	Complementary filter fusion	Static+dynamic calibration	Vicon Motion Systems	hip and knee joints	Overground walking
M.Hossain et al., 2022 (43)	10, 23.9 ± 2.9	Avanti wireless IMUs (148 Hz) (2)	Dorsum of the foot	Ensemble deep learning	N/A	Vicon Motion Systems	hip, knee, and ankle joints	Treadmill, overground walking

T.McGrath et al., 2022 (44)	12, 24.6±3.0	Opal IMUs (200 Hz) (4)	Thigh and shank	Levenberg-Marquardt	Functional calibration+self-calibrating estimation	Vicon Motion Systems	hip and knee joints	Treadmill walking
M.El Fezazi et al., 2023 (45)	7, 26.0 ± 4.0	IMUs Xsens MTw Awinda (60 Hz) (2)	Thigh and shank	A quaternion-based sensor fusion	Static+functional calibration	Vicon Motion Systems	knee joints	Overground walking
B.L Scheltinga et al., 2023 (46)	16, 31.6 ± 9.0	Xsens MTx IMUs (240 Hz) (8)	Feet, tibias, thighs, pelvis, and trunk.	Artificial neural networks	Anatomical calibration	3D force plates	GRFs	Running
C.Ackland et al., 2025 (47)	30, 28 ± 4	BlueTrident (225 Hz) (4)	Pelvis, thighs, shanks, feet	Generative adversarial network	N/A	MOCAP motion system	hip, knee, and ankle joints	Walking, running
L. Forsyth et al., 2024 (48)	34, (20-24.1±3.85, 14-71 ± 5)	MotionSense (100 Hz) (2)	Thigh and shank	Madgwick filter	Mean-offset correction	Vicon Motion Systems	knee joints	Treadmill walking
U.Gupta et al., 2025 (49)	30, 27.1 ± 7.4	KIMIA Recover (20 Hz) (1)	Near the knee	N/A	Functional calibration	Vicon Motion Systems	knee joints	Overground walking

G. Weber et al., 2024 (50)	40, 31.0 ± 9.6	Xsens DOT, (60 Hz) (1)	Around the knee	Specialized alignment method	Mathematical calibration	KneeKG optical motion capture	knee joints	Overground walking
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8.1.2. Primary Outcomes

A total of 22 studies, including 357 participants, contributed data to the meta-analysis. IMU-based estimates of joint RoM were compared with OMC measurements, whereas GRF estimates were assessed against force-plate data. RMSE values were pooled using random-effects models. Given the very high heterogeneity across most RoM outcomes (I^2 around 90–96%), these pooled values should be viewed as overall averages across varied study methods rather than universal reference values. Differences in device configuration, sensor placement, calibration, and walking conditions should therefore be considered when interpreting the results.

For ankle sagittal-plane RoM, IMUs showed acceptable concurrent validity, with a pooled RMSE of 4.62° (95% CI 3.34–5.90) (24, 27, 29–31, 36, 39–41, 43). Errors were lower during overground walking (4.15°) than during treadmill walking (5.46°) (Figure 2).

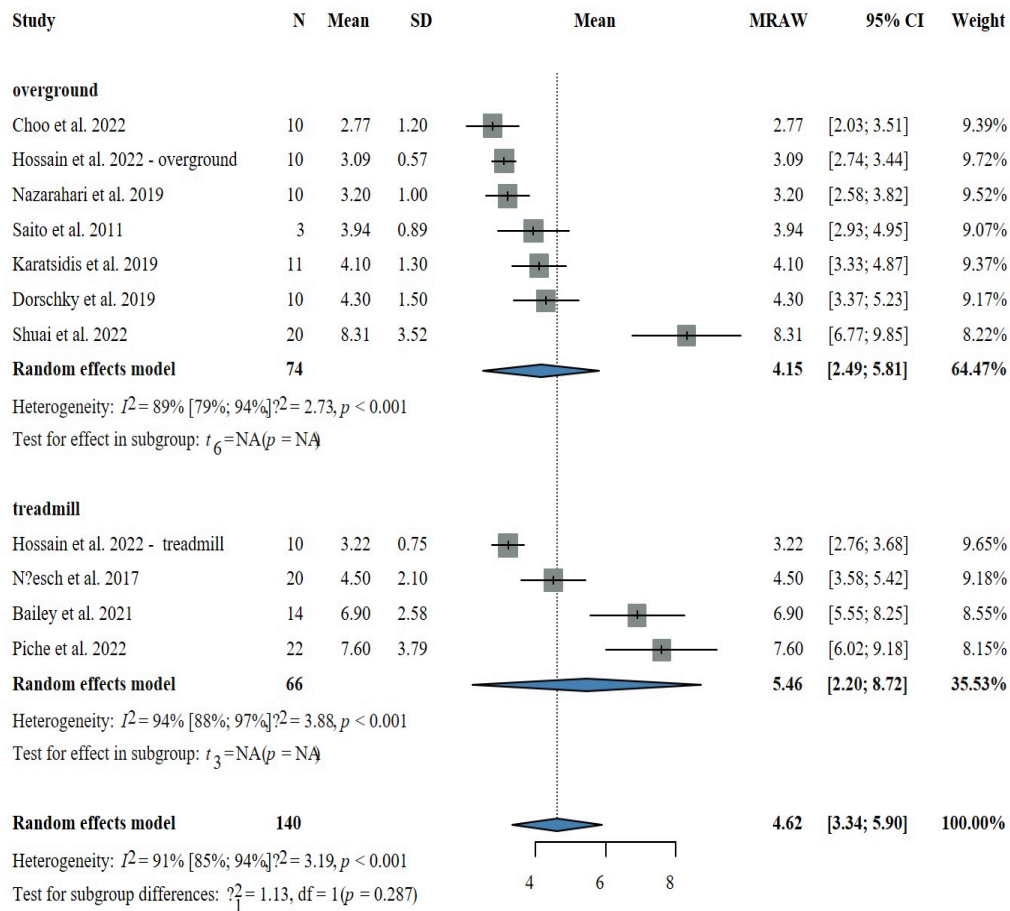


Figure 2. Forest plot of the RMSE for the ankle joint RoM in the sagittal plane, comparing IMUs to OMC systems. Random-effects model. CI = confidence interval.

For knee sagittal-plane RoM, concurrent validity was also acceptable overall, with a pooled RMSE of 4.60° (95% CI 3.60–5.60) (24, 27, 29-31, 33, 34, 36, 37, 39-45, 48-50). Subgroup results were similar for overground (4.51°) and treadmill (4.78°) walking, although heterogeneity remained very high (Figure 3).

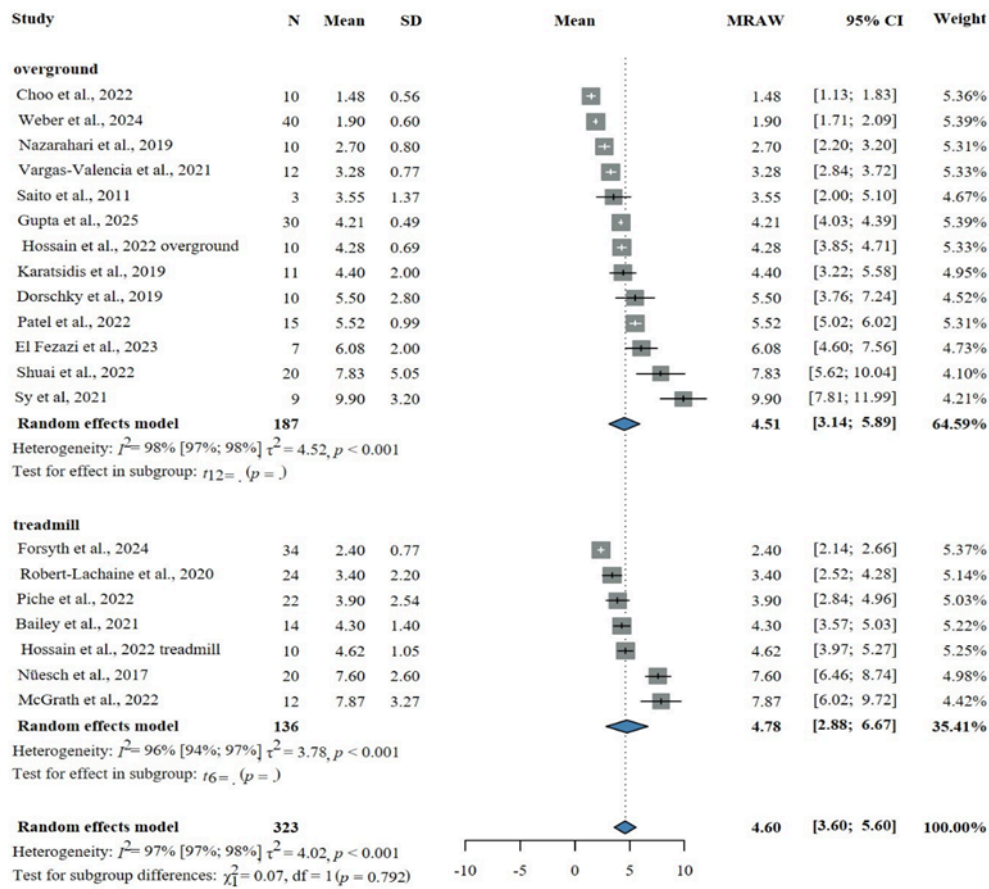


Figure 3. Forest plot of the RMSE for the knee joint RoM in the sagittal plane, comparing IMUs to OMC systems. Random-effects model. CI = confidence interval.

For hip sagittal-plane RoM, IMUs performed less well, with a pooled RMSE of 5.79° (95% CI 4.39–7.19) (24, 27-31, 36, 37, 39-44), exceeding the commonly accepted

threshold $\leq 5^\circ$. Overground walking was closer to the threshold (5.08°), while treadmill walking showed higher error (6.94°) (Figure 4).

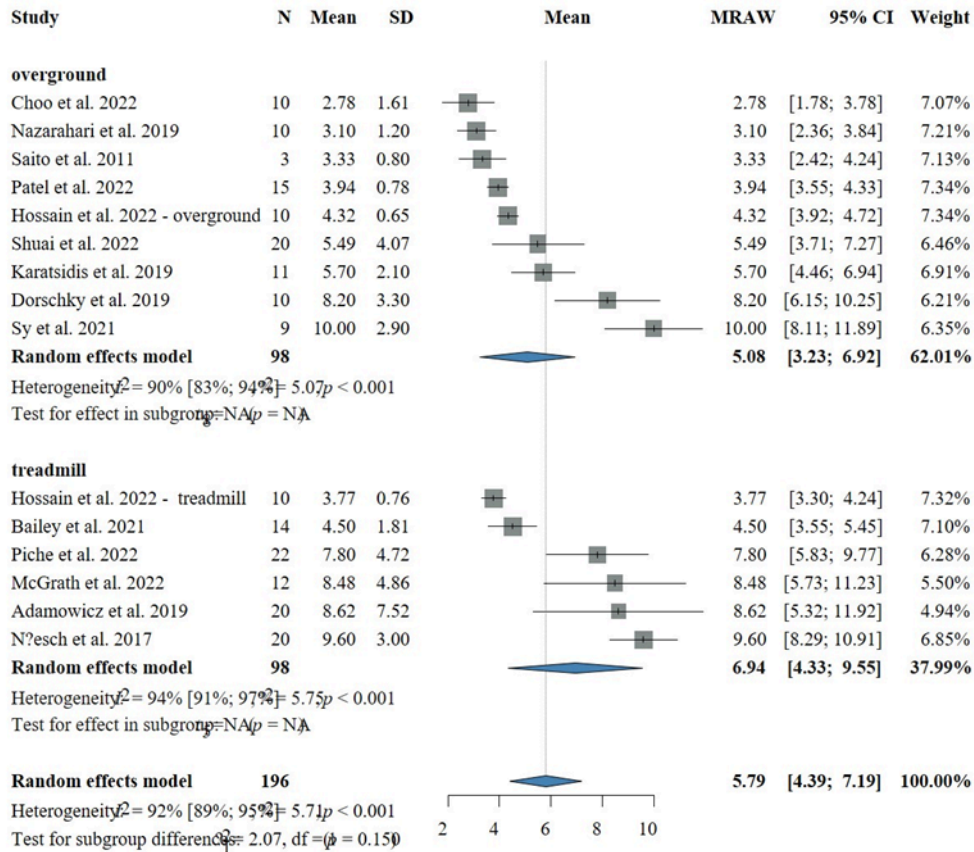
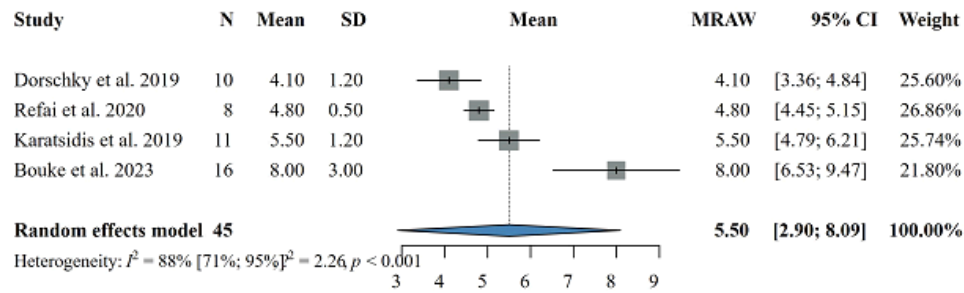


Figure 4. Forest plot of the RMSE for the hip joint RoM in the sagittal plane, comparing IMUs to OMC systems. Random-effects model. CI = confidence interval.

Only four studies evaluated IMU-based GRF estimates (29, 31, 32, 46). The pooled RMSE was 8.37 %BW (95% CI 5.14–11.61) for vertical GRF and 5.50 %BW (95% CI 2.90–8.09) for AP GRF, with high heterogeneity in both (Figure 5). These GRF findings are therefore best viewed as exploratory and sensitive to modelling approach and protocol differences.

A



B

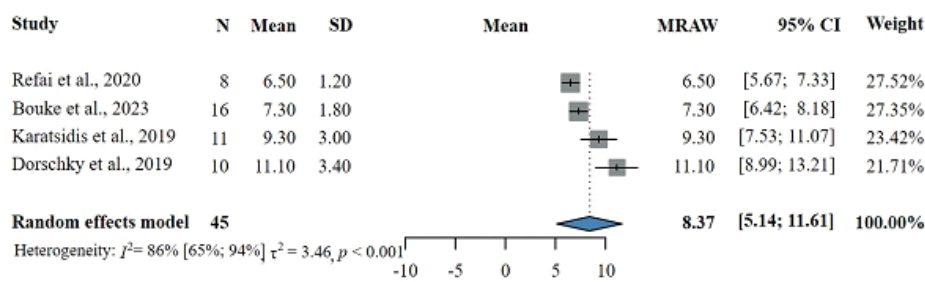


Figure 5. Forest plots of RMSE for estimated GRFs, comparing IMUs to laboratory-based force plate systems. (A) AP GRFs. (B) Vertical GRFs. Random-effects model. CI = confidence interval.

8.1.3 Risk of Bias Assessment

In the QUADAS-2 assessment, the reference-standard and flow-and-timing domains were consistently rated as having a low risk of bias, and the index-test domain was mostly rated as low risk. The main concern was patient selection, which was the most frequent source of bias and the main applicability issue, largely because the included samples were predominantly healthy young adults.

8.2. Concurrent Validity of Wearable Inertial Sensors for Postural Sway

Assessment During Quiet Standing Compared With Force Plates: A Systematic Review and Meta-Analysis

8.2.1. Study Search and Selection

The search yielded 12,548 records. After duplicate removal and screening, 22 studies met the inclusion criteria and were included in the review and quantitative synthesis.

Inter-rater agreement for study selection was high, with Cohen's kappa ranging from 0.91 to 0.97. Most included studies were published after 2014. The PRISMA flowchart of the study selection process is presented in Figure 6, while the main characteristics of the included studies are summarized in Table 2.

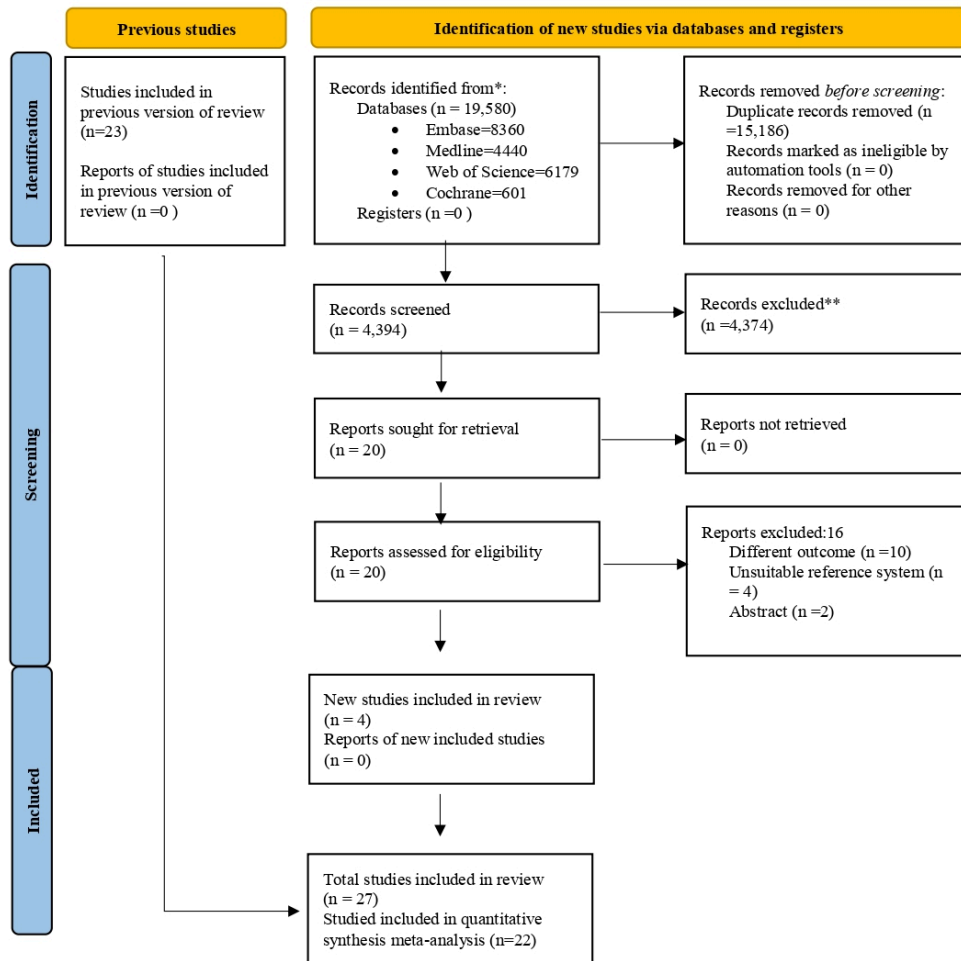


Figure 6. PRISMA 2020 flowchart representing the study selection process.

Table 2 Basic characteristics of included studies included in Study II

Study	Population (n; age: mean $\pm$ SD)	IMU System (n) (Hz)	Sensor Placement	Reference System	Sway parameters	Task for Validation	Testing protocol and technical details
S. Whitney et al., 2011 (51)	81 healthy adults; 47.8 $\pm$ 21.2 years	Dual-axis accelerometer (ADXL213AE) (1), 100 Hz	Around the pelvis	EquiTest® (NeuroCom SMART EquiTest®)	Length, RMS, P2P	Static standing, 90 s, eyes open/closed	Eyes open/closed, 90 s, 3 trials, pelvis; 100 Hz, filtered

M.Mancini et al., 2012 (52)	Study I: 13 individuals with PD (60.4 ± 8.5 years) and 12 healthy controls (60.2 ± 8.2 years). Study II: 17 individuals with PD (67.1 ± 7.3 years) and 17 healthy controls (67.9 ± 6.1 years).	MTX Xsens (1), 50 Hz	L5	AMTI force plate	Time-domain: jerk, dist, RMS, path, range, MV, MF, area Frequency-domain: PWR, F50, F95, CF, FD	Static standing, 30 s, eyes-open; Study II: repeated after 30 m	Eyes open, 30 s; 3 trials; L5; 50 Hz; filtered
<u>S.Ozinga</u> et al., 2014 (53)	12 healthy adults; 68.3 ± 6.9 years	iPad (third generation) (1), (100 Hz)	S2	Motion analysis corporation eagle system	P2P, path length, RMS, 95% area, total power	Static standing, 60 s, eyes open/closed	Eyes open/closed, 60 s, S2, 100 Hz, filtered

A.Rouis et al., 2014 (54)	15 healthy adults; 37.7 ± 15.0 years.	BodyTrack (1), (50 Hz)	L5	Force platform (AMTI Force and Motion)	RMS, range, path length, sway area, velocity, MF, TP	Static standing in a yoga position, 30 s, eyes open/closed.	Eyes open/closed, 30 s, 3 trials, L5, 50 Hz, filtered
M.Kosse et al., 2015(55)	60 healthy adults; 45.7 ± 5.32 years.	iPod touch G4 (1), (88–92 Hz)	L3	DynaPort hybrid unit	RMS, MPF, sway Area	Static standing, 60 s, eyes open/closed, and dual-task conditions.	Eyes open/closed, 60 s. L3, 88–92 Hz, filtered
J.Alberts et al., 2015 (56)	32 healthy adults; mean age 20.9 years.	iPad (1), (100Hz)	Sacral level	3D motion capture (8-camera system, Motion Analysis Corp.)	RMS, P2P, NPL (AP, ML, TR), sway volume	Static standing, 20 s, eyes-closed	Eyes-closed, 20 s, sacrum, 100 Hz, filtered

S.Ozinga et al., 2015 (57)	17 individuals with PD and 17 healthy controls; 62.59 $\pm$ 9.70 years.	iPad (third generation) (1), (100 Hz)	S2	Motion analysis corporation eagle system	P2P, path length, RMS, sway area, TP	Static standing, 60 s, eyes open/closed	Eyes open/closed, 60 s, S2, 100 Hz, filtered
M.Alessandrini et al., 2017 (58)	13 individuals with unilateral vestibular failure and 13 healthy controls; 48.6 $\pm$ 6.4 years.	Movit® by Captiks (1), (50 Hz)	L5	EDM Euroclinic®, 1 device	distance, RMS, path, range, MF, area, PWR, F50, F95, CF, FD	Static standing, 60 s, eyes open / closed	Eyes open/closed, 60 s, L5, 50 Hz, MATLAB processing
M.Burghart et al., 2017 (59)	26 healthy adults; 29.7 $\pm$ 10.9 years.	iPad (1), (10 Hz)	sternum	AMTI force platform (ground-embedded)	Sway score (jerk), COP sway area, RMS, velocity	Static standing, 10 s, eyes open/closed	Eyes open/closed, 10 s, sternum, 10 Hz

S.Ozinga et al., 2017 (60)	14 individuals with PD and 14 healthy controls; 63 ± 8 years.	iPad (1), (100 Hz)	Sacrum level	NeuroCom Smart Balance Master (NeuroCom International, Clackamas, OR)	P2P, path length, RMS, sway area	Static standing, 20 s, eyes open/closed	Eyes open/closed, 20 s, 3 trials, sacrum, 100 Hz, filtered
T. Hsieh et al., 2018 (61)	39 children with Down syndrome; 17.15 ± 0.9 years.	iPod Touch (6th generation, Apple) (1), (100 Hz)	S2	Force plate (Kistler, type 9260AA6,)	Length, RMS, P2P.	Static standing, 40 s, eyes open/closed	Eyes open/closed 40 s, S2, 100 Hz, MATLAB
L.McGough et al., 2018 (62)	27 participants (23 with mild cognitive impairment, 4 with mild dementia); 85.6 ± 4.8 years.	ISway (Inertial sensor) (1), (20–200 Hz)	L5	Kistler force plate, Kistler Instrument Corp., Amherst, NY	Path length, mean velocity, RMS	Static standing, 30 s, eyes open/closed	Eyes open/closed, 30 s, L5, 20–200 Hz, filtered

R.Sun et al., 2018 (63)	39 individuals with multiple sclerosis and 15 healthy controls; 58.01 $\pm$ 10.7 years.	BioStamp® (1), (50 Hz)	L5	Force plate (Bertec FP4060-05-PT-1 000)	Area, RMS, velocity, path length, TP.	Static standing, 30 s, eyes open/closed	Eyes open/closed, 30 s, 2 trials, L5, 50 Hz, filtered
E. Hansson et al., 2019 (64)	32 healthy adults; 29.8 $\pm$ 13.3 years.	Snubblometer (1); sampling frequency not reported.	L4	Good Balance™ force plate (Metitur Ltd)	Medio-lateral sway (mm/s), Anterior-posterior sway (mm/s)	Static standing, 30 s, eyes open/closed.	Eyes open/closed, 30 s, 3 trials, L4.
V.Shieh et al., 2020 (65)	18 healthy participants; 7–17 years old.	MobilityLab (APDM) (3), (128 Hz.)	S2, bilateral dorsal aspect of each foot	Forceplate (NeuroCom system)	Sway area, length, velocity	Static standing, 30 s, eyes open/closed	Eyes open/closed, 3 trials, S2/feet, 128 Hz, MATLAB

K.Hsieh et al., 2021 (66)	27 individuals with multiple sclerosis; 53.43 ± 10.59 years.	Smartphone (Samsung Galaxy S6) (1), (200 Hz)	sternum	Force plate (Bertec Inc., Columbus, OH)	RMS, area	static standing, 30 s, eyes open/closed	Eyes open/closed, 30 s, 2 trials, 100 Hz, sternum, filtered.
L.Rodrigues et al., 2022 (67)	26 healthy adults; 31 ± 7 years.	Smartphone (Samsung Galaxy A10) (1), (50 Hz)	L3-L5	Force platform (BIOMECH400 by EMG System)	Total deviation, sway area, RMS	Static standing, 60 s, eyes open/closed	Eyes open/closed, 60 s, 3 trials, L3–L5, 50 Hz, filtered
D.German et al., 2022 (68)	29 healthy adults; 28 ± 5.11 years.	iPhone 4S (Customized Smartphone App [CSA], (1), (100 Hz)	S1-S2	AMTI AccuSway force plate	Path length, sway area	Static standing, 40 s, eyes-closed	Eyes-closed, 40 s, 3 trials, S1–S2, 100 Hz, filtered

A.Vagnini et al. 2022 (69)	30 healthy adults; 18–30 years.	BTS G-Walk (BTS S.p.A., Italy) (1), (100 Hz)	S2	Optoelectronic system (Smart-DX, BTS S.p.A., Italy)	Sway area, range, length, RMS, speed	Static standing, 60 s, eyes open/closed	Eyes open/closed, 60 s, 3 trials, S2, 100 Hz, filtered
G.Telles et al., 2022 (70)	39 individuals with low back pain; 33. ± 11	Inertial sensors (Steval-stlkt01v1, STMicroelectronics) (1), (50 Hz)	L5	Force Plate (AMTI AccuSwayPLUS)	Sway area, length, RMS.	Static standing, 40 s, eyes-open	Eyes-open, 40 s, L5, 50 Hz, filtered
Jaworski et al., 2024 (71)	29 healthy non-athlete students (mean age 21.67 ± 0.88 years)	1 GYKO IMU sensor	T1–T2	Forceplate (NeuroCom system)	Sway area, distance, velocity	Static standing, 30 s, eyes-open	Eyes-open, 30 s, T1–T2, GYKO software processing
S.D'Emanuele et al., 2024 (72)	38 healthy adults; 25 ± 3 years.	GYKO IMU sensor (1) (500 Hz)	Lumbar level	AMTI force platform (1 unit)	Area, RMS, Velocity, path length, distance	Static standing, 30 s, eyes-open	Eyes-open, 30 s, 3 trials, lumbar, 500 Hz, filtered

8.2.2. Basic Characteristics of Included Studies

The 22 included studies involved a total of 761 participants aged 7 to 85 years. The majority of studies were carried out in healthy adults, though several also enrolled participants with Parkinson's disease, multiple sclerosis, vestibular disorders, or chronic low back pain. The devices used spanned both consumer-grade tools — such as tablet computers — and dedicated commercial inertial sensor systems, including Xsens, GYKO, Movit, and BTS G-Walk. Sampling frequencies varied widely, from 10 to 500 Hz, with the 50–100 Hz range being the most frequently reported. In terms of placement, sensors were most commonly positioned in the lumbosacral region, particularly between L3 and S2.

8.2.3. Primary Outcomes

Across the 22 included studies, wearable inertial sensors demonstrated moderate-to-strong correlations with force-plate-derived postural sway measures. Nevertheless, considerable heterogeneity was observed across most analyses, with I^2 values ranging from 70% to 94%.

For the sway area, pooled correlations were strong under both visual conditions. In the eyes-open condition, 11 studies contributed data, yielding a pooled correlation of $r = 0.80$ (95% CI 0.57–0.91; $I^2 = 91\%$; $n = 302$) (52-54, 57-59, 63, 65-67, 70). In the eyes-closed condition, 10 studies were included (53, 54, 57-59, 63, 65-68), with a pooled correlation of $r = 0.82$ (95% CI 0.51–0.94; $I^2 = 92.7\%$; $n = 267$) (Figure 7).

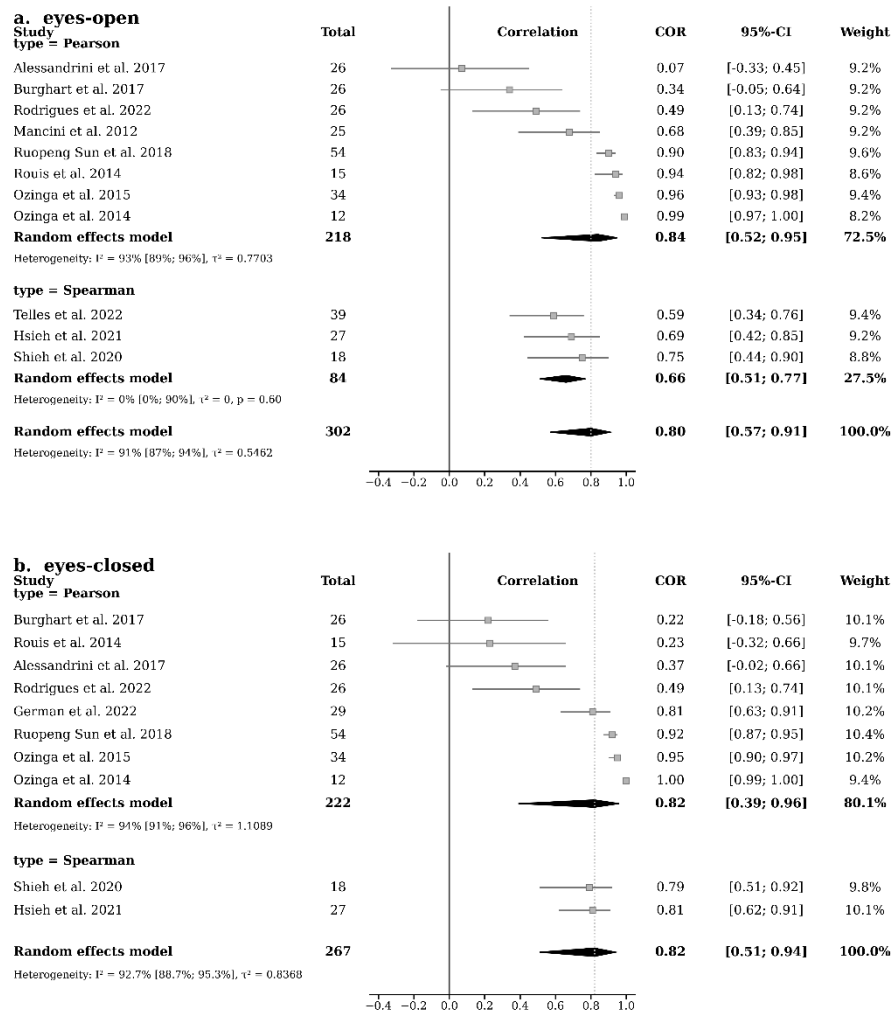


Figure 7. Forest plots of the correlation between inertial-sensor-derived sway area and force-plate measures under (a) eyes-open and (b) eyes-closed conditions.

For path length, pooled correlations also indicated strong concurrent validity. The overall pooled correlation was $r = 0.75$ (95% CI 0.57–0.86; $I^2 = 85.6\%$; $n = 250$) in the eyes-open condition (52–54, 57, 58, 62, 63, 65, 70) and $r = 0.85$ (95% CI 0.75–0.91; $I^2 = 70.5\%$; $n = 215$) in the eyes-closed condition (53, 54, 57, 58, 62, 63, 65, 68) (Figure 8). Direction-specific analyses showed similar findings. For anteroposterior path length, pooled correlations were $r = 0.77$ in the eyes-open condition (53, 57, 62, 65) and $r = 0.76$ in the eyes-closed condition (53, 56, 57, 62, 65). For mediolateral path length, pooled correlations were $r = 0.75$ in both conditions (53, 56, 57, 62, 65).

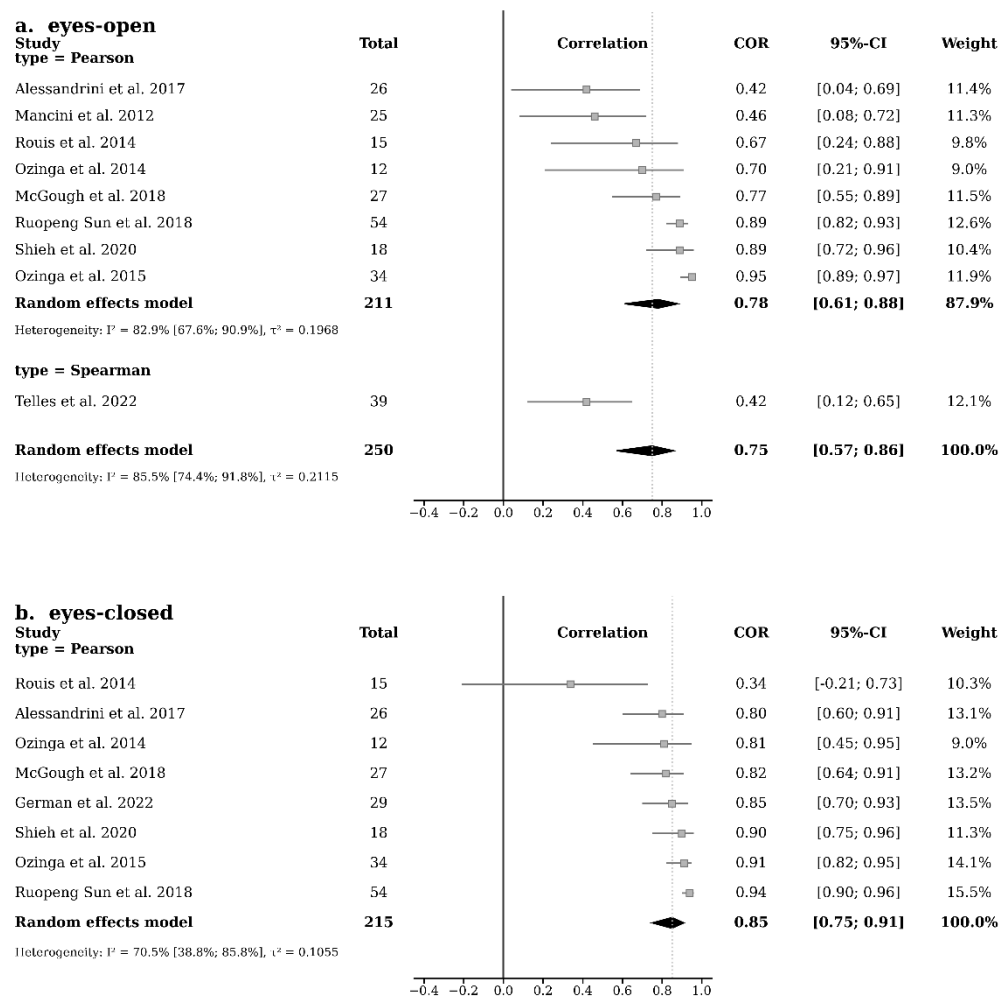


Figure 8. Forest plots of the correlation between inertial-sensor-derived path length and force-plate measures under (a) eyes-open and (b) eyes-closed conditions.

For total power, pooled correlations were among the strongest observed. Six studies contributed eyes-open data, resulting in a pooled correlation of $r = 0.84$ (95% CI 0.57–0.95; $I^2 = 91.3\%$; $n = 166$) (52–54, 57, 58, 63). Five studies contributed eyes-closed data, with the same pooled estimate of $r = 0.84$ (95% CI 0.47–0.96; $I^2 = 93.3\%$; $n = 183$) (53, 54, 57, 58, 63) (Figure 9).

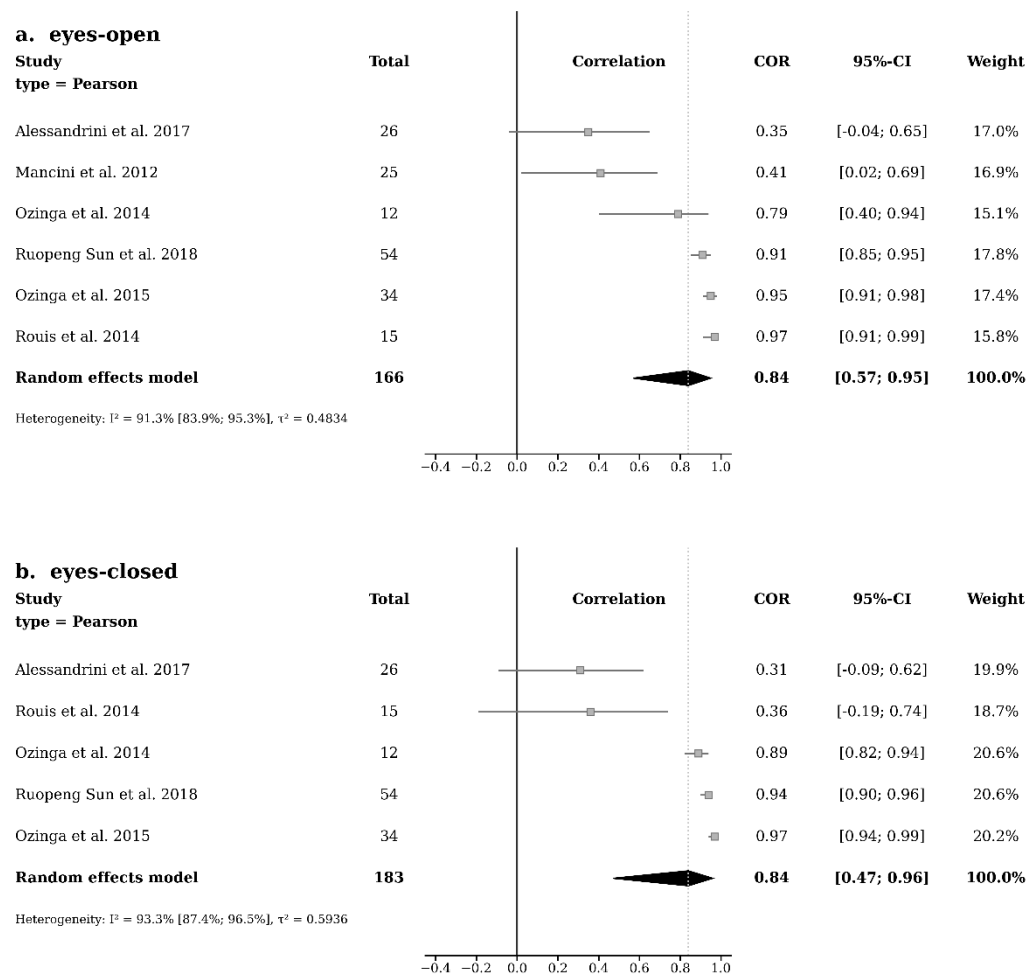


Figure 9. Forest plots of the correlation between inertial-sensor-derived total power and force-plate measures under (a) eyes-open and (b) eyes-closed conditions.

For RMS of sway amplitude, pooled correlations were also strong. Resultant RMS showed a pooled correlation of $r = 0.77$ (95% CI 0.54–0.89; $I^2 = 88.4\%$; $n = 204$) in the eyes-open condition (52-54, 57-59, 62, 70) and $r = 0.74$ (95% CI 0.28–0.93; $I^2 = 93.6\%$; $n = 140$) in the eyes-closed condition (53, 54, 57-59, 62) (Figure 10). Direction-specific analyses showed similar or slightly higher correlations for both anteroposterior and mediolateral RMS outcomes.

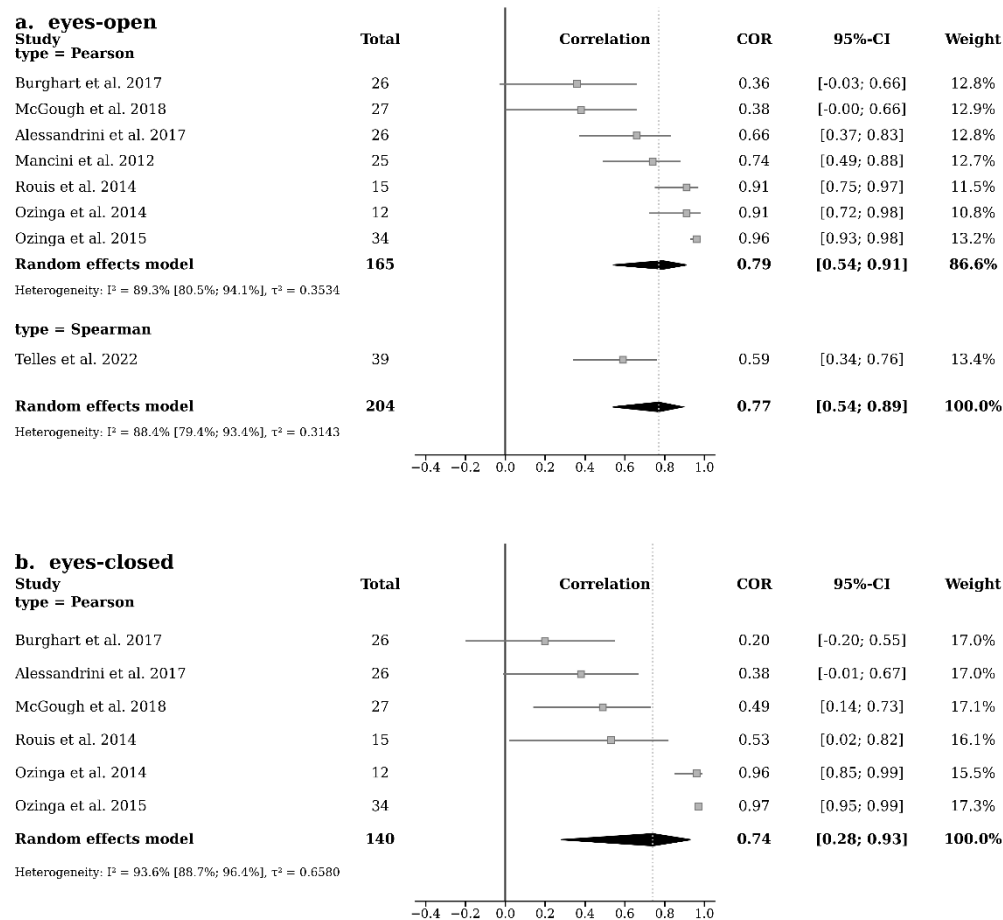


Figure 10. Forest plots of the correlation between inertial-sensor-derived resultant RMS and force-plate measures under (a) eyes-open and (b) eyes-closed conditions.

For sway velocity, pooled correlations were lower than for the other sway outcomes. In the eyes-open condition, the pooled correlation was $r = 0.45$ (95% CI 0.17–0.66; $I^2 = 72.6\%$; $n = 165$) (52, 54, 59, 62, 63, 65), while in the eyes-closed condition it was $r = 0.53$ (95% CI 0.19–0.75; $I^2 = 80.6\%$; $n = 140$) (54, 59, 62, 63, 65) (Figure 11).

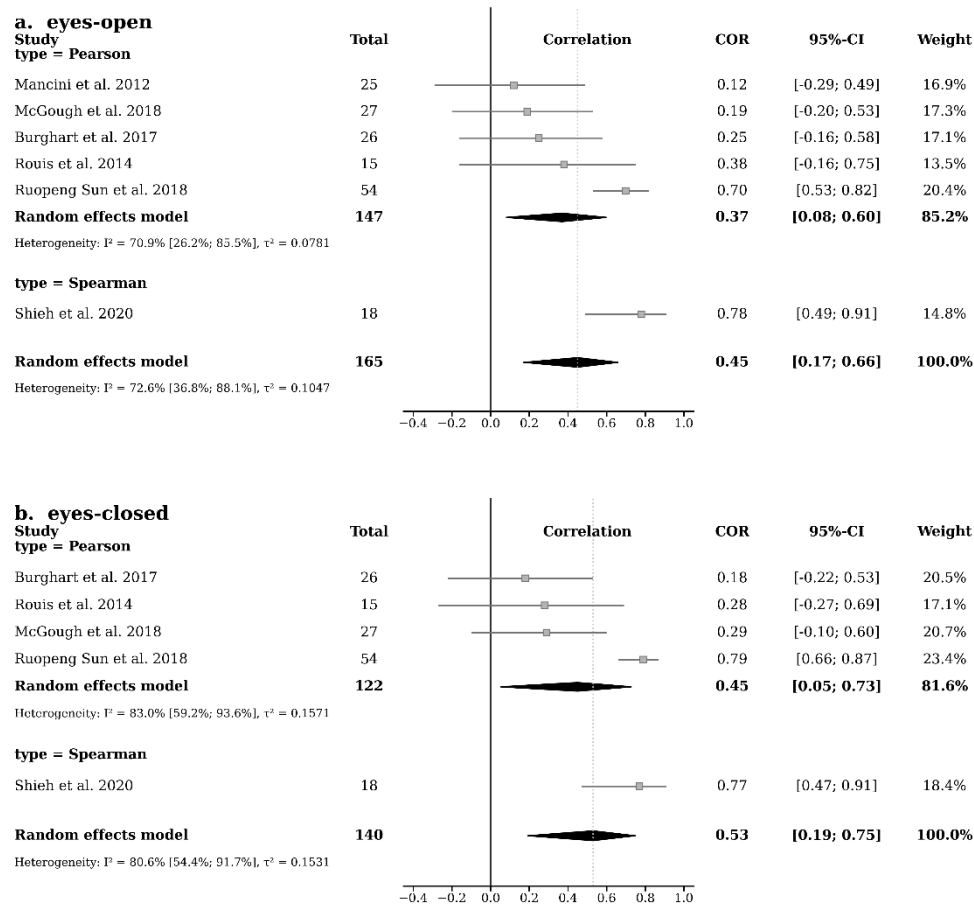


Figure 11. Forest plots of the correlation between inertial-sensor-derived sway velocity and force-plate measures under (a) eyes-open and (b) eyes-closed conditions.

For sway range, only three studies contributed eyes-open data (52, 54, 58). The pooled correlation was $r = 0.74$ (95% CI 0.59–0.83; $I^2 = 0\%$; $n = 66$), with individual study estimates ranging from 0.64 to 0.83 (Figure 12). There were insufficient data to perform a meta-analysis for the eyes-closed condition.

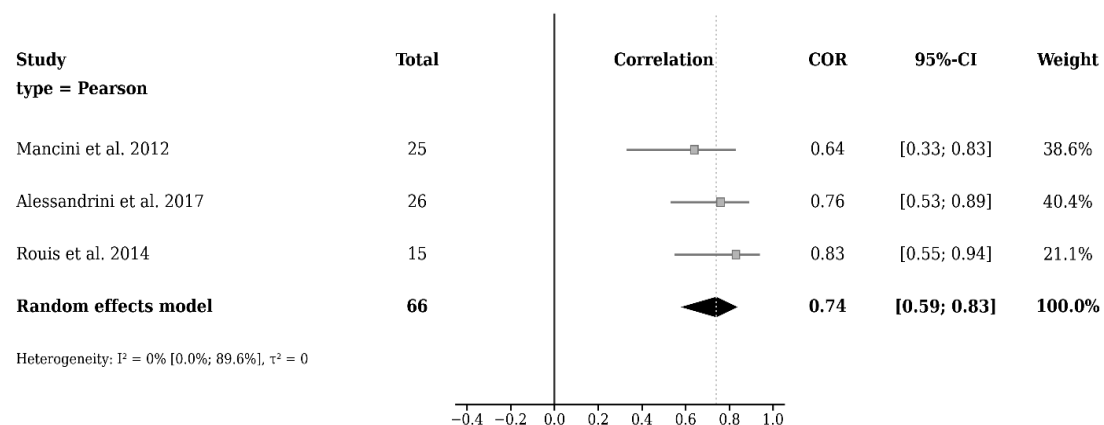


Figure 12. Forest plot of the correlation between inertial-sensor-derived sway range and force-plate sway range measures under eyes-open conditions.

Overall, the strongest pooled correlations were observed for sway area, path length, RMS amplitude, and total power, whereas sway velocity showed the lowest pooled correlations with force-plate measures.

8.2.4. Strength of Evidence

Based on the van Tulder framework, the overall strength of evidence across outcomes was graded as moderate.

8.2.5. Methodological Quality

Of the 22 included studies, 3 studies (14%) were rated as high quality, 13 (59%) as moderate quality, and 6 (27%) as low quality. The most common methodological limitations were the absence of sample size justification and inadequate adjustment for potential confounding factors.

8.2.6. ICC-Based Reliability

ICC values were reported in notably different ways across the included studies — with variations in the ICC models used and frequent gaps in methodological detail — making it impossible to combine these results into a single quantitative analysis. Reliability findings were therefore summarized descriptively. Some sway parameters showed moderate-to-good reliability, while others produced highly variable results that were difficult to interpret consistently across studies. The results are shown in Table 3.

Table 3. ICC-based reliability summary of inertial-sensor-derived sway parameters.

Outcome	Condition	Studies	Quality	Total (n)	ICC	Interpretation
Sway area	Eyes-open	(52, 55, 59, 60, 63, 71, 72)	54.5%-83.3%	252	0.82 (0.27 – 0.99)	Moderate evidence for good reliability
	Eyes-closed	(55, 59, 60, 63, 68)	54.5%-83.3%	197	0.87 (0.53 – 0.99)	Moderate evidence for good reliability
Path length	Resultant eyes-open	(51, 52, 63, 72)	62.5%-95.8%	190	0.83 (0.72 – 0.98)	Moderate evidence for good reliability
	Resultant eyes-closed	(51, 63, 68)	79.2% -95.8%	164	0.81 (0.72 – 0.97)	Moderate evidence for good reliability
	AP eyes-open	(60, 71, 72)	62.5%-83.3%	95	0.68 (0.46 – 0.79)	Moderate evidence for moderate reliability
	AP eyes-closed	(60)	81.8%	28	0.78 (0.58 – 0.89)	Limited evidence for good reliability
	ML eyes-open	(60, 71, 72)	62.5%-83.3%	95	0.77 (0.70 – 0.83)	Moderate evidence for good reliability
	ML eyes-closed	(60)	81.8%	28	0.82 (0.67–0.91)	Limited evidence for good reliability

Total power	Eyes-open	(52, 63)	83.3%	71	0.89 (0.61–0.98)	Moderate evidence for good reliability
	Eyes-closed	(63)	83.3%	54	0.99 (0.99–0.99)	Limited evidence for excellent reliability
RMS	Resultant eyes-open	(51, 52, 59, 72)	54.5–95.8%	162	0.33 (0.16 – 0.71)	Conflicting evidence for poor reliability
	Resultant eyes-closed	(51, 59)	54.5–95.8%	107	0.50 (0.46 – 0.63)	Limited evidence for moderate reliability
	AP eyes-open	(55, 60, 63, 71, 72)	62.5–83.3%	209	0.80 (0.35 – 0.99)	Moderate evidence for good reliability
	AP eyes-closed	(55, 60, 63)	81.8–83.3%	142	0.94 (0.74 – 0.99)	Moderate evidence for excellent reliability
	ML eyes-open	(55, 60, 63, 71, 72)	62.5–83.3%	209	0.78 (0.41 – 0.99)	Moderate evidence for good reliability
	ML eyes-closed	(55, 60, 63)	81.8–83.3%	142	0.95 (0.78 – 0.99)	Moderate evidence for excellent reliability
Sway velocity	Resultant eyes-open	(52, 59, 63, 72)	54.5–83.3%	135	0.76 (0.35 – 0.95)	Conflicting evidence for good reliability
	Resultant eyes-closed	(59, 63)	54.5–83.3%	80	0.92 (0.79 – 0.99)	Limited evidence for excellent reliability

	AP eyes-open	(64, 71, 72)	62.5–83.3%	99	0.59 (0.46–0.774)	Conflicting evidence for moderate reliability
	AP eyes-closed	(64)	77.2%	32	0.61 (0.42–0.77)	Limited evidence for moderate reliability
	ML eyes-open	(64, 71, 72)	62.5–83.3%	99	0.56 (0.476–0.70)	Moderate evidence for moderate reliability
	ML eyes-closed	(64)	77.2%	32	0.67 (0.50–0.81)	Limited evidence for moderate reliability
Range	Eyes-open	(52)	83.3%	17	0.74 (0.41 – 0.90)	Limited evidence for good reliability

9. DISCUSSION

9.1 Summary of Findings

The results of this dissertation indicate that one method for assessing both the RoM of the lower limbs and postural sway parameters during quiet standing is to use wearable inertial sensors. IMUs showed acceptable concurrent validity for ankle and knee RoM and several postural sway measures. Concurrent validity with IMUs did vary based on placement, calibration, device settings, how data were processed, and the conditions during testing. Performance was less for hip motion, GRF estimation, and sway velocity. Heterogeneity was substantial for most outcomes. Therefore, IMUs should currently be used as complementary tools rather than replacements for OMC and force plates.

Study I included 27 studies with a total of 441 participants. The pooled errors for ankle and knee sagittal-plane RoM were within the commonly used RMSE threshold of $\leq 5^\circ$. Hip RoM, however, exceeded this threshold, particularly during treadmill walking. Evidence on IMU-based GRF estimation was much more limited and should still be considered preliminary. The large differences between studies also indicate that device configuration, sensor placement, calibration, and walking protocol can substantially influence measurement accuracy.

Study II brought together data from 22 studies involving 761 participants aged 7 to 85 years. The studies included both healthy adults and individuals with Parkinson's disease, multiple sclerosis, vestibular disorders, and chronic low back pain. Inertial sensors showed strong correlations with force plates for sway area, path length, total power, and RMS amplitude, whereas sway velocity showed weaker correlations. The lumbosacral region, particularly between L3 and S2, was the most commonly studied sensor location and generally produced strong correlations with force-plate measures. According to the van Tulder framework, the overall strength of evidence was rated as moderate.

9.2 Interpretation in Light of Existing Literature

Findings from Study I on the concurrent validity of lower-limb RoM measured while walking in ambulatory individuals were very similar to those previously reported by Kobsar et al. and Poitras et al for both error magnitudes and errors at each of the

lower-limb joints studied (5, 19). The present review extends those findings by explicitly benchmarking results against the $\text{RMSE} \leq 5^\circ$ criterion and by simultaneously evaluating all three lower-limb joints and GRF estimation within a single synthesis—an integration that, to our knowledge, had not been provided by previous meta-analyses.

Hip measurements showed the largest errors, reaching 5.79° overall and 6.94° during treadmill walking. Several anatomical and technical factors may account for this pattern. Because the hip is a complex multi-axis joint covered by substantial muscle and subcutaneous tissue, soft-tissue movement can interfere with the sensor signal and make accurate sensor-to-segment alignment difficult (73). Treadmill testing may introduce an additional source of error, as motors and metal components can disturb the magnetic field and affect magnetometer-based heading estimates (74). IMU-derived hip kinematics should therefore be interpreted cautiously, particularly when clinical decisions depend on accurate assessment of proximal joint motion.

To our knowledge, Study II provides the first quantitative synthesis of this evidence and builds on the earlier descriptive review by Ghislieri et al. (4). The fact that sway area, path length, total power, and RMS all showed correlations of $r \geq 0.75$ suggests that a sensor placed in the lumbosacral region may capture the main amplitude-related and spatial features of postural sway during quiet standing. Sway velocity showed weaker results. One possible explanation is that sway velocity is calculated from displacement over time and may therefore be sensitive to sampling frequency and signal-processing methods (75). This can be seen clearly in the contrast between Burghart et al., who reported a low correlation for velocity at 10 Hz ($r = 0.25$), and Shieh et al., who found a much stronger correlation at 128 Hz ($r = 0.78$) (59, 65). Taken together, these findings support further investigation of minimum sampling-frequency requirements in future validation studies.

In general, higher point estimates were found under eyes-closed conditions, particularly for path length and total power. These findings may have plausible biomechanical and clinical explanations. One possible explanation is that removing visual input increases sway magnitude and variability, producing a larger signal that may be easier for inertial sensors to detect (76, 77). This is also clinically relevant, since many commonly used

balance assessments, such as the Sensory Organization Test and the modified CTSIB, intentionally include eyes-closed conditions (52).

9.3 Methodological Sources of Heterogeneity

Both studies were characterized by substantial statistical heterogeneity, with I^2 exceeding 80% in most analyses. These differences are most likely a result of variations in the designs of the studies, types of sensors used, participant characteristics and analytical methods. Also, these variations mean that the overall statistics derived from both studies cannot be applied consistently to each setting.

In Study I, sampling frequencies ranged from 20 to 1000 Hz. The number of sensors used varied from 1 to 17. In addition to varying sampling frequency, calibration procedures for subjects varied from purely anatomically based static calibration to functionally based calibration using physiological data. Thus, the measurement process was inconsistent across the studies.

Study II results showed similar variability in device type (from research-grade IMUs to smartphones), sensor placement, and studied populations. Together, these factors likely contributed to the wide variation in reported results.

The above-mentioned heterogeneity has two important implications for this literature review. Firstly, the pooled RMSEs and correlation coefficients should be interpreted as average estimates across all studies, rather than fixed benchmarks that apply equally in every situational context. Secondly, the high level of heterogeneity indicates a need for greater standardization in future studies; sampling frequency evaluation and reporting, standardized sensor placement protocols and calibration procedures, consistent outcome reporting and other such standards will benefit future studies.

9.4 Strengths and Limitations

Both studies were prospectively registered in PROSPERO and conducted in accordance with the PRISMA 2020 guidelines. Study selection and data extraction were performed independently by two reviewers, with high inter-rater agreement ($\kappa = 0.90$ – 0.97). Study I used QUADAS-2—the appropriate tool for accuracy and validity questions—while Study II applied a modified 12-item psychometric checklist in conjunction with the van Tulder evidence-grading framework, ensuring that quality assessment was fit for

purpose in each case. Further strengths included comprehensive evidence synthesis, clinically relevant outcome selection, and the use of random-effects models to account for variation between studies. Study I also benchmarked joint-specific errors against an established RMSE criterion, while Study II provided, to our knowledge, the first quantitative synthesis of several commonly used postural sway measures.

The main limitation shared by both studies is the restricted generalizability of their findings. Study I predominantly included healthy younger adults, with only limited representation of older participants and no adequately represented clinical populations, which restricts the generalizability of the findings. In such groups, altered gait patterns, comorbidities, and medication effects may all influence IMU performance. On the other hand, Study II included several clinical populations, including individuals with Parkinson's disease, multiple sclerosis, and vestibular disorders, which may have increased variability in sway magnitude and motor strategies and contributed to the observed inter-study variation in results.

Study-specific limitations should also be considered. In Study I, the decision to use RMSE as the primary outcome may have introduced a degree of selection bias, as studies reporting other relevant validity metrics, such as correlations or limits of agreement, were not included in the quantitative synthesis. In Study II, the main issue is that correlation describes the strength of association rather than true agreement between methods. Therefore, future research needs to give greater attention to Bland-Altman analyses and ICC reporting, and to provide sufficient methodological details so that results may be quantitatively pooled.

10. CONCLUSIONS

10.1 Study I

Study I showed that wearable IMUs can provide useful estimates of ankle and knee sagittal-plane RoM during overground walking, with generally better performance. There was relatively low concurrent validity for hip RoM, as well as a still limited body of evidence for IMU-based GRF estimation. IMUs should therefore be used alongside laboratory-based gait analysis rather than in place of it. More consistent methods for sensor placement, calibration, and data processing will be needed before they can be adopted more widely in clinical practice.

10.2 Study II

Study II found moderate-to-strong concurrent validity for several commonly used postural sway measures, particularly sway area, path length, RMS amplitude, and total power. Results were generally favorable when sensors were placed in the lumbosacral region, whereas sway velocity showed weaker validity. Therefore, a lumbosacral IMU would be a useful tool for practical, complementary assessment of postural sway. To move toward clinical application of this type of assessment technique, we will need further study of protocol-specific validations and improved methodology.

10.3 Synthesis

Taken together, the two studies showed a consistent pattern. Wearable IMUs performed most favorably for ankle and knee kinematics during walking and for several basic measures of postural sway during quiet standing. Their performance was less consistent for hip kinematics, GRF estimation, and sway velocity, which are more complex or derived outcomes. Therefore, current research appears to support the use of IMUs as practical complementary tools rather than a direct replacement for laboratory-based reference systems.

11. IMPLEMENTATIONS FOR PRACTICE

11.1 Study I

IMUs may support repeated orthopaedic and rehabilitation assessments for gait analysis at the ankle and knee level—for example, in post-operative recovery monitoring following total knee arthroplasty, anterior cruciate ligament reconstruction, or ankle fracture fixation—where repeated laboratory-based assessments are logistically and financially impractical. Although these configurations were not directly established as optimal, clinicians may consider devices with sampling rates between 100 and 240 Hz, static anatomical calibration, and sensor placement selected according to the joint of interest. Hip kinematics during treadmill walking should still be interpreted with caution and should not be used on their own for clinical decisions. IMU-based GRF estimation should also still be viewed as investigational and mainly reserved for research settings.

11.2 Study II

A single wearable sensor placed in the lumbosacral region may be a practical tool for monitoring balance and could potentially support fall-risk assessment, disease monitoring in neurological conditions, and evaluation of vestibular rehabilitation. However, these applications require specific clinical validation. Based on the present findings, the most promising parameters for clinical assessment appear to be total power, path length, sway area, and RMS amplitude. These measures showed the strongest correlations with force-plate measurements. More caution is needed when interpreting sway velocity. This parameter appears to depend more strongly on adequate sampling frequency. In particular, higher sampling frequencies may be preferable for sway-velocity assessment.

12. IMPLEMENTATIONS FOR RESEARCH

12.1. Study I

More research is needed on the validity of IMUs in clinical populations. For example, none of the included studies examined older adults or patients who had undergone joint replacement. Similarly, the included evidence also did not cover children with cerebral palsy or patients with neurologically related gait disorders. Future research is therefore needed to determine whether the findings of the present study also apply to these populations. More direct comparisons of calibration methods are also needed. Additional research is required on the estimation of GRFs using IMUs, especially in larger studies with more standardized methods. Machine-learning approaches also need to be investigated further. Finally, better reporting standards should be developed so that future researchers can more clearly understand and compare previous work.

12.2. Study II

Future studies should go beyond correlation coefficients and include measures that better reflect agreement between methods. These could include Bland–Altman analysis and absolute error metrics. More validation studies are also needed in populations at high risk of balance impairment, such as frail older adults, post-stroke patients, and children with developmental coordination disorder. Future research should also investigate the minimum sampling frequency required to accurately measure sway velocity. In addition, single-sensor and multi-sensor approaches should be compared to determine whether additional sensors improve validity. Lastly, there is a need for field-based research to evaluate the accuracy of this technology under real-world conditions prior to its widespread implementation across all areas of medical and community practice.

13. IMPLEMENTATIONS FOR POLICYMAKERS

13.1 Study I

The results of Study I suggest that IMUs may have a role in gait analysis during musculoskeletal rehabilitation. Regulatory bodies and professional organizations should work towards evidence-based guidance on technical specifications such as sampling frequency, calibration procedures, and sensor placement. Early implementation frameworks should prioritize outcomes with the strongest validation evidence, particularly ankle and knee kinematics, while requiring additional validation for hip measurements and treadmill-based assessment. Finally, policymakers should support further research validating the use of IMUs in older adults, paediatric populations, and clinical populations.

13.2. Study II

Concurrent validity between wearable inertial sensors and force-plate-based assessments of postural sway was found to be moderate to strong. This suggests that a single low-cost inertial sensor serves as a practical complementary option to more expensive plate systems in community, rural and home settings. Policymakers could support pilot implementation and further validation of sway assessment based on the prevention of falls and community monitoring programs. However, before widespread adoption, further research is needed on real-world feasibility, usability, cost-effectiveness, and ongoing technical validation.

14. FUTURE PERSPECTIVES

In the past decade, this area of research has developed considerably. Over the next decade, advances in magnetometer-free sensor fusion, wearable technology, and machine-learning-based data processing may help address current limitations in measuring hip kinematics, conducting treadmill-based assessments, and GRFs. At the same time, a major challenge, particularly for gait applications, is validation in populations beyond healthy young adults. More studies are needed in older adults, children, and patients with orthopaedic, neurological, or musculoskeletal conditions. Long-term studies under real-world conditions are also important.

15. REFERENCES

1. Baker N, Gough C, Gordon SJ. Inertial Sensor Reliability and Validity for Static and Dynamic Balance in Healthy Adults: A Systematic Review. *Sensors (Basel)*. 2021;21(15).
2. Mancini M, Horak FB. The relevance of clinical balance assessment tools to differentiate balance deficits. *Eur J Phys Rehabil Med*. 2010;46(2):239-48.
3. Hulleck AA, Menoth Mohan D, Abdallah N, El Rich M, Khalaf K. Present and future of gait assessment in clinical practice: Towards the application of novel trends and technologies. *Front Med Technol*. 2022;4:901331.
4. Ghislieri M, Gastaldi L, Pastorelli S, Tadano S, Agostini V. Wearable Inertial Sensors to Assess Standing Balance: A Systematic Review. *Sensors (Basel)*. 2019;19(19).
5. Poitras I, Dupuis F, Biellmann M, Campeau-Lecours A, Mercier C, Bouyer LJ, et al. Validity and Reliability of Wearable Sensors for Joint Angle Estimation: A Systematic Review. *Sensors (Basel)*. 2019;19(7).
6. Chandler J, Hopewell S. Cochrane methods--twenty years experience in developing systematic review methods. *Syst Rev*. 2013;2:76.
7. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *Bmj*. 2021;372:n71.
8. Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A. Rayyan-a web and mobile app for systematic reviews. *Syst Rev*. 2016;5(1):210.
9. Cohen J. A Coefficient of Agreement for Nominal Scales. *Educational and Psychological Measurement*. 1960;20(1):37-46.
10. McGinley JL, Baker R, Wolfe R, Morris ME. The reliability of three-dimensional kinematic gait measurements: a systematic review. *Gait Posture*. 2009;29(3):360-9.
11. Whiting PF, Rutjes AWS, Westwood ME, Mallett S, Deeks JJ, Reitsma JB, et al. QUADAS-2: a revised tool for the quality assessment of diagnostic accuracy studies. *Annals of internal medicine*. 2011;155(8):529-36.
12. Knapp G, Hartung J. Improved tests for a random effects meta-regression with a single covariate. *Statistics in Medicine*. 2003;22(17):2693-710.

13. IntHout J, Ioannidis JPA, Borm GF. The Hartung-Knapp-Sidik-Jonkman method for random effects meta-analysis is straightforward and considerably outperforms the standard DerSimonian-Laird method. *BMC Medical Research Methodology*. 2014;14(1):25.
14. Veroniki AA, Jackson D, Viechtbauer W, Bender R, Bowden J, Knapp G, et al. Methods to estimate the between-study variance and its uncertainty in meta-analysis. *Res Synth Methods*. 2016;7(1):55-79.
15. Harrer M, Cuijpers, P., Furukawa, T., & Ebert, D. *Doing Meta-Analysis with R: A Hands-On Guide* (1st ed.). Chapman and Hall/CRC. 2021:500.
16. Higgins JP, Thompson SG. Quantifying heterogeneity in a meta-analysis. *Stat Med*. 2002;21(11):1539-58.
17. Team RC. *R: A Language and Environment for Statistical Computing*. 2021.
18. Harrer MC, P.; Furukawa, T.; Ebert, D. D. *dmetar: Companion R Package For The Guide 'Doing Meta-Analysis in R'*. 0.1.0 ed2019.
19. Kobsar D, Charlton JM, Tse CTF, Esculier JF, Graffos A, Krowchuk NM, et al. Validity and reliability of wearable inertial sensors in healthy adult walking: a systematic review and meta-analysis. *J Neuroeng Rehabil*. 2020;17(1):62.
20. van Tulder M, Furlan A, Bombardier C, Bouter L. Updated method guidelines for systematic reviews in the cochrane collaboration back review group. *Spine (Phila Pa 1976)*. 2003;28(12):1290-9.
21. Schwarzer G. *Meta: General Package for Meta-Analysis* 2025.
22. Team RC. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing; 2025.
23. Koo TK, Li MY. A Guideline of Selecting and Reporting Intraclass Correlation Coefficients for Reliability Research. *J Chiropr Med*. 2016;15(2):155-63.
24. Saito H, Watanabe T. Kalman-filtering-based joint angle measurement with wireless wearable sensor system for simplified gait analysis. *IEICE Trans Inf Syst*. 2011;E94.D(8):1716-20.
25. Kun L, Inoue Y, Shibata K. Physical sensor difference-based method and virtual sensor difference-based method for visual and quantitative estimation of lower limb 3D gait posture using accelerometers and magnetometers. *Comput Methods Biomech Biomed Engin*. 2012;15(2):203-10.

26. Tadano S, Takeda R, Miyagawa H. Three dimensional gait analysis using wearable acceleration and gyro sensors based on quaternion calculations. *Sensors (Basel)*. 2013;13(7):9321-43.
27. Nüesch C, Roos E, Pagenstert G, Mündermann A. Measuring joint kinematics of treadmill walking and running: Comparison between an inertial sensor based system and a camera-based system. *J Biomech*. 2017;57:32-8.
28. Adamowicz L, Gurchiek RD, Ferri J, Ursiny AT, Fiorentino N, McGinnis RS. Validation of novel relative orientation and inertial sensor-to-segment alignment algorithms for estimating 3D hip joint angle. *Sensors (Basel)*. 2019;19(23):5143.
29. Dorschky E, Nitschke M, Seifer AK, van den Bogert AJ, Eskofier BM. Estimation of gait kinematics and kinetics from inertial sensor data using optimal control of musculoskeletal models. *J Biomech*. 2019;95:109278.
30. Nazarahari M, Noamani A, Ahmadian N, Rouhani H. Sensor-to-body calibration procedure for clinical motion analysis of lower limb using magnetic and inertial measurement units. *J Biomech*. 2019;85:224-9.
31. Karatsidis A, Jung M, Schepers HM, Bellusci G, de Zee M, Veltink PH, et al. Musculoskeletal model-based inverse dynamic analysis under ambulatory conditions using inertial motion capture. *Med Eng Phys*. 2019;65:68-77.
32. Refai MIM, van Beijnum BF, Buurke JH, Veltink PH. Portable gait lab: Estimating 3D GRF using a pelvis IMU in a foot IMU defined frame. *IEEE Trans Neural Syst Rehabil Eng*. 2020;28(6):1308-16.
33. Robert-Lachaine X, Parent G, Fuentes A, Hagemeister N, Aissaoui R. Inertial motion capture validation of 3D knee kinematics at various gait speed on the treadmill with a double-pose calibration. *Gait Posture*. 2020;77:132-7.
34. Vargas-Valencia LS, Schneider FBA, Leal-Junior AG, Caicedo-Rodriguez P, Sierra-Arevalo WA, Rodriguez-Cheu LE, et al. Sleeve for knee angle monitoring: An IMU-POF sensor fusion system. *IEEE J Biomed Health Inform*. 2021;25(2):465-74.
35. Sung J, Han S, Park H, Cho HM, Hwang S, Park JW, et al. Prediction of lower extremity multi-joint angles during overground walking by using a single IMU with a low frequency based on an LSTM recurrent neural network. *Sensors (Basel)*. 2021;22(1).

36. Bailey CA, Uchida TK, Nantel J, Graham RB. Validity and sensitivity of an inertial measurement unit-driven biomechanical model of motor variability for gait. *Sensors (Basel)*. 2021;21(22):7690.
37. Sy L, Raitor M, Del Rosario M, Khamis H, Kark L, Lovell NH, et al. Estimating lower limb kinematics using a reduced wearable sensor count. *IEEE Trans Biomed Eng*. 2021;68(4):1293-304.
38. Bessone V, Hörschele N, Schwirtz A, Seiberl W. Validation of a new inertial measurement unit system based on different dynamic movements for future in-field applications. *Sports Biomech*. 2022;21(6):685-700.
39. Piche E, Guilbot M, Chorin F, Guerin O, Zory R, Gerus P. Validity and repeatability of a new inertial measurement unit system for gait analysis on kinematic parameters: Comparison with an optoelectronic system. *Measurement*. 2022;198:111442.
40. Shuai Z, Dong A, Liu H, Cui Y. Reliability and validity of an inertial measurement system to quantify lower extremity joint angle in functional movements. *Sensors (Basel)*. 2022;22(3).
41. Choo CZY, Chow JY, Komar J. Validation of the Perception Neuron system for full-body motion capture. *PLoS One*. 2022;17(1):e0262730.
42. Patel G, Mullerpatan R, Agarwal B, Shetty T, Ojha R, Shaikh-Mohammed J, et al. Validation of wearable inertial sensor-based gait analysis system for measurement of spatiotemporal parameters and lower extremity joint kinematics in sagittal plane. *Proc Inst Mech Eng H*. 2022;236(5):686-96.
43. Bin Hossain MS, Dranetz J, Choi H, Guo ZS. DeepBBWAE-Net: A CNN-RNN based deep superlearner for estimating lower extremity sagittal plane joint kinematics using shoe-mounted IMU sensors in daily living. *IEEE J Biomed Health Inform*. 2022;26(8):3906-17.
44. McGrath T, Stirling L. Body-worn IMU-based human hip and knee kinematics estimation during treadmill walking. *Sensors (Basel)*. 2022;22(7):2544.
45. El Fezazi M, Achmamad A, Jbari A, Jilbab A. A convenient approach for knee kinematics assessment using wearable inertial sensors during home-based rehabilitation: Validation with an optoelectronic system. *Sci Afr* 2023;20.

46. Scheltinga BL, Kok JN, Buurke JH, Reenalda J. Estimating 3D ground reaction forces in running using three inertial measurement units. *Front Sports Act Living*. 2023;5:1176466.
47. Ackland DC, Fang Z, Senanayake D. A machine learning approach to real-time calculation of joint angles during walking and running using self-placed inertial measurement units. *Gait Posture*. 2025;118:85-91.
48. Forsyth L, Ligeti A, Blyth M, Clarke JV, Riches PE. Validity of wearable sensors for total knee arthroplasty (TKA) rehabilitation: A study in younger and older healthy participants. *Knee*. 2024;51:292-302.
49. Gupta U, Kai JHJ, Mohamadou Y, Ramzeen A, Seth A, Guo RZ, et al. -Validation and reliability of knee kinematics and gait analysis using flexible wearable sensors. *Health Technol (Berl)*. 2025;15(4):733-43.
50. Weber JG, Ortigas-Vásquez A, Sauer A, Dupraz I, Utz M, Maas A, et al. Comparison of IMU-Based Knee Kinematics with and without Harness Fixation against an Optical Marker-Based System. *Bioengineering (Basel)*. 2024;11(10).
51. Whitney SL, Roche JL, Marchetti GF, Lin CC, Steed DP, Furman GR, et al. A comparison of accelerometry and center of pressure measures during computerized dynamic posturography: a measure of balance. *Gait Posture*. 2011;33(4):594-9.
52. Mancini M, Salarian A, Carlson-Kuhta P, Zampieri C, King L, Chiari L, et al. ISway: a sensitive, valid and reliable measure of postural control. *J Neuroeng Rehabil*. 2012;9:59.
53. Ozinga SJ, Alberts JL. Quantification of postural stability in older adults using mobile technology. *Exp Brain Res*. 2014;232(12):3861-72.
54. Rouis A, Rezzoug N, Gorce P. Validity of a low-cost wearable device for body sway parameter evaluation. *Comput Methods Biomech Biomed Engin*. 2014;17 Suppl 1:182-3.
55. Kosse NM, Caljouw S, Vervoort D, Vuillerme N, Lamothe CJ. Validity and Reliability of Gait and Postural Control Analysis Using the Tri-axial Accelerometer of the iPod Touch. *Ann Biomed Eng*. 2015;43(8):1935-46.
56. Alberts JL, Thota A, Hirsch J, Ozinga S, Dey T, Schindler DD, et al. Quantification of the Balance Error Scoring System with Mobile Technology. *Med Sci Sports Exerc*. 2015;47(10):2233-40.

57. Ozinga SJ, Machado AG, Miller Koop M, Rosenfeldt AB, Alberts JL. Objective assessment of postural stability in Parkinson's disease using mobile technology. *Mov Disord*. 2015;30(9):1214-21.
58. Alessandrini M, Micarelli A, Viziano A, Pavone I, Costantini G, Casali D, et al. Body-worn triaxial accelerometer coherence and reliability related to static posturography in unilateral vestibular failure. *Acta Otorhinolaryngol Ital*. 2017;37(3):231-6.
59. Burghart M, Craig J, Radel J, Huisinga J. Reliability and validity of a mobile device application for use in sports-related concussion balance assessment. *Current Research: Concussion*. 2017;4(1):e1-e6.
60. Ozinga SJ, Linder SM, Alberts JL. Use of Mobile Device Accelerometry to Enhance Evaluation of Postural Instability in Parkinson Disease. *Archives of Physical Medicine and Rehabilitation*. 2017;98(4):649-58.
61. Hsieh TH, Peng CW, Chen KY, Huang YZ, Lin YH, Zhong WZ, et al. The applications of smart mobile device for detecting balance dysfunction in individuals with down syndrome. *Biomedical Engineering - Applications, Basis and Communications*. 2018;30(1).
62. McGough EL, Hsu LY, Thompson H, Teri L. Concurrent Validity of Postural Sway Measures in Older Adults with Cognitive Impairment. *Phys Occup Ther Geriatr*. 2018;36(4):399-410.
63. Sun R, Moon Y, McGinnis RS, Seagers K, Motl RW, Sheth N, et al. Assessment of Postural Sway in Individuals with Multiple Sclerosis Using a Novel Wearable Inertial Sensor. *Digit Biomark*. 2018;2(1):1-10.
64. Ekvall Hansson E, Tornberg Å. Coherence and reliability of a wearable inertial measurement unit for measuring postural sway. *BMC Res Notes*. 2019;12(1):201.
65. Shieh V, Sansare A, Jain M, Bulea T, Mancini M, Zampieri C. Body-Worn Sensors Are a Valid Alternative to Forceplates for Measuring Balance in Children. *Journal for the Measurement of Physical Behaviour*. 2020;3:1-6.
66. Hsieh KL, Sosnoff JJ. Smartphone accelerometry to assess postural control in individuals with multiple sclerosis. *Gait Posture*. 2021;84:114-9.

67. Rodrigues LA, Santos EGR, Santos PSA, Igarashi Y, Oliveira LKR, Pinto GHL, et al. Wearable Devices and Smartphone Inertial Sensors for Static Balance Assessment: A Concurrent Validity Study in Young Adult Population. *J Pers Med*. 2022;12(7).
68. German D, Bahat HS. Validity and Reliability of a Customized Smartphone Application for Postural Sway Assessment. *J Manipulative Physiol Ther*. 2021;44(9):707-17.
69. Vagnini A, Furone R, Zanotti G, Adamo P, Temporiti F, Gatti R. Agreement between inertial measurement unit and optoelectronic system to measure postural sway. *Technol Health Care*. 2022;30(3):757-62.
70. Telles GF, Ferreira AS, Junior PMP, Lemos T, Bittencourt JV, Nogueira LAC. Concurrent validity of the inertial sensors for assessment of balance control during quiet standing in patients with chronic low back pain and asymptomatic individuals. *J Med Eng Technol*. 2022;46(5):354-62.
71. Jaworski J, Lech G, Witkowski K, Kubacki R, Piepiora P. Evaluation of measurement reliability for selected indices of postural stability based on data from the GYKO Inertial Sensor System. *Biol Sport*. 2024;41(2):155-61.
72. D'Emanuele S, Nardello F, Garau F, Campaci D, Schena F, Tarperi C. Test-Retest and Inter-Rater Reliability for Selected Outcomes from a Wearable 3D Inertial Sensor Over Different Stable and Unstable Postural Conditions: A Validation Study. *Measurement in Physical Education and Exercise Science*. 2024.
73. Peters A, Galna B, Sangeux M, Morris M, Baker R. Quantification of soft tissue artifact in lower limb human motion analysis: a systematic review. *Gait Posture*. 2010;31(1):1-8.
74. Chen H, Schall MC, Jr., Fethke N. Effects of Movement Speed and Magnetic Disturbance on the Accuracy of Inertial Measurement Units. *Proc Hum Factors Ergon Soc Annu Meet*. 2017;61(1):1046-50.
75. Quijoux F, Nicolaï A, Chairi I, Bargiotas I, Ricard D, Yelnik A, et al. A review of center of pressure (COP) variables to quantify standing balance in elderly people: Algorithms and open-access code. *Physiol Rep*. 2021;9(22):e15067.
76. Sozzi S, Ghai S, Schieppati M. The 'Postural Rhythm' of the Ground Reaction Force during Upright Stance and Its Conversion to Body Sway—The Effect of Vision, Support Surface and Adaptation to Repeated Trials. *Brain Sciences*. 2023;13(7):978.

77. Ruhe A, Fejer R, Walker B. The test-retest reliability of centre of pressure measures in bipedal static task conditions - A systematic review of the literature. *Gait and Posture*. 2010;32(4):436-45.

16. BIBLIOGRAPHY

16.1 Publications related to the thesis

1. Bissenov A, Zhubi E, Engh MA, et al. Concurrent validity of wearable IMUs for sagittal plane lower-limb range of motion during walking and estimated ground reaction forces: a systematic review and meta-analysis. *J Orthop Surg Res.* 2025;20:891. doi:10.1186/s13018-025-06322-w
2. Bissenov A, Zhubi E, Czibere R, Engh MA, Gresits O, Tóth R, Hegyi P, Terebessy T. Concurrent Validity of Wearable Inertial Sensors for Postural Sway Assessment During Quiet Standing Compared With Force Plates: A Systematic Review and Meta-Analysis. *Scientific Reports.* doi:10.1038/s41598-026-63005-0.

16.2 Publications not related to the thesis

1. Zhubi E, Bissenov A, Engh MA, et al. Bridging therapy versus direct endovascular thrombectomy in basilar artery occlusion stroke: a systematic review and meta-analysis. *GeroScience.* 2025. doi:10.1007/s11357-025-01887-0
2. Zhubi E, Bissenov A, Lengyel AS, et al. Association of FLAIR positivity and worse outcomes after intravenous thrombolysis in known-onset strokes: a systematic review and meta-analysis. *J Clin Med.* 2025;14:8031. doi:10.3390/jcm14228031

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