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# 100 Normative Gait Profiles with 5-year fall tracking: Benchmark Dataset for Southeast Asian Movement Science

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**Abstract**

Gait assessment is fundamental for the evaluation of mobility. The 10-meter walk test is an established measure of gait speed, yet its simplicity in administration contrasts with the substantial wealth of biomechanical information that is unreported when it is conducted in a conventional manner. Integrating motion capture technology into the 10-meter walk test elevates gait assessment into a high-definition, granular analysis. This Data Descriptor presents the only large-scale, fast-gait 10-meter walk test dataset from Southeast Asia, comprising 100 healthy older adults (43 males and 57 females, aged 50–80 years). In addition, a five-year follow-up model of fall risk in these participants is reported. The dataset is deposited in DR-NTU (Nanyang Technological University Research Data Repository, powered by Dataverse) (https://doi.org/10.21979/N9/3Z2N2Z) and represents a unique normative resource with high potential for reuse in both clinical and research contexts.

## Background & Summary

Maintaining mobility is central to functional independence and healthy ageing, with declines in physical function closely linked to increased disability, falls, and healthcare utilisation in older adults[1]. A range of standardized physical performance assessments are therefore used in clinical and research settings to evaluate functional status in ageing populations, including tests of balance, strength, endurance, and mobility[2,3]. Among these, gait assessment occupies a central role, as walking integrates multiple physiological systems into a single, observable behavior and serves as a key indicator of overall health and functional independence[4,5]. Other standardized physical performance tests commonly used in older adults, such as the Timed Up and Go (TUG), 6-minute walk test (6MWT), and Short Physical Performance Battery (SPPB), assess complementary domains including balance, endurance, and task-based mobility[6,7]. However, gait assessment remains widely used in clinical practice and provides a common reference point across clinical and research settings.



Alterations in gait can signal aging-related decline, neurological disorders, musculoskeletal impairments, or an increased risk of falls, making gait assessment a valuable tool in both clinical and research settings[8]. Technically, the 10-meter walk test (10MWT) evaluates walking performance by recording the time taken to traverse a defined walkway[9]. Unlike habitual gait, fast walking increases mechanical and control demands, influencing spatiotemporal parameters, joint kinematics and kinetics, and ground reaction forces[10]. Under such conditions, subtle impairments may become evident that are not apparent during comfortable walking, where compensatory strategies can mask underlying deficits. Accordingly, this data descriptor includes participants performing a fast-walking task along a 10-meter walkway at a self-selected fast gait speed. Here, the middle six meters were used to calculate walking speed, measured from when the leading foot crosses the 2-meter mark to when it crosses the 8-meter mark. The first and final meters of the walkway account for acceleration and deceleration, ensuring that the measured speed reflects a constant walking velocity. Walking speed is then calculated by dividing the time taken over the middle six meters, yielding a measure in meters per second (m/s).

Normative age and gender stratified reference ranges for gait speed have been established in the local context of Singapore[11–15], with cut-offs for slow gait speed widely accepted as powerful prognostic markers for critical outcomes such as mortality in older adults[16–18]. Despite the breadth of literature supporting the predictive capacity of gait speed, traditional assessments such as the 10MWT fail to capture the extensive biomechanical nuances of gait that may contain markedly more predictive physical biomarkers. Traditional assessments, often referred to as paper-and-pencil assessments, whether stopwatch-based (e.g., 10MWT) or scaled-score assessments, lack granularity in temporal, spatial, kinematic and kinetic domains. This highlights the need for refinement and expansion of current assessment methods[19–21]. Integrating three-dimensional motion capture (MoCap) into the 10MWT adds biomechanical layers that elevate the precision of gait analysis. From a population health perspective, this is of particular interest as studies suggest that postural adaptions predate gait speed decline in older adults[22]. Furthermore, fast gait speed induces greater biomechanical variability and better reflects physical reserve than habitual gait speed[23].

This dataset contains motion capture data from 100 healthy older adult Singaporeans (aged 50–75) completing the 10MWT at a self-selected fast gait speed. It is derived from the Movement Database Study[21,24] and has already served as a normative comparator for pathological gait studies in stroke[25] and amputee populations[26]. The dataset also contributed to the development of a statistical parametric modelling application used in gait studies of cyclical and non-cyclical tasks in knee osteoarthritis populations[27–29]. In addition, the dataset played a significant role in developing a validated multi-camera markerless motion capture (M-MoCap) system, capable of detecting granular biomechanical metrics during gait and other standardized clinical tasks[7,30]. M-MoCap holds strong potential to reveal predictive physical biomarkers, integrate movement science into clinical settings, and transform population health functional screening due to its unobtrusive nature and rapid data and report generation.

To advance the integration of movement science insights in a scalable manner, test standardization is imperative. Among currently available motion capture databases of able-bodied individuals, two datasets report gait data that included self-selected fast gait speed from a 10-meter walkway, but not specifically the 10MWT[31–34]. Only two other datasets provide data from more than 100 participants, but neither specifically focuses on fast gait speed from a standardized clinical task, nor on populations representing current and future seniors[35–38].

In this current article, and to our knowledge, we provide the only normative fast gait 10MWT dataset, in a Southeast Asian older adult cohort. This study positions itself as a unique dataset of normative gait analyses with high potential for reuse. In addition, we present a five-year follow-up model on fall risk among these 100 individuals, highlighting the value of sharing observational datasets with long-term health monitoring. Such data are essential to integrate granular movement science into population-level screening for age-related conditions.

## Methods

### *Participants*

Parent study (Ability Data (AD) - Asian-centric human movement database)

This dataset stems from a larger study, Ability Data (AD) - the Asian-centric human movement database, whose protocol was described in detail previously[39]. Individuals were excluded if they reported: (1) prior neurological conditions, surgeries, or medical conditions requiring active medical or therapy intervention within the previous three months; (2) depression or mental health conditions affecting daily task performance; (3) visual impairments associated with a recent accident, fall, or near-fall; (4) skin conditions that would interfere with marker placement; (5) inability to perform activities of daily living due to pain; or (6) pregnancy. Accordingly, participants included in the present dataset represent community-dwelling adults without active medical, neurological, or functional limitations affecting mobility. A total of 695 healthy participants, aged 21–80 years and of Asian ethnicity, were recruited between October 2018 and February 2024. Traditional marker-based motion capture was employed to create a normative movement database encompassing kinematic and kinetic data of 12 tasks (6 upper- and 6 lower-body) relevant to everyday functional activities, one of which was the 10MWT.

Current dataset (this manuscript)

In this manuscript, we present data from 100 healthy older adult participants from the AD study, completing the10MWT at a self-selected fast gait speed, who were subsequently followed up at 5-years to assess their fall history and risk. Those participants who had consented to be re-contacted for future research formed the current data set, with the eligibility criteria restricted to age 50-80 years, resulting in 311 eligible participants. Of these, 175 were re-contacted as they were within the 5-year follow-up window for fall risk; 49 did not respond, 19 declined participation, 4 could not be reached because contact information was not retrievable and 3 were excluded for technical reasons, yielding a final sample of 100 participants.

This sample consists of 43 males and 57 females, with a mean age of 60.88 years (SD = 6.39). By age group, there were 22 participants (8 males, 14 females) aged 50–54 years, 20 (7 males, 13 females) aged 55–59 years, 25 (8 males, 17 females) aged 60–64 years, 23 (12 males, 11 females) aged 65–69 years, and 10 (8 males, 2 females) aged 70–74 years. All variables were recorded at the time of the original AD data collection.

This study received approval from the NTU Institutional Review Board (IRB-2024-682) and was conducted in accordance with the ethical principles of medical research outlined in the Declaration of Helsinki. Informed consent for participation and data sharing was obtained for both the parent study (written informed consent provided onsite after verbal explanation of the study procedures) and the current dataset (written informed consent obtained electronically via an online Qualtrics form prior to participation).

***Experimental set-up and equipment***

The MoCap data collection phase of the 100 participants took place between September 2019 and September 2021 at the motion capture laboratory of the Rehabilitation Research Institute of Singapore (RRIS), NTU.

Whole-body kinematics were recorded using a Qualisys Miqus M3 optical motion capture system (Qualisys AB, Sweden) consisting of 16 cameras and two video cameras with a resolution of 2 megapixels and a field of view (FOV) of 64 × 41 degrees. Retroreflective optical markers were affixed to anatomical landmarks according to a modified Calibrated Anatomical System Technique (CAST) protocol, with marker diameters of 12.5 mm for body placements. Data acquisition and synchronization with external devices were controlled using Qualisys Track Manager (QTM) software (version 2020). Following the established protocol in the laboratory, marker trajectories were recorded at 200Hz, with analogue and force signals at 2000 Hz, respectively. A few of the marker datasets were recorded at 240 Hz, with analogue and force signals recorded at 2400 Hz, instead. These transient sampling-rate adjustments reflect the M-MoCaP development phase; implicated files are detailed in the Data Records. Ground reaction forces were captured using two force plates (Type 9260AA6, Kistler, Switzerland), each measuring 60 × 50 × 5 cm.

For additional methodological details, including the marker placement set and force plate coordinate system orientation, readers are referred to Figures 1 and 2. In August 2021, the AD database introduced an additional marker over the 2nd metatarso -cuneiform joint to create a two segment foot model and explore forefoot-to-rearfoot kinematics in prospectively collected data[40,41]. Subsequently, five participants included in this shared dataset contain this additional marker bilaterally.



***General Procedures***

Participants wore appropriately-sized standard black shorts and sleeveless top (without reflective material). Markers were set on the body following the aforementioned marker placement set, with hand markers removed (see Figure 1). Retroreflective markers were placed according to recommended guidelines and remained fixed throughout data collection[42]. After marker placement, a static calibration trial in standing posture was captured before the 10MWT task. Participants stood for two seconds with shoulders abducted to 45°, elbows fully extended, and palms facing forward, then abducted the shoulders to 90° with palms facing down for a further two seconds. Additional static calibration trials would be captured if markers fell off and could not be confidently placed back to their original positions. The task sequence was determined using block randomization to minimize fatigue-related bias across the 12 tasks. Full task details can be found in the parent study[39].

***Specific Procedures of 10MWT***

Participants were instructed to walk barefoot at a self-selected "fast but safe walking speed" for 10 metres, from a demarcated start point to an end point. Prior to the trial, the instructor provided both a standardized verbal explanation and demonstration. Participants were required to fix their gaze on a visual cue (a round yellow spot printed on the wall) and were not informed about the presence of the force plates (Figure 3). Participants completed the task in both directions, with operators exercising their best judgement to ensure that at least three clean heel strikes were obtained bilaterally; however, in a small number of cases fewer than three strikes were recorded, likely due to operator error. Valid heel strikes were defined as single-foot contacts fully contained within one force plate, verified in real time by the instructor's visual inspection and cross-checked by the Qualisys operator.

### *Data Processing*

MoCap data encompassed three-dimensional marker coordinates synchronized with force plate recordings. Raw marker trajectories were labelled and gap-filled using Qualisys Track Manager (QTM v2020.2 build 5700; Qualisys, Gothenburg, Sweden). Vertical force curves (Fz) were screened for atypical distribution indicative of unclean heel strikes. These trials were visually inspected in QTM, with recordings discarded if determined to reflect artefacts rather than normal variation in healthy participants.



## Data Records

The dataset described in this study has been deposited in the NTU data repository, DR-NTU (Nanyang Technological University Research Data Repository, powered by Dataverse)[43]. It is organized into two major folders:

1. c3d folder

This folder contains 100 participant subfolders, each labelled as *PXXX*, where *XXX* denotes the participant ID (e.g., the first participant is P001 and the last is P100). Within each folder, files are stored in **.**c3d format. For example, in participant P001:

*P001_static_01.c3d* corresponds to the static calibration trial.

*P001_10MWT_01.c3d* contains the first valid 10MWT trial.

*P001_10MWT_02.c3d* contains the second valid trial.

*P001_10MWT_03.c3d* contains the third valid trial.

Each file contains marker trajectory data and synchronized force plate data (see Table 1)[24].

2. Information folder

This folder contains two subfolders, each with one Excel file:

*Participants demographics and MoCap characteristics:* provides individual-level variables for all 100 participants, including participant ID, gender, age range, ethnicity, height, weight, point frame rate, analog and force frame rate, and whether the additional cuneiform marker was included.

*File Characteristics:* contains a complete list of all c3d files, including participant ID, filename, task, and the corresponding static filename, which refers to the static file to which the 10MWT is calibrated.

**Data Overview**

Labelled marker data from the 10MWT were exported to Visual3D Professional software (v2025.02.1, C-Motion Inc., Germantown, MD, USA) to generate kinematic profiles. Using the Automatic Gait Events command in Visual3D, the different phases of the gait cycle were identified by first establishing the point of heel strike and toe off when participants made physical contact with the force plates. The command then uses pattern recognition to identify these events on the remaining cycles that lies outside the force plates. Visual3D is then used to generate gait reports with comparable spatiotemporal values to locally established references (Figure 4)[12,15]. Marker data was processed via a fourth-order, zero-phase-shift Butterworth low-pass filter (12 Hz), with joint coordinate computation and modelling performed according to recommended practices[44,45]. The resulting kinematic profiles produced smooth, repeatable waveforms, enabling characterization of normative ranges of motion across the gait cycle (Figure 5).

An a priori selection of temporospatial and kinematic variables, including their variability and symmetry, resulted in 68 candidate biomechanical variables for predictive modelling. Models were adjusted for demographic covariates (age, gender, race, height, and weight). Preliminary filtering was conducted using independent t-tests and Mann–Whitney U tests to exclude non-predictive variables. To minimize redundancy, highly correlated variables were removed via Pearson correlation analysis. The remaining variables were entered into a stepwise logistic regression model to evaluate their predictive capacity on fall risk.

Eligible participants were recontacted five years after their initial motion capture trial, between September 2024 and July 2025. Recruitment methods consisted of contacting participants via SMS or WhatsApp, reminding them of their previous participation in the parent study and briefly describing the follow-up. If participants expressed interest, the study information sheet was sent along with a link to access a Qualtrics e-form. This included the informed consent form, followed by an e-form with self-reported assessments, and a telephone questionnaire scheduled at their convenience. Participation in this study was incentivized with SGD 30.

In line with screening recommendations, fall risk was assessed subjectively using the Three Key Questions (3KQ); (1) Have you fallen in the past year? (2) Do you feel unsteady when standing or walking? (3) Do you have worries about falling?. As participants were not objectively screened at follow-up, we applied a modified binary criterion to categorize individuals into two groups: Low risk (0) and High risk (1). A positive response to any of the 3KQ resulted in classification as high risk.

Of the 100 participants, 46 were identified as low fall risk, 54 high fall risk. Stepwise logistic regression identified five baseline predictors, with gait speed, increased arm swing, stride length variability (SLV), Dorsiflexion Swing variability (DSwV) and peak dorsiflexion (Peak DF) during stance emerging as the strongest contributors to future fall risk (Figure 6). At a threshold of 0.5, the final model achieved an area under operating curve (AUC) of 0.77, sensitivity 0.70 and specificity 0.57 (Table 2a and 2b). While some predictors aligned with established fall risk markers, others showed counterintuitive associations. This may reflect sample size, cohort characteristics, and task-specific dynamics, underscoring the need for external validation before clinical translation[47,48]. Together, these data establish a comprehensive normative reference for fast gait in healthy older Singaporean adults and highlight the translational potential of marker-based motion capture metrics for clinical risk prediction.



**Technical Validation**

The parent study spanned six years (October 2018–February 2024). Conducting such a large-scale dataset over this duration posed logistical and manpower challenges. The most significant extrinsic, human-dependent aspect of MoCap data collection is the placement of reflective markers on anatomical landmarks. To address this, an intra- and inter-rater reliability study was conducted involving two raters, with results previously reported[39]. These two raters subsequently trained a substantial portion of the additional personnel who joined the project, following a structured protocol.

To ensure consistency as the study progressed, additional intra- and inter-rater reliability assessments focusing on marker placement were conducted in July 2023 over a two-day period. Reliability was defined as the extent to which MoCap marker coordinates (mm) are consistent and free from error. A volunteer (not part of the main cohort of 100 participants) was selected for the reliability study. For each assessment, a full body marker set was applied according to the AD protocol, and a static trial was performed to record marker positions. Each anatomical marker's 3D position was converted into a scalar Euclidean distance from the fixed cluster origin within its local coordinate system, thereby isolating the magnitude of displacement. Motion trials were deliberately excluded to ensure that any observed discrepancies could be attributed exclusively to marker placement error, without the influence of soft tissue artefact or movement-related deviation[49,50]. A complete marker placement reliability protocol can be found in Supplementary material (Supplementary File 1).

Inter-rater reliability was defined as the agreement in marker placement within the same day between a Marker Placement Personnel (MPP) and a "Gold Standard" MPP, the latter being a physiotherapist with advanced musculoskeletal palpation skills and extensive experience in identifying bony anatomical landmarks (OR). Four pairs of raters (each pair comprising one MPP and one Gold Standard MPP) independently placed markers on the same subject. Intra-rater reliability was defined as the repeatability of marker placement by a single MPP across two trials within the same day, accounting for adequate time to prevent recollection of landmark identification and absence of erythema secondary to marker placement. Mean Euclidean distance per rater was derived, and these continuous values were used to compute inter-rater Intraclass Correlation Coefficients (ICCs). ICCs were calculated using a two-way mixed-effects model for absolute agreement [ICC(3,1)] for both intra- and inter-rater reliability to quantify consistency of marker placement. This model was selected because all inter-rater comparisons were made relative to a single fixed gold-standard rater, and all the included participants were measured by this group of fixed raters[51].

The resulting ICC values are reported in Table 3. Based on commonly accepted interpretation thresholds, inter-rater reliability was moderate to good (ICC=0.650-0.710), while intra-rater reliability was good (ICC=0.836-0.889)[52]. Based on prior simulation studies, our mean marker placement errors (6.37 mm intra-rater; 8.53 mm inter-rater) are unlikely to induce kinematic deviations exceeding 5°, particularly in the sagittal and coronal planes[53–55]. However, greater caution is warranted in the transverse plane, where even small displacements may cause larger rotational errors. These findings confirm that marker placement within this study was both consistent across raters and highly repeatable within raters, ensuring robustness of the collected MoCap dataset.

**Data Availability**

The dataset is available from the NTU data repository, DR-NTU, at https://doi.org/10.21979/N9/3Z2N2Z and is released under a Creative Commons Attribution 4.0 (CC BY 4.0) license. Additional information regarding the repository's data usage agreement is provided in the Supplementary Materials (Appendix).

**Code availability**

The software tools used in the processing have been described in the Methods section under the Data processing and Data overview. No custom developed code was used in curation and validation of this dataset.

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**Authors Contributions**

All authors contributed to the conceptualization and design of the study. **Data Curation** - OR, TLW, LSL, AS. **Formal Analysis** – OR, TLW, AS. **Funding** –WTA. **Investigation** – OR, TLW, LSL, IOT, AS, PK. **Methodology** – OR, PCG, LSL, AS, PK, KC, WTA. **Project Administration** – OR, PCG. **Resources** – AS, WTA. **Software** – TLW. **Supervision** – KC, WTA, BYT. **Validation** – OR, TLW, LX, IOT. **Visualization** – OR, PCG, TLW. **Writing – original draft** – OR, PCG, AKKP. **Writing – review & editing** – OR, PCG, AKKP, TLW, LSL, LX, IOT, AS, PK, KC, WTA, BYT. All authors approved the final version submitted to the journal and have agreed to be personally accountable for their own contributions.

**Competing Interests**

The authors declare no competing interests.

**AI declaration**

ChatGPT was used to generate the forest plot based on the data provided, which was subsequently cross-referenced in a statistical software. ChatGPT was also used to assist with language editing and drafting responses to reviewer and editor comments. The authors reviewed and validated all outputs. The final submitted manuscript was screened for similarity using iThenticate.

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**Figures**

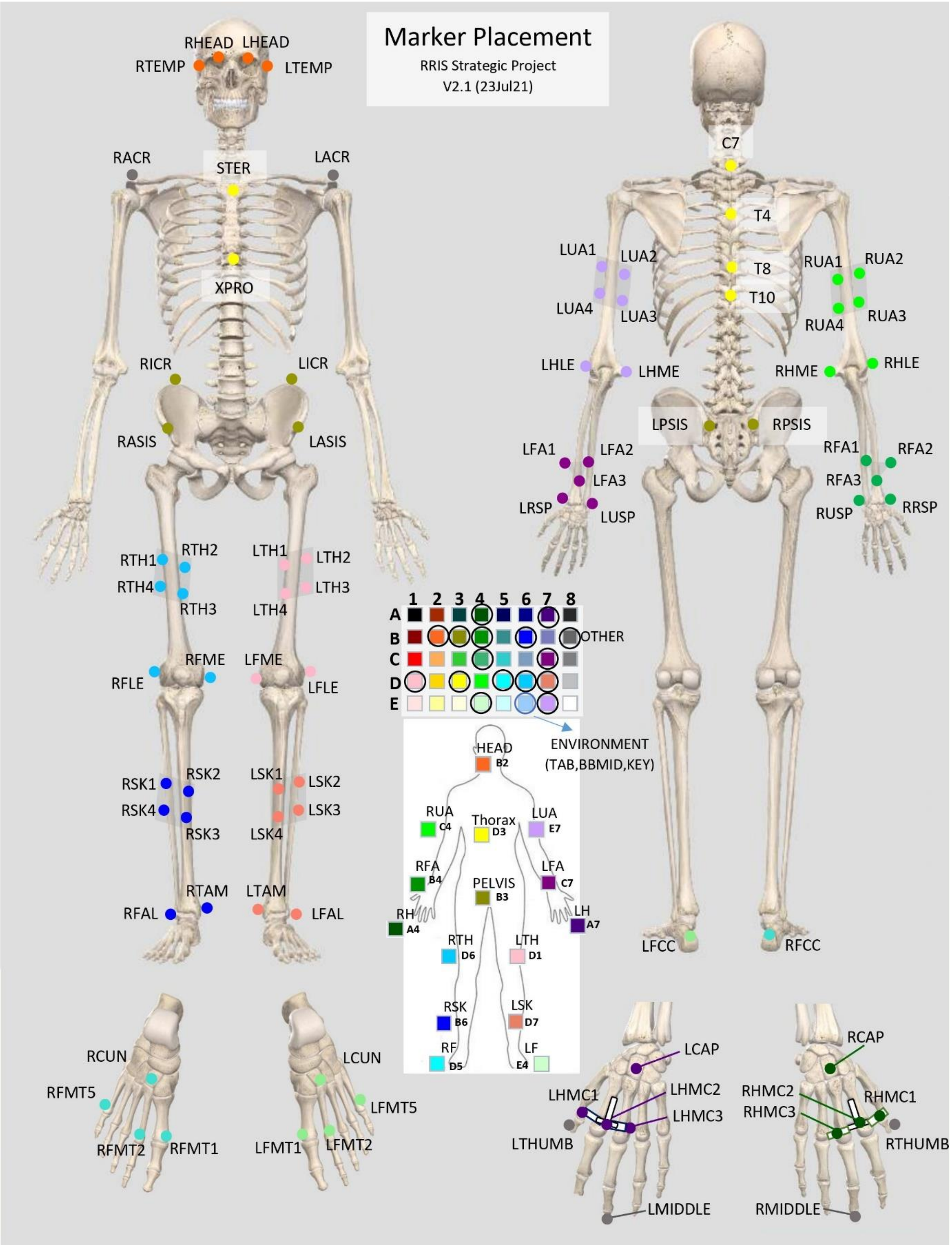


**Figure 1.** Marker placements (based on modified Calibrated Anatomical System Technique). Reproduced from Liang *et al.*, 2020, *Scientific Data*, with permission[21].

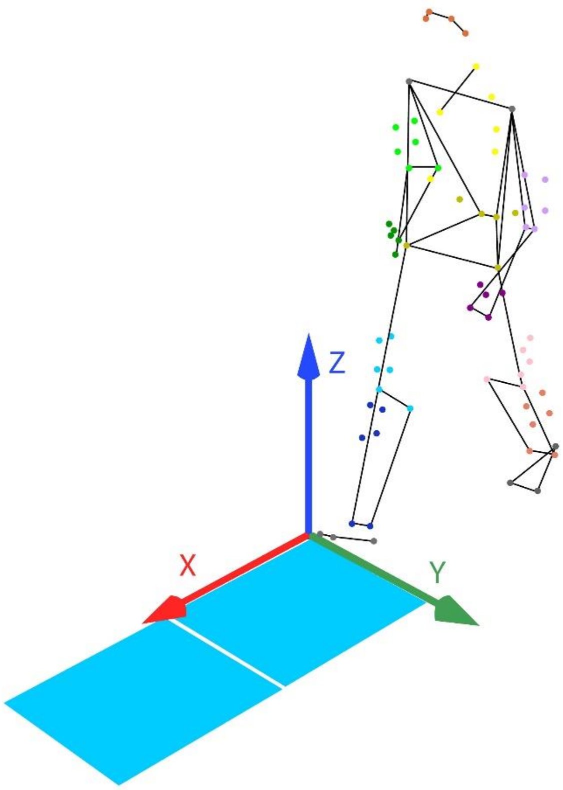


**Figure 2.** Schematic representation of the force plates and corresponding coordinate axes. Reproduced from Liang *et al.*, 2020, *Scientific Data*, with permission[21].

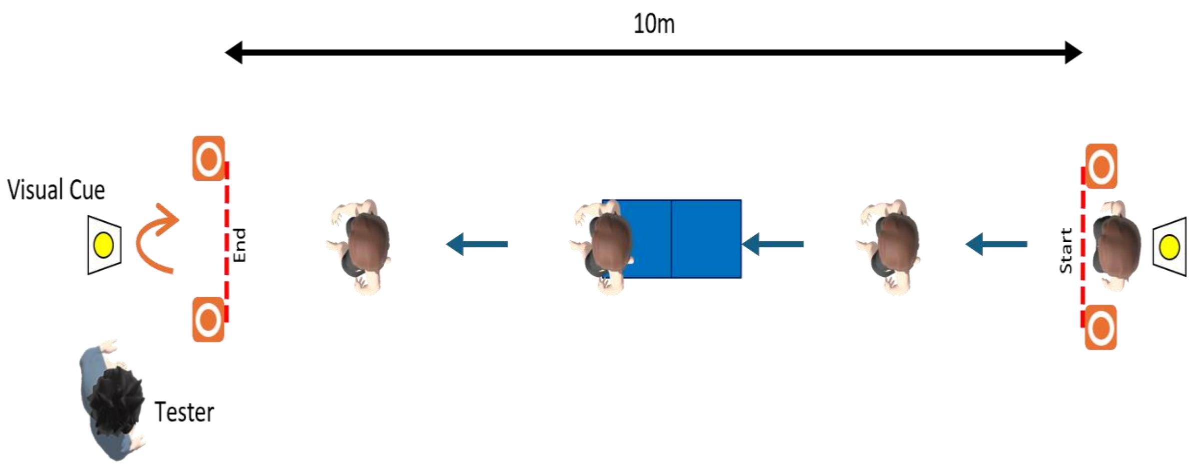

**Figure 3.** Illustration of 10MWT protocol with demarcated start and end points, visual cue and task execution in both directions.

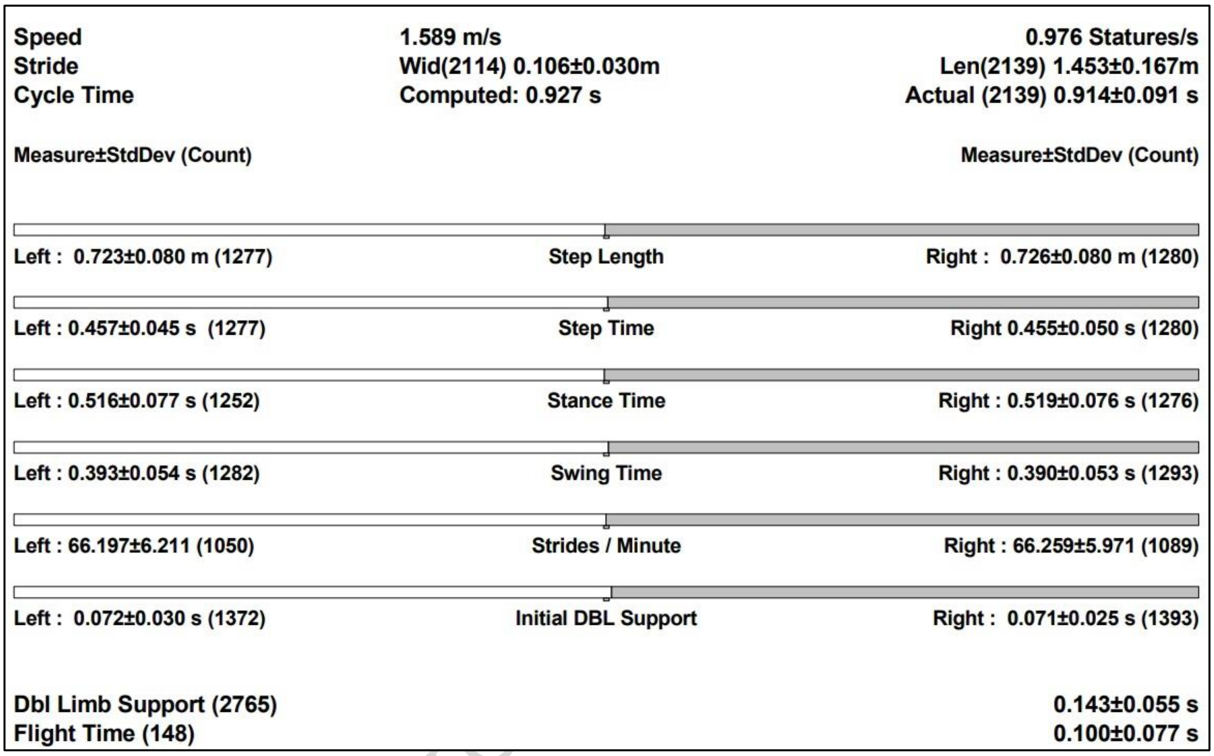


**Figure 4. Normative MoCap temporospatial metrics from 100 participants.** m/s: meters per second; m = meter; s = second; Wid = width; Len = length; StdDev = standard deviation; DBL = double support.

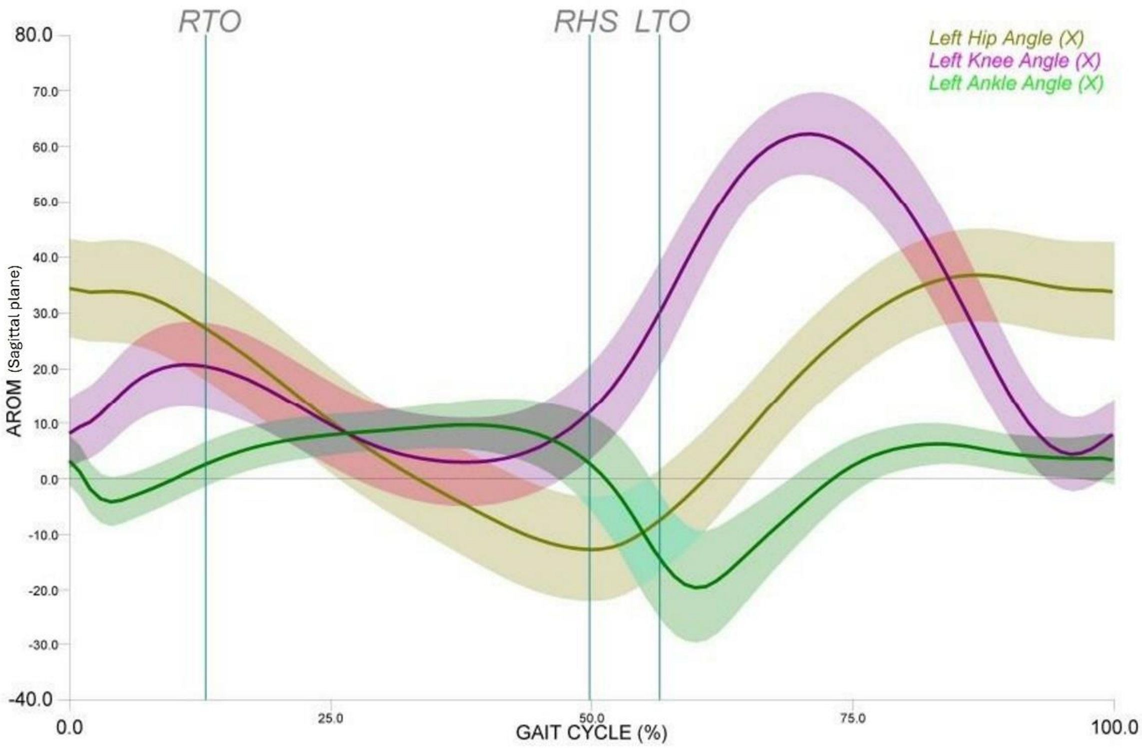


**Figure 5. Gait cycle is illustrated from Left Heel Strike (LHS) to the subsequent LHS.** Other significant gait events are labeled accordingly: RTO: Right Toe Off; RHS: Right Heel Strike; LTO: Left Toe Off. X-axis: % of gait cycle; Y-axis: Active Range of Motion (AROM) in the sagittal plane for all major lower limb joints. The shaded area denotes the standard deviation, whilst the boldened line marks the mean range of motion for all 100 participants.

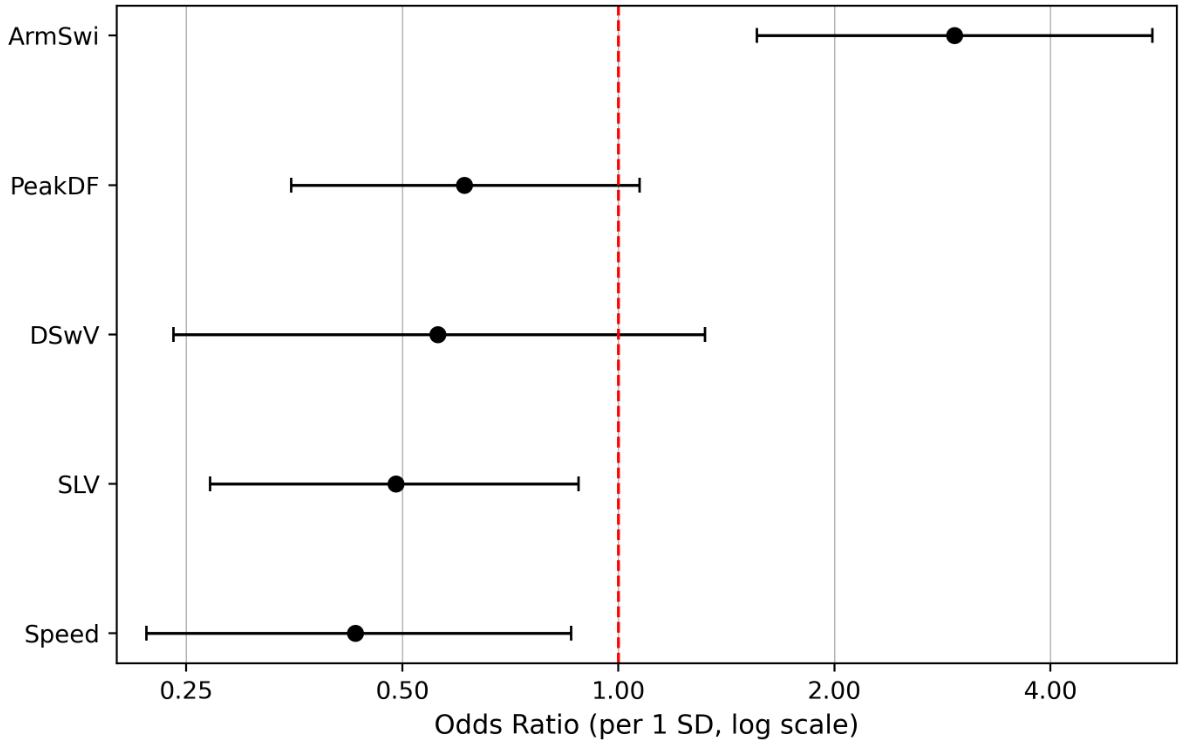


**Figure 6: Falls Risk Prediction Forest Plot.** Logistic regression results showing baseline biomechanical predictors of falls risk at 5-year follow-up, expressed per 1 SD change in each variable. Odds ratios (ORs) are plotted on a log scale with 95% confidence intervals. The dashed line indicates the null effect (OR = 1). ArmSwi: Arm swing; DSwV: Dorsiflexion Swing Variability; PeakDF: Peak Dorsiflexion in Stance Phase; SLV: Stride Length Variability.

**Tables**

**Table 1.** Force component labels in the C3D file (under Analog data) follow the naming convention and calculation procedures described in Vaughan et al. (see https://isbweb.org/software/movanal/vaughan/kistler.pd. Reproduced from Liang *et al.*, 2020, *Scientific Data*, with permission[21,24].

| **For component label in C3D file** | **Force Signal** |
|---|---|
| Channel_01 | force plate 1: fx12 |
| Channel_02 | force plate 1: fx34 |
| Channel_03 | force plate 1: fy14 |
| Channel_04 | force plate 1: fy23 |
| Channel_05 | force plate 1: fz1 |
| Channel_06 | force plate 1: fz2 |
| Channel_07 | force plate 1: fz3 |
| Channel_08 | force plate 1: fz4 |
| Channel_09 | force plate 2: fx12 |
| Channel_10 | force plate 2: fx34 |
| Channel_11 | force plate 2: fy14 |
| Channel_12 | force plate 2: fy23 |
| Channel_13 | force plate 2: fz1 |
| Channel_14 | force plate 2: fz2 |
| Channel_15 | force plate 2: fz3 |
| Channel_16 | force plate 2: fz4 |

**Table 2a:** Logistic regression coefficients and adjusted odds ratios for baseline predictors of falls risk

| Predictor | OR (per 1 SD) | 95% CI (OR) | p |
|---|---|---|---|
| SLV | 0.489 | 0.273–0.875 | 0.016 |
| DSwV | 0.561 | 0.239–1.315 | 0.184 |
| ArmSwi | 2.937 | 1.555–5.548 | 0.001 |
| Speed | 0.433 | 0.218–0.859 | 0.017 |
| PeakDF | 0.613 | 0.351–1.071 | 0.085 |

*Dorsiflexion Swing Variability (DSwV) denotes the variability in peak dorsiflexion during swing phase. Arm swing (ArmSwi) magnitude was quantified from sagittal-plane shoulder kinematics during one gait cycle. Peak Dorsiflexion in Stance Phase (PeakDF) refers to the peak passive dorsiflexion angle during mid stance. Stride length variability (SLV) was calculated as the within-participant standard deviation of stride length across valid gait cycles. Odds ratios (ORs) represent the multiplicative change in the odds of being classified as high fall risk associated with a one standard deviation (1 SD) increase in the predictor variable. A "p" value of less than 0.05 is considered statistically significant.*

*ArmSwi: Arm Swing; CI: Confidence interval; DSwV: Dorsiflexion Swing Variability; PeakDF; Peak Dorsiflexion in Stance Phase; OR: Odds ratio; SD: Standard deviation. SLV: Stride Length Variability.*

**Table 2b:** Performance metrics of logistic regression models predicting falls risk

| Metric | Value |
|---|---|
| AUC (95% CI) | 0.773 (0.679-0.857) |
| Sensitivity | 0.704 |
| Specificity | 0.565 |

*AUC: Area under the receiver operating characteristic curve quantifies model discrimination, with values ranging from 0.5 (no discrimination) to 1.0 (perfect discrimination). Sensitivity denotes the proportion of true positive cases (individuals classified as high fall risk) correctly identified by the model, while specificity denotes the proportion of true negative cases (individuals classified as low fall risk) correctly identified. A classification threshold of 0.5 was applied to predicted probabilities to dichotomize participants into low- and high-risk groups.*

**Table 3:** Inter- and Intra-Rater Reliability

| Comparison / Rater | ICC | 95% CI (Lower–Upper) | Koo & Li (2016) |
|---|---|---|---|
| **Inter-rater** | | | |
| Rater 1 vs Rater 2 | 0.710 | 0.608 – 0.792 | Good |
| Rater 1 vs Rater 3 | 0.700 | 0.584 – 0.783 | Moderate |
| Rater 1 vs Rater 4 | 0.710 | 0.612 – 0.792 | Good |
| Rater 1 vs Rater 5 | 0.650 | 0.540 – 0.742 | Moderate |
| **Intra-rater** | | | |
| Rater 1 (Test vs same day retest) | 0.889 | 0.849 – 0.927 | Good |
| Rater 2 (Test vs same day retest) | 0.846 | 0.786 – 0.892 | Good |
| Rater 3 (Test vs same day retest) | 0.836 | 0.770 – 0.885 | Good |
| Rater 4 (Test vs same day retest) | 0.850 | 0.789 – 0.895 | Good |
| Rater 5 (Test vs same day retest) | 0.856 | 0.816 – 0.907 | Good |

*ICC: Interclass correlation coefficient. CI: Confidence interval. Intraclass correlation coefficient; ICC(3,1) refers to a two-way mixed-effects model assessing absolute agreement between individual measurements made by a fixed set of raters. ICC values were interpreted according to the thresholds proposed by Koo and Li (2016): < 0.5 indicates poor reliability, 0.5–0.75 moderate reliability, 0.75–0.9 good reliability, and ≥ 0.9 excellent reliability.*