

Data-Efficient Personalization of Gait Biomechanics: The Predominant Contribution of Subject-Specific Waveform Shape

Syed Riyas Ahamed

Vellore Institute of Technology University

Sandip Saha

Vellore Institute of Technology University

Awani Bhushan

`awani.bhushan@vit.ac.in`

Vellore Institute of Technology University

Article

Keywords:

Posted Date: October 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11223064/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Data-Efficient Personalization of Gait Biomechanics: The Predominant Contribution of Subject-Specific Waveform Shape

Syed Riyas Ahamed¹, Sandip Saha^{1*}, Awani Bhushan^{2*}

¹School of Advanced Sciences, Vellore Institute of Technology, Vandalur-Kelambakkam Road, Melakottaiyur, Chennai, 600127, Tamil Nadu, India.

^{2*}School of Mechanical Engineering, Vellore Institute of Technology, Vandalur-Kelambakkam Road, Melakottaiyur, Chennai, 600127, Tamil Nadu, India.

*Corresponding author(s). E-mail(s): sandip.saha@vit.ac.in;
awani.bhushan@vit.ac.in;

Contributing authors: syed.riyasahameds2024@vitstudent.ac.in;

Abstract

Gait biomechanics specific to particular subjects have utility for rehabilitation and assistive-device control applications, but per-subject measurement is difficult. In this study, the potential for predicting joint-moment waveforms of lower-limb joints from limited data and the source of the advantage of subject-specific calibration, namely waveform shape or amplitude, were assessed. Gait data for 42 participants in 328 trials were analyzed for six lower-limb joints. Joint-moment waveforms were represented using a five-harmonic Fourier basis over normalized gait phase and predicted via Ridge regression employing gait speed as the population-wide predictor and validating using 42-subject leave-one-subject-out (LOSO) cross-validation. Subject-specific calibration was performed based on three trials (T01-T03); three independent trials (T04-T06) were held back for evaluation. The calibration correction was decomposed into a normalized waveform shape and a scalar amplitude, allowing ablations of shape, amplitude, and both, employing nested LOSO without test-subject leakage. For independent T04-T06 testing of calibration, full calibration resulted in 11.3-34.1% pooled RMSE reduction compared with population predictions with speed only. Shape-only calibration resulted in 14.0-25.2% RMSE reduction, whereas amplitude-only

calibration yielded only 0.5-1.9% RMSE reduction. After Holm correction, shape-only calibration yielded significant improvement over the population model for all six joints; full calibration was significant only at the hips compared with shape-only calibration. The personalization benefit was driven primarily by the temporal shape of the residual correction rather than its amplitude.

Keywords: gait analysis, joint moment prediction, subject-specific calibration, functional data, leave-one-subject-out cross-validation

Nomenclature

Symbol	Definition
$y(\phi)$	Joint-moment waveform at normalized gait phase ϕ
ϕ	Normalized gait-cycle phase, $0 \leq \phi \leq 1$
K	Number of Fourier harmonics ($K = 5$)
a_0	Fourier-series constant coefficient
a_k, b_k	Cosine and sine Fourier coefficients for harmonic k
β_i	11-element Fourier-coefficient vector for trial i
$\mathbf{B}$	Matrix of Fourier-coefficient targets
$\mathbf{X}$	Standardized predictor matrix
$\mathbf{W}$	Ridge-regression coefficient matrix
α	Ridge regularization parameter ($\alpha = 1$)
$\mathbf{r}_{s,j,c}$	Residual waveform for subject s , joint j , trial c
$\mathbf{c}_{s,j}$	Subject-specific three-trial calibration correction
$A_{s,j}^{\text{full}}$	Magnitude of the full subject-specific correction
$\mathbf{s}_{s,j}$	Normalized subject-specific correction shape
A_j^{common}	Common residual amplitude from nested-LOSO training subjects
$A_{s,j}^{\text{subj}}$	Subject-specific projected amplitude
$\mathbf{s}_j^{\text{pop}}$	Population residual correction shape
s	Subject index
j	Joint index
c	Calibration-trial index
e	Evaluation-trial index

1 Introduction

Instrumented gait analysis is still considered the gold standard in moment estimation of lower limb joints; however, its laboratory conditions do not allow the use of this technique in clinical screening and control of assistive devices. Machine learning methods that are applied to laboratory or wearable sensors data attempt to eliminate the need for full instrumenting, including the creation of open-access databases with

combined data from wearable sensors and kinetics as a reference [1, 2] and simulation-based personalization of sensors [3]. An alternative strategy is to develop a population model of joint moment waveforms from covariates present at the point of deployment – typically gait speed – and, when some information about the subject can be acquired, to personalize this prediction with respect to the individual. Previous work has shown advantages of such personalization to both the specific individual and particular condition in the context of powered lower limb prosthetics and exoskeletons [4–6].

Speed is a well-known variable influencing gait kinematics and kinetics, with changes in speed being associated with corresponding changes in the joint moments of the lower extremity [7–9]. What needs further research is which particular element of a later individual correction is responsible for its effectiveness: the unique pattern of deviation from the group trajectory (shape) or the total value of that deviation (amplitude). If amplitude is the dominant contributor, a single scalar per individual could suffice for calibration; however, if shape is the dominant contributor, calibration must capture the phase-resolved temporal pattern of the individual’s residual.

This question is conceptually related to the amplitude-phase separation problem in functional data analysis, where curves are decomposed into timing (phase) and magnitude (amplitude) variation [10–13]. Our decomposition is different in one key aspect: We decouple the fixed-phase residual form of the subject from the amplitude, without any model for temporal warping, something that we discuss again in Section 3. Nevertheless, current research on personalization tends to test if personal adaptation to the subject results in better predictions or controllers, without specifying what exactly contributes to the gain.

The purpose of this study was to: (i) develop a speed-dependent population model for six lower limb joint moments using 42-subject LOSO validation; (ii) test the hypothesis that a small number of subject-specific calibration trials will enhance the ability to predict unseen trials; and (iii) test the hypothesis that this enhancement results primarily from shape, not amplitude.

2 Results

2.1 Population-level prediction from gait speed

The speed-only model achieved substantial accuracy under 42-subject LOSO evaluation across all trials (Table 1; Fig. 1).

The calibration experiments (§2.3) instead require a population baseline restricted to the T04-T06 evaluation subset for direct comparability with the calibrated conditions; this subset-restricted baseline (Table 4, “Population” column) is numerically different from Table 1 because it is computed on a different trial subset, not because of a model change.

2.2 Contribution of anthropometric covariates

Adding anthropometric covariates to gait speed reduced pooled RMSE for five of the six joints, with the largest relative reduction at the left hip (LHip: 0.1317 to 0.1222, a

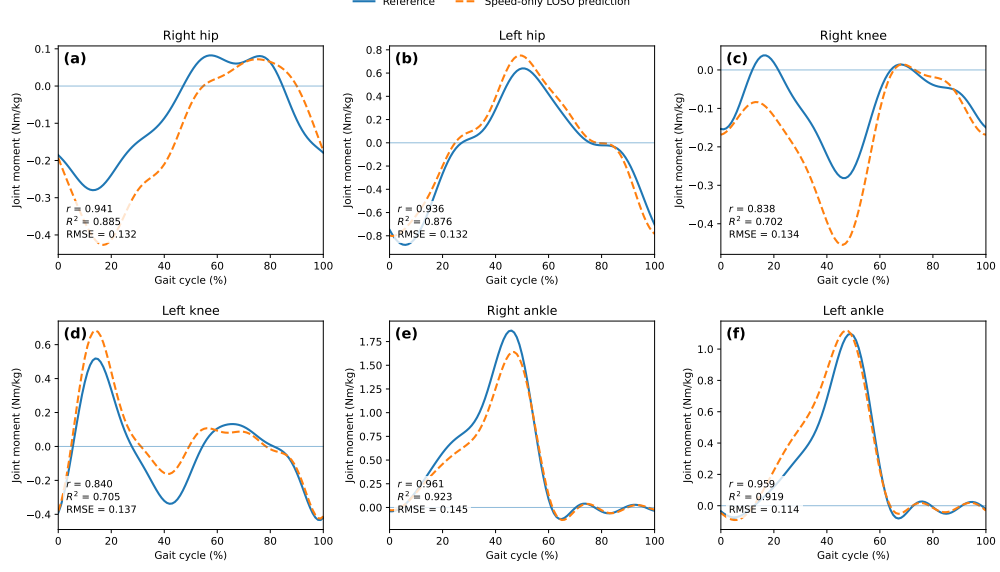


Fig. 1 Population-level joint-moment prediction from gait speed.

Table 1 LOSO performance of the speed-only population model, evaluated across all 328 trials.

Joint	r	R^2	RMSE	MAE
RHip	0.9406	0.8847	0.1316	0.0894
LHip	0.9362	0.8765	0.1317	0.0903
RKnee	0.8376	0.7016	0.1344	0.0856
LKnee	0.8397	0.7050	0.1370	0.0859
RAnkle	0.9607	0.9229	0.1447	0.0854
LAnkle	0.9587	0.9191	0.1144	0.0680

7.2% reduction) and comparable reductions at the left knee (0.1370 to 0.1308, 4.5%) and left ankle (0.1144 to 0.1094, 4.4%); smaller reductions were observed at the right hip (RHip: 0.1316 to 0.1282, 2.6%) and right ankle (0.1447 to 0.1418, 2.0%). The exception to this was the right knee, where inclusion of anthropometric covariates increased RMSE from 0.1344 to 0.1348. Thus, gait speed was the strongest single predictor configuration, while adding anthropometric covariates provided additional joint-specific information for five of the six joints, most notably at the left hip.

The speed-only values in Table 2 reproduce the corresponding baseline values in Table 1, because both use the same $K = 5$ gait-speed-only LOSO model evaluated across all 328 trials.

Table 2 Pooled RMSE for the anthropometry-only, speed-only, and speed-plus-anthropometry population models under 42-subject LOSO evaluation ($K = 5$).

Joint	Anthropometry only	Speed only	Speed + anthropometry
RHip	0.2015	0.1316	0.1282
LHip	0.1845	0.1317	0.1222
RKnee	0.1658	0.1344	0.1348
LKnee	0.1690	0.1370	0.1308
RAngle	0.1565	0.1447	0.1418
LAngle	0.1203	0.1144	0.1094

2.3 Residual structure and calibration benefit

Phase-resolved residual-anthropometry associations were strongest at the ankles (LAnkle vs. height: Spearman $\rho \approx 0.77$; vs. leg length: $\rho \approx 0.81$). Three-trial calibration reduced pooled RMSE for all six joints (Table 3; Fig. 2), by 11.3-34.1%.

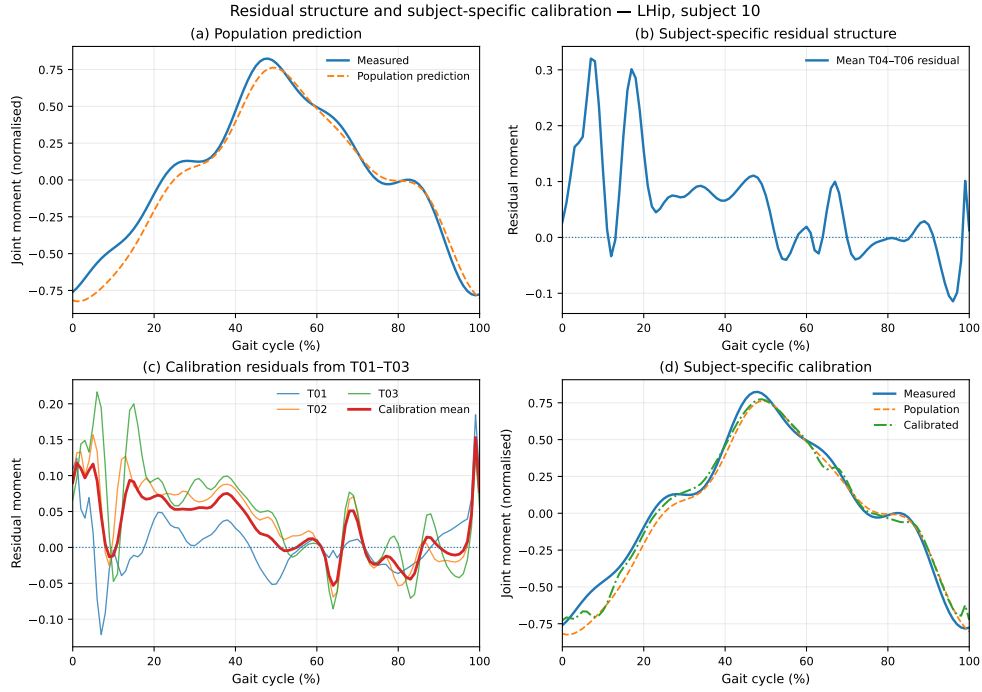


Fig. 2 Residual structure and subject-specific calibration.

Table 3 Pooled RMSE before/after three-trial calibration (T01-T03), evaluated on T04-T06.

Joint	Population	Full calibration	Improvement (%)
RHip	0.1455	0.0972	33.17
LHip	0.1435	0.0946	34.08
RKnee	0.1295	0.1050	18.93
LKnee	0.1327	0.1010	23.90
RAnkle	0.1461	0.1271	12.98
LAnkle	0.1185	0.1052	11.28

2.4 Shape versus amplitude

Shape-only calibration produced substantial RMSE reductions across all six joints (14.0-25.2%), comparable to or exceeding the full-calibration reduction at the ankles, whereas amplitude-only calibration produced only 0.5-1.9% reductions (Table 4; Fig. 3-4).

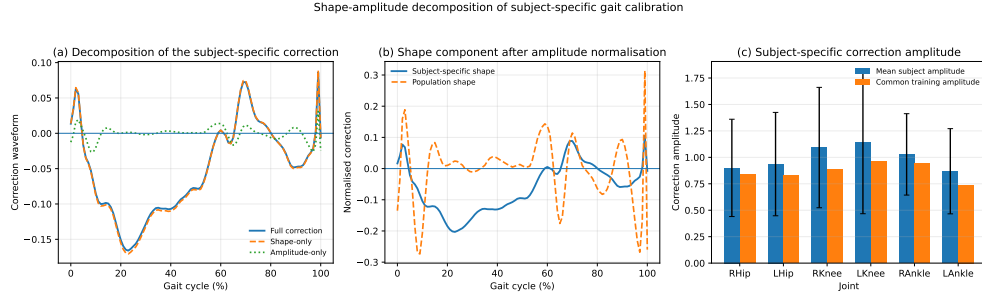


Fig. 3 Shape-amplitude decomposition of subject-specific correction.

Table 4 Pooled RMSE, population and calibration conditions, T04-T06.

Joint	Population	Full	Shape-only	Amplitude-only
RHip	0.1455	0.0972	0.1102	0.1441
LHip	0.1435	0.0946	0.1073	0.1411
RKnee	0.1295	0.1050	0.1079	0.1288
LKnee	0.1327	0.1010	0.1133	0.1302
RAnkle	0.1461	0.1271	0.1256	0.1441
LAnkle	0.1185	0.1052	0.1018	0.1169

Amplitude of correction exhibited considerable inter-subject variability (coefficient of variation 37-59%; full details in Supplementary Table S1), making insufficient

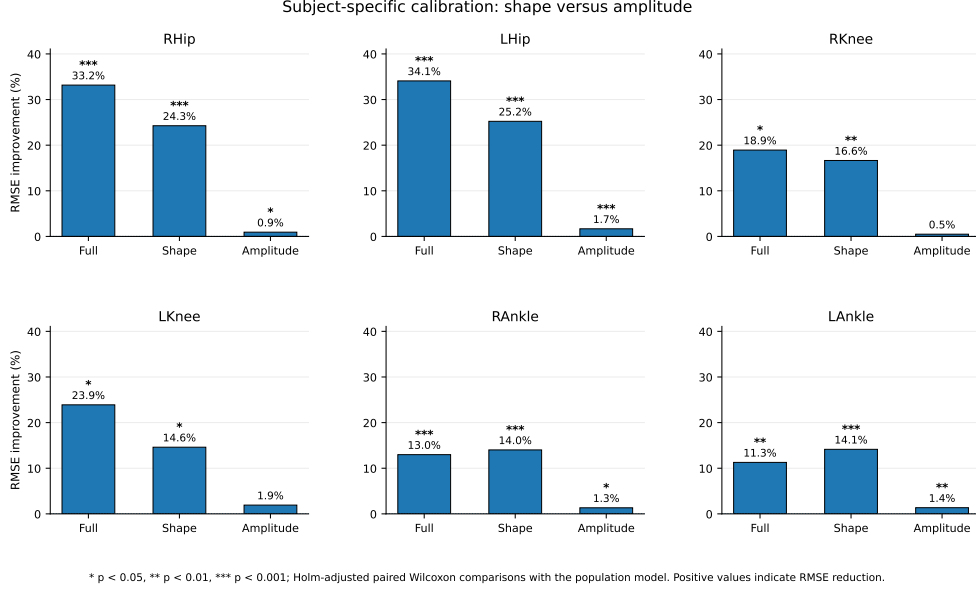


Fig. 4 Joint-specific calibration benefit from correction shape and amplitude.

between-subject amplitude variability an unlikely explanation for the limited predictive benefit of amplitude-only calibration.

2.5 Subject-level statistical comparisons

Participant-level RMSE/MAE (mean of the three T04-T06 trials) were compared via paired Wilcoxon signed-rank tests across four contrasts: full vs. population, shape-only vs. population, amplitude-only vs. population, and full vs. shape-only. Multiple comparisons were corrected within each six-joint family using the Holm step-down procedure ($\alpha = 0.05$).

The Holm-corrected significance results for the four paired comparisons across the six joints are summarized in Table 5.

Table 5 Holm-corrected significance ($p < 0.05$) of paired participant-level RMSE comparisons.

Comparison	RHip	LHip	RKnee	LKnee	RAnkle	LAnkle
Full vs. population	Yes	Yes	Yes	Yes	Yes	Yes
Shape-only vs. population	Yes	Yes	Yes	Yes	Yes	Yes
Amplitude-only vs. pop.	Yes	Yes	No	No	Yes	Yes
Full vs. shape-only	Yes	Yes	No	No	No	No

Full calibration and shape-only calibration both significantly outperformed the population model at all six joints; amplitude-only calibration was significant everywhere except the knees; full calibration exceeded shape-only significantly only at the hips. Exact per-joint p -values are reported in Supplementary Table S2.

3 Discussion

3.1 Principal findings and information hierarchy

Three findings emerged. First, gait speed alone gave strong population-level prediction of all six joint moments under subject-independent evaluation (Table 1). Second, three subject-specific calibration trials substantially reduced prediction error on independent trials without retraining the population model. Third, most of the gain was maintained when the subject-specific normalized residual shape was retained and its amplitude was replaced by the common training-population amplitude, whereas amplitude-only correction yielded only marginal improvements. The resulting information hierarchy is:

gait speed $\rightarrow$ population waveform $\rightarrow$ subject-specific residual shape $\rightarrow$
subject-specific amplitude.

This hierarchy describes the relative information content under this framework and dataset rather than a universal ranking.

3.2 Mechanistic interpretation: shape, amplitude, and joint-dependence

The shape-only condition retained each individual’s temporal correction pattern while replacing its magnitude with the common population amplitude, and this proved effective across all six joints. In contrast, the amplitude-only condition retained each individual’s projected correction amplitude while replacing its temporal pattern with the population shape, and provided little improvement, with performance varying by joint. Since correction amplitudes varied substantially between individuals (CV 37-59%), the limited performance of amplitude-only calibration cannot be explained by insufficient amplitude variability.

This decomposition is a fixed-phase shape/amplitude split, not a formal amplitude-phase separation in the sense developed for functional data[10, 12], where phase captures timing misalignment of curve features and amplitude captures their magnitude after alignment. Elastic registration approaches based on the square-root velocity function explicitly estimate warping functions to separate these two sources of variation[11, 13]. Since our shape component analysis is done on a fixed normalized gait-cycle axis without considering timing warps, part of what we call “shape” could actually be subject-specific timing of certain events, which from a formal registration approach standpoint would actually be classified as phase rather than amplitude. However, this does not make the practical observation any less valid, which is that the temporal-pattern component of the correction accounts for most of the calibration

gain, regardless of its decomposition; it does reduce the strength of our claim that gait “shape” is intrinsically more biomechanically significant than “amplitude,” in a formal, dimensionally consistent sense, because the shape component has much more freedom than the one-dimensional amplitude variable.

3.3 Limitations

The dataset comprises healthy participants only; generalization to pathological or amputee gait is untested. This limitation is particularly relevant to assistive-device applications, where adaptive prosthetic control must ultimately be validated under real-world conditions [14]. Calibration and evaluation trials were partitioned within the same session, not across independent sessions. The Fourier order ($K = 5$) and Ridge penalty ($\alpha = 1$) were fixed rather than tuned, and sensitivity to alternative hyperparameter settings was not evaluated. The Holm correction was applied to comparisons within families, not across families. The OpenSim stage is a computational verification pipeline rather than an ideal or fully validated reference; systematic hip bias and a right-knee amplitude mismatch were observed. These discrepancies are consistent with known differences between generically scaled and fully subject-specific musculoskeletal models[15].

4 Conclusion

A speed-based Fourier-Ridge model provided accurate population-level prediction of six lower-limb joint moments, while three-trial subject-specific calibration substantially improved prediction of unseen trials. Decomposition of the calibration correction showed that its temporal shape accounted for most of the personalization benefit, whereas amplitude provided additional predictive benefit primarily at the hip joints. These findings support shape-focused, data-efficient calibration as a candidate foundation for personalized rehabilitation and assistive-device applications, pending validation in clinical populations and downstream control settings.

5 Methods

5.1 Study overview

The analysis proceeded in four stages: (1) biomechanical preprocessing and verification using the Fukuchi dataset[16] and an OpenSim[17] musculoskeletal model; (2) a population-based Fourier-Ridge prediction model based on walking speed; (3) calibration of subjects using three trials (T01-T03), tested on three trials (T04-T06); and (4) separation of the calibration correction into waveform shape and amplitude. The overall study workflow is summarized in Fig. 5.

5.2 Dataset

The Fukuchi Walking Biomechanics Dataset[16] comprises 42 healthy participants and 328 walking trials, with synchronized motion-capture (150 Hz) and ground-reaction-force (300 Hz) data. Trials T01-T03 were used for subject-specific calibration; T04-T06

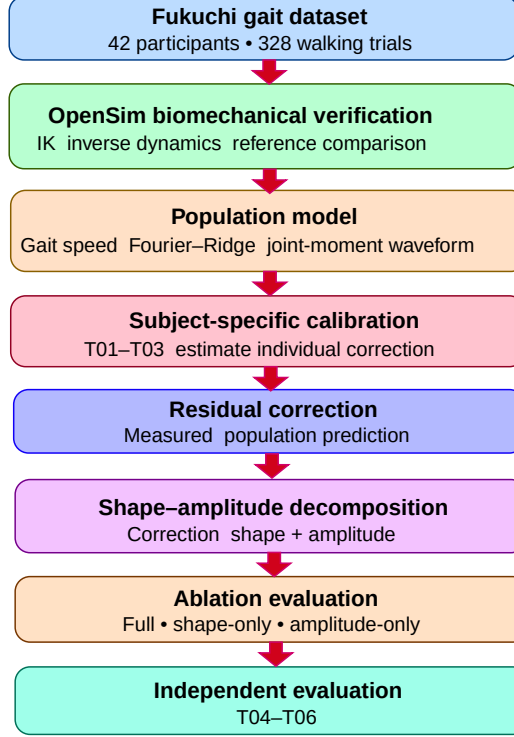


Fig. 5 Study workflow.

were reserved for independent evaluation. Six sagittal-plane joint moments were considered: RHip, LHip, RKnee, LKnee, RAnkle, LAnkle, each represented over 101 normalized gait-cycle points. Joint moments were expressed as body-mass-normalized moments (Nm/kg). Gait speed was the principal population predictor, while body mass, height, leg length, and age were considered as additional predictors (§5.5). The waveforms of the joint moments from each trial and joint were plotted against the standardized gait cycle phase scale, such that the trial waveforms could be directly compared or modelled using the identical 101 phase points. The calibration and evaluation sets remained strictly separate: T01-T03 were used only to estimate the subject-specific correction, whereas T04-T06 were reserved exclusively for independent evaluation.

5.3 OpenSim biomechanical verification

The Rajagopal full-body musculoskeletal model[18], implemented in OpenSim[17], was scaled to a representative participant (subject 25, mass 67.5 kg) using pelvis, bilateral shank, and bilateral foot measurements. The IK calculation was done for the entire 30 s trial. The ground reaction forces were low-pass filtered at 10 Hz and applied as external loads, followed by inverse-dynamics (ID) analysis. The mean and maximum marker RMS errors were 4.84 mm and 10.24 mm, respectively, while the mean maximum

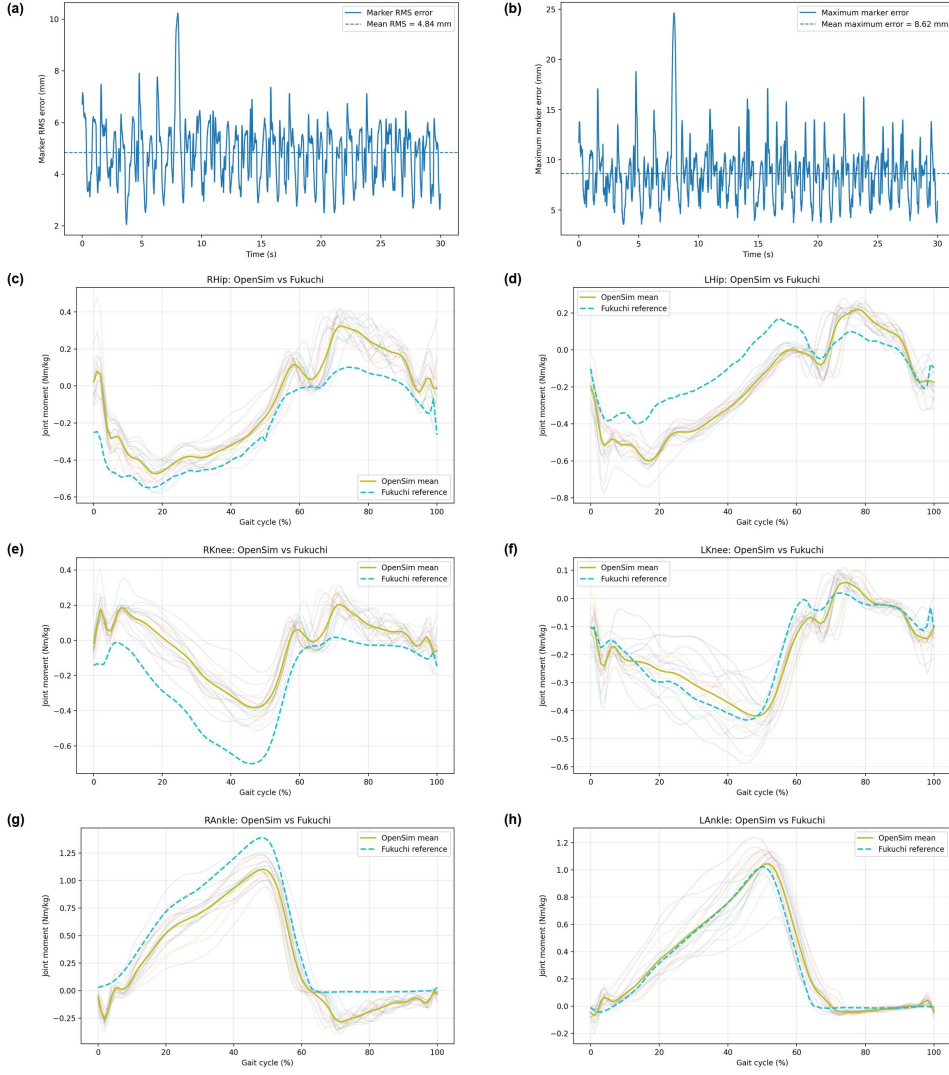


Fig. 6 OpenSim biomechanical verification.

marker error was 8.62 mm. These values were within accepted ranges for OpenSim IK solutions[19]. Comparison of the pipeline with the Fukuchi reference kinetics showed close agreement at the left ankle and left knee, a similar waveform shape but amplitude mismatch at the right knee, an underestimation of magnitude at the right ankle, and a systematic hip bias. The pipeline was kept frozen without correction and served solely as a biomechanical verification stage (Fig. 6).

Representative OpenSim processing views for subject 25 are shown in Fig. 7, illustrating the participant-specific model scaling, inverse-kinematics processing, and subsequent inverse-dynamics analysis.

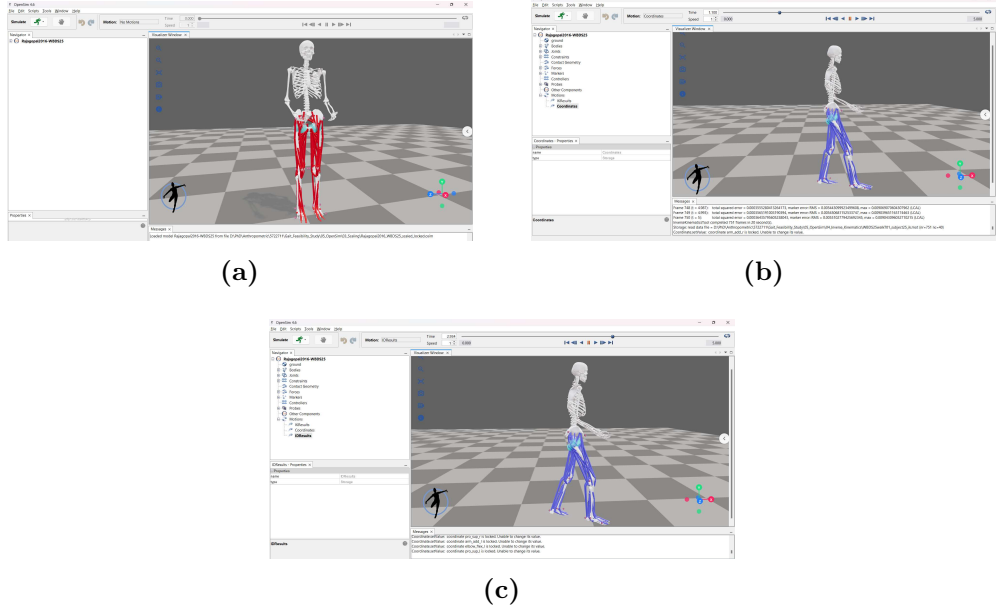


Fig. 7 Representative OpenSim processing for the representative participant (subject 25). (a) Participant-specific scaling of the Rajagopal full-body musculoskeletal model. (b) Inverse-kinematics processing using the experimental marker trajectory. (c) Inverse-dynamics processing following application of the external ground-reaction loads.

5.4 Population model: Fourier-Ridge regression

Each waveform $y(\phi)$ over normalized gait phase $\phi \in [0, 1]$ was represented using a K -harmonic Fourier basis, following the basis-function representation of functional data [13]. Fourier representations have also been used to compactly describe cyclic human movement waveforms [20].

$$y(\phi) = a_0 + \sum_{k=1}^K [a_k \cos(2\pi k\phi) + b_k \sin(2\pi k\phi)], \quad K = 5, \quad (1)$$

giving an 11-coefficient vector β_i per trial. Gait speed predicted β_i via Ridge regression [21],

$$\mathcal{L}(\mathbf{W}) = \|\mathbf{B} - \mathbf{XW}\|_F^2 + \alpha \|\mathbf{W}\|_F^2, \quad \alpha = 1, \quad (2)$$

with predictor standardization fit on training subjects only, under 42-subject LOSO cross-validation, which estimates generalization to unseen subjects and reduces subject-dependent evaluation bias [22]. The process for each trial and joint involved reducing the 101-point waveform to its 11 Fourier coefficients, which served as the multivariate regression target. The resulting regression therefore involves mapping the input predictors to this vector of Fourier coefficients. For each joint, the regression target was thus an 11-dimensional Fourier-coefficient vector, with one vector of coefficients for each trial. The predicted coefficients were then substituted into Eq. 1 to reconstruct the complete 101-point waveform. All joints were analyzed using the same

five harmonic basis and Ridge penalty, to ensure that any differences in prediction performance were due to the choice of predictors or calibration approach, not increased model complexity.

For every LOSO fold, all of the trials belonging to one subject were left out as the test set, while the trials belonging to all other subjects were used as the training set. The process of predictor standardization and model training was done based on training subjects, and the trained model was applied to the left out subject. The process was done until every one of 42 subjects had been left out once.

5.5 Covariate comparison

The comparison was done for three predictor combinations using the same leave-one-subject-out scheme with 42 subjects: anthropometric measurements alone, gait speed alone, and gait speed along with anthropometric measurements. The joint moment waveforms were expressed as five-harmonic Fourier basis vectors ($K = 5$) in all three cases, and Ridge regression with $\alpha = 1$ was used to predict the coefficients. The predictor normalization was performed based on the training subjects in each leave-one-subject-out fold. Performance was evaluated in terms of waveform RMSE.

5.6 Phase-resolved residual-anthropometry analysis

To explore phase-resolved associations of population model residuals with anthropometric measures, mean waveforms of residual data were first calculated for each individual at each of the 101 normalized gait cycle phases. Pearson and Spearman correlations of residuals for each individual with each anthropometric measure were subsequently calculated at each phase separately.

5.7 Residual analysis and calibration

The residual $\mathbf{r}_{s,j,c} = \mathbf{y}_{s,j,c} - \hat{\mathbf{y}}_{s,j,c}$ was computed for each calibration trial $c \in \{1, 2, 3\}$; the three-trial correction was

$$\mathbf{c}_{s,j} = \frac{1}{3} \sum_{c=1}^3 \mathbf{r}_{s,j,c}, \quad \hat{\mathbf{y}}_{s,j,e}^{\text{cal}} = \hat{\mathbf{y}}_{s,j,e} + \mathbf{c}_{s,j}, \quad e \in \{4, 5, 6\}. \quad (3)$$

Thus, the calibration correction was estimated entirely from trials T01-T03 and then incorporated without modification into the population prediction for the independent evaluation trials T04-T06. No measurement from T04-T06 was used to estimate the correction.

5.8 Shape-amplitude decomposition and nested-LOSO ablation

Functional data analysis commonly distinguishes variation in the magnitude and temporal behavior of curves [10, 11, 13]. Our decomposition is not a conventional amplitude-phase registration model; rather, because all gait waveforms were already expressed on a common normalized gait-phase grid, we separated the fixed-phase

subject-specific residual correction into its Euclidean magnitude and normalized temporal form. The full subject-specific correction was therefore defined as

$$\mathbf{c}_{s,j} = A_{s,j}^{\text{full}} \mathbf{s}_{s,j}, \quad A_{s,j}^{\text{full}} = \|\mathbf{c}_{s,j}\|_2, \quad \mathbf{s}_{s,j} = \frac{\mathbf{c}_{s,j}}{A_{s,j}^{\text{full}}}, \quad (4)$$

where $\mathbf{s}_{s,j}$ is the normalized subject-specific correction shape.

For the shape-amplitude ablation, four conditions were compared: *population* (no correction), *full* correction ($\mathbf{c}_{s,j}$), *shape-only* correction ($A_j^{\text{common}} \mathbf{s}_{s,j}$), and *amplitude-only* correction ($A_{s,j}^{\text{subj}} \mathbf{s}_j^{\text{pop}}$).

The common amplitude A_j^{common} was calculated as the median value of the amplitude values extracted from the nested-LOSO training subjects. The population shape $\mathbf{s}_j^{\text{pop}}$ was derived from the average of the normalized correction shapes of the nested-LOSO training subjects followed by normalization of the waveform. For the amplitude-only condition, the subject-specific amplitude was estimated as the least-squares projection coefficient of each calibration residual onto the population shape [13]. This projection provides the scalar amplitude that minimizes the squared Euclidean distance between the residual waveform and a scalar multiple of the population shape. The three projection coefficients were then averaged:

$$A_{s,j}^{\text{subj}} = \frac{1}{3} \sum_{c=1}^3 \frac{\mathbf{r}_{s,j,c}^T \mathbf{s}_j^{\text{pop}}}{(\mathbf{s}_j^{\text{pop}})^T \mathbf{s}_j^{\text{pop}}}. \quad (5)$$

Therefore, only shape calibration retains the subject-specific temporal pattern but substitutes its magnitude by the training population’s amplitude. In contrast, amplitude-only calibration retains the subject-specific projected magnitude but replaces the temporal pattern by the population shape. All population parameters were calculated within the outer training set via nested LOSO, in which the outer held-out subject is not used for calculating population-shape and population-amplitude estimates. No T04-T06 reference data were used for fitting and ablation construction.

5.9 Performance metrics

Prediction error was calculated in terms of root mean square error (RMSE) and mean absolute error (MAE) between predicted and reference waveforms. The waveform data from all trials in the defined evaluation set were combined to calculate these measures. Pearson correlation coefficient (r) and coefficient of determination (R^2) were also provided for the population level evaluation.

5.10 Statistical analysis

Participant-level RMSE, calculated as the mean of the three T04-T06 trial-level RMSEs, was used as the primary inferential metric and compared via paired Wilcoxon signed-rank tests [23] across four contrasts: full vs. population, shape-only vs. population, amplitude-only vs. population, and full vs. shape-only. MAE was also computed as a secondary error metric. Multiple comparisons were corrected within each six-joint

comparison family using the Holm step-down procedure[24] ($\alpha = 0.05$). Participant level aggregation was employed to ensure that multiple trials conducted by the same participant were not considered independent trials. The paired design compares calibration conditions within the same participants.

Supplementary information. Supplementary Tables S1 and S2 provide additional correction-amplitude statistics and exact per-joint statistical test results, respectively.

Declarations

- Funding No funding was received for this study.
- Competing interests The authors declare no competing interests.
- Ethics approval and consent to participate This study involved secondary analysis of data from the publicly available Fukuchi Walking Biomechanics Dataset. The original data collection study received ethical approval, and informed consent was obtained from all participants[16].
- Data availability The Fukuchi Walking Biomechanics Dataset is publicly available [16].
- Code availability The analysis scripts used in this study are available from the corresponding author on reasonable request.
- Author contribution SRA: conceptualization, methodology, software, formal analysis, data curation, visualization, and drafting the manuscript. SS: supervision, methodology, interpretation, and review of the manuscript. AB: supervision, interpretation of the biomechanical results, and review of the manuscript. All authors approved the final manuscript.

References

- [1] Halilaj, E., Rajagopal, A., Fiterau, M., Hicks, J.L., Hastie, T.J., Delp, S.L.: Machine learning in human movement biomechanics: best practices, common pitfalls, and new opportunities. *Journal of Biomechanics* **81**, 1–11 (2018)
- [2] Camargo, J., Ramanathan, A., Flanagan, W., Young, A.: A comprehensive, open-source dataset of lower limb biomechanics in multiple conditions of stairs, ramps, and level-ground ambulation and transitions. *Journal of Biomechanics* **119**, 110320 (2021)
- [3] Derungs, A., Amft, O.: Estimating wearable motion sensor performance from personal biomechanical models and sensor data synthesis. *Scientific Reports* **10**, 11450 (2020)
- [4] Quintero, D., Villarreal, D.J., Lambert, D.J., Kapp, S., Gregg, R.D.: Continuous-phase control of a powered knee-ankle prosthesis: amputee experiments across speeds and inclines. *IEEE Transactions on Robotics* **34**(3), 686–701 (2018)

- [5] Zhang, J., Fiers, P., Witte, K.A., Jackson, R.W., Poggensee, K.L., Atkeson, C.G., Collins, S.H.: Human-in-the-loop optimization of exoskeleton assistance during walking. *Science* **356**(6344), 1280–1284 (2017)
- [6] Slade, P., Kochenderfer, M.J., Delp, S.L., Collins, S.H.: Personalizing exoskeleton assistance while walking in the real world. *Nature* **610**(7931), 277–282 (2022)
- [7] Stansfield, B.W., Hillman, S.J., Hazlewood, M.E., Lawson, A.A.M., Mann, A.M., Loudon, I.R., Robb, J.E.: Sagittal joint kinematics, moments, and powers are predominantly characterized by speed of progression, not age, in normal children. *Journal of Pediatric Orthopaedics* **21**(3), 403–411 (2001)
- [8] Fukuchi, C.A., Fukuchi, R.K., Duarte, M.: Effects of walking speed on gait biomechanics in healthy participants: a systematic review and meta-analysis. *Systematic Reviews* **8**, 153 (2019)
- [9] Ardestani, M.M., Ferrigno, C., Moazen, M., Wimmer, M.A.: From normal to fast walking: impact of cadence and stride length on lower extremity joint moments. *Gait & Posture* **46**, 118–125 (2016)
- [10] Kneip, A., Ramsay, J.O.: Combining registration and fitting for functional models. *Journal of the American Statistical Association* **103**(483), 1155–1165 (2008)
- [11] Tucker, J.D., Wu, W., Srivastava, A.: Generative models for functional data using phase and amplitude separation. *Computational Statistics & Data Analysis* **61**, 50–66 (2013)
- [12] Marron, J.S., Ramsay, J.O., Sangalli, L.M., Srivastava, A.: Functional data analysis of amplitude and phase variation. *Statistical Science* **30**(4), 468–484 (2015)
- [13] Ramsay, J.O., Silverman, B.W.: *Functional Data Analysis*, 2nd edn. Springer, New York (2005)
- [14] Ahamed, S.R., Saha, S., Bhushan, A.: Lower-limb prosthetic mechanisms: recent progress, control innovations and barriers to real-world adoption. *BioMedical Engineering OnLine* (2026)
- [15] Kainz, H., Wesseling, M., Jonkers, I.: Generic scaled versus subject-specific models for the calculation of musculoskeletal loading in cerebral palsy gait: effect of personalized musculoskeletal geometry outweighs the effect of personalized neural control. *Clinical Biomechanics* **87**, 105402 (2021)
- [16] Fukuchi, C.A., Fukuchi, R.K., Duarte, M.: A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals. *PeerJ* **6**, 4640 (2018)

- [17] Delp, S.L., Anderson, F.C., Arnold, A.S., Loan, P., Habib, A., John, C.T., Guendelman, E., Thelen, D.G.: OpenSim: open-source software to create and analyze dynamic simulations of movement. *IEEE Transactions on Biomedical Engineering* **54**(11), 1940–1950 (2007)
- [18] Rajagopal, A., Dembia, C.L., DeMers, M.S., Delp, D.D., Hicks, J.L., Delp, S.L.: Full-body musculoskeletal model for muscle-driven simulation of human gait. *IEEE Transactions on Biomedical Engineering* **63**(10), 2068–2079 (2016)
- [19] Hicks, J.L., Uchida, T.K., Seth, A., Rajagopal, A., Delp, S.L.: Is my model good enough? best practices for verification and validation of musculoskeletal models and simulations of movement. *Journal of Biomechanical Engineering* **137**(2), 020905 (2015)
- [20] Skej , S.D., Lund, M.E., Stensvig, M., Kaae, N.M., Rasmussen, J.: Running in circles: Describing running kinematics using fourier series. *Journal of biomechanics* **115**, 110187 (2021)
- [21] Hoerl, A.E., Kennard, R.W.: Ridge regression: biased estimation for nonorthogonal problems. *Technometrics* **12**(1), 55–67 (1970)
- [22] Gholamiangonabadi, D., Kiselov, N., Grolinger, K.: Deep neural networks for human activity recognition with wearable sensors: leave-one-subject-out cross-validation for model selection. *IEEE Access* **8**, 133982–133994 (2020)
- [23] Wilcoxon, F.: Individual comparisons by ranking methods. *Biometrics Bulletin* **1**(6), 80–83 (1945)
- [24] Holm, S.: A simple sequentially rejective multiple test procedure. *Scandinavian Journal of Statistics* **6**(2), 65–70 (1979)

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [supplementary.pdf](#)