

PAPER

Evaluation of Lower Limb Gait Pattern Generation from BMI-Based Angular Velocity Estimation for Personalized Robotic Rehabilitation

Dimas Adiputra¹ ,
Helisyah Nur Fadhilah^{1,2},
Rifdatun Ni'mah¹ ,
Kadek Heri Sanjaya³ ,
Kok Swee Sim⁴ ,
Nur Khozin⁵ 

¹Telkom University,
Surabaya, Indonesia

²Institut Teknologi
Sepuluh Nopember,
Surabaya, Indonesia

³National Research and
Innovation Agency (BRIN),
Bandung, Indonesia

⁴Multimedia University,
Melaka, Malaysia

⁵Universitas Negeri Surabaya,
Surabaya, Indonesia

[dimasze@
telkomuniversity.ac.id](mailto:dimasze@telkomuniversity.ac.id)

ABSTRACT

This study assesses the ability of gait angle patterns produced by a phase-averaged velocity estimation NN-15 model based on BMI and walking speed to serve as personalized joint motion references. A total of 424 gait cycles from 24 seen subjects and 131 gait cycles from 8 unseen subjects across four BMI categories (underweight (U), normal (N), overweight (Ov), and obese (Ob)) and both limb sides were analyzed. Similarity was quantified using root mean square error (RMSE), mean absolute error (MAE), Pearson correlation coefficient (r), and Bland–Altman analysis. The hip joint achieved the strongest agreement ($r = 0.82\text{--}0.94$, $\text{RMSE} = 4.24\text{--}8.42^\circ$), followed by the ankle ($r = 0.19\text{--}0.81$, $\text{RMSE} = 6.17\text{--}12.39^\circ$) and the knee ($r = 0.15\text{--}0.83$, $\text{RMSE} = 9.28\text{--}23.80^\circ$). The Ov group consistently demonstrated the best performance at the hip and ankle. Significant left–right accuracy at the hip remained bilaterally accurate. Based on these findings, the NN-15 framework is validated as a personalized hip joint reference for a rehabilitation robot called Picobot. However, adopting different gait phase schemes is advised for the ankle, and a position-hold strategy during Phases 1 and 2 is proposed for the knee to improve joint estimation.

KEYWORDS

gait pattern generation, joint angle estimation, angular velocity, rehabilitation robot, personalized gait control

1 INTRODUCTION

Stroke is a leading cause of long-term disability worldwide, frequently resulting in impaired locomotor function that necessitates prolonged and intensive rehabilitation [1]. Among the most significant consequences of stroke is the disruption of normal (N) gait, which diminishes patients' independence and quality of life [2], [3]. Rehabilitation robots have emerged as a promising tool to support gait recovery by

Adiputra, D., Fadhilah, H. N., Ni'mah, R., Sanjaya, K. H., Sim, K. S., Khozin, N. (2026). Evaluation of Lower Limb Gait Pattern Generation from BMI-Based Angular Velocity Estimation for Personalized Robotic Rehabilitation. *International Journal of Online and Biomedical Engineering (iJOE)*, 22(10), pp. 179–202. <https://doi.org/10.3991/ijoe.v22i10.62264>

Article submitted 2026-05-13. Revision uploaded 2026-07-19. Final acceptance 2026-07-22.

© 2026 by the authors of this article. Published under CC-BY.

delivering repetitive, task-specific training with reduced burden on clinical therapists [4]. However, for such systems to be truly effective, they must provide gait references that closely reflect the natural motion of the individual patient in healthy condition instead of a generic, population-averaged trajectory. This requirement for personalization is crucial when patients present with diverse body compositions, as body mass has been shown to fundamentally alter lower limb joint kinematics during walking [5], [6]. However, generating personalized gait trajectories remains challenging, as the process often requires time-consuming calibration procedures, limiting its practicality in clinical settings with long queues of patients.

Existing methods for personalized gait reference generation typically model joint angle trajectories directly. This joint angle trajectory is a high-dimensional, phase-sensitive, continuously varying signal that is inherently difficult to generalize across individuals. Motion capture-based approaches [7], [8], [9] provide highly accurate measurements of joint angles but are limited to laboratory environments due to their complexity and cost. Machine learning models, including LSTM and CNN architectures, have demonstrated high accuracy in reconstructing gait angle trajectories from IMU or EMG signals [10], [11], but require large, subject-specific training datasets and substantial computational resources, constraining their practicality for real-time embedded control. Regression-based parametric methods offer simpler implementations and have been used to generate three-dimensional ankle and joint trajectories from anthropometric and motion parameters [12], [13], but often fail to capture nonlinear biomechanical relationships. Meanwhile, approaches such as Complementary Limb Motion Estimation (CLME) generate reference trajectories from the contralateral limb [14], making them unsuitable for patients with bilateral impairment.

A simpler alternative approach is to model the average angular velocity of each joint within discrete gait phases, rather than the full continuous angle trajectory. This phase-averaged velocity is a compact, scalar descriptor that can be estimated from basic, non-invasive inputs. Our previous study [15], [16] demonstrated that Body Mass Index (BMI) and walking speed can be used as predictors of lower limb joint angular velocity across four gait phases (P1: initial contact to foot flat, P2: foot flat to heel off, P3: heel off to toe off, and P4: toe off to next initial contact) for the hip, knee, and ankle joints. A neural network model with 15 hidden layers (NN-15) achieved a correlation coefficient of $R = 0.895$ for the hip joint in Phase 2, outperforming linear, logarithmic, and polynomial regression models across all joints and phases. These estimated phase-averaged velocities were subsequently integrated with the Picobot rehabilitation robot's gait control system, which uses foot contact sensing to detect gait phase and drives each joint at the corresponding estimated velocity [17]. If the joint position reaches the maximum range of motion (ROM), then it will be kept until the gait phase detection changes to the next. While the velocity estimation model showed strong statistical correlation, it remains unclear whether such low-dimensional, phase-based representations can be used to reconstruct physiologically meaningful joint angle trajectories.

The answer to this question is not trivial, because the quality of gait pattern reproduction is expected to vary across clinically relevant subgroups. BMI is known to significantly alter gait kinematics. Obese (Ob) individuals exhibit reduced knee flexion, greater hip and knee adduction angles, and altered ankle ROM compared to N-weight counterparts [5], [6], [18]. Overweight (Ov) individuals show greater hip joint angles and shorter knee and ankle trajectory lengths [19]. These BMI-related kinematic differences mean that a single universal estimate of

angular velocity may reproduce healthy gait well for one group but poorly for another, which is making group-stratified validation essential. Furthermore, gait is basically symmetrical activity that does not rely heavily on limb dominance [20]. The NN-15 provides a symmetrical gait control reference value for both limbs. Since another study also reports that kinematics between limbs side is slightly different but significant due to the limb-dominance [21], evaluating the method accuracy on each limb can be insightful for bilateral rehabilitation reference. Finally, the three joints (ankle, knee, and hip) differ substantially in their biomechanical complexity and the stability of their phase-averaged velocity [15], warranting separate evaluation by joint type.

This paper evaluates the similarity between lower limb joint angle patterns generated by the NN-15 angular velocity model [15] and real joint angle trajectories measured using a Vicon motion capture system to understand whether the model can serve as a practical alternative to conventional trajectory-based methods for personalized rehabilitation. Gait data from healthy adults spanning four BMI categories (underweight (U), N, Ov, and Ob) and both left and right limbs are used to assess pattern fidelity across three joints (ankle, knee, and hip). Similarity is quantified using root mean square error (RMSE), mean absolute error (MAE), Pearson correlation coefficient, and Bland–Altman analysis. The specific contributions of this work are as follows:

1. Trajectory-level validation of phased-averaged angular velocity modelling to evaluate whether joint angle trajectories reconstructed from phase-averaged angular velocity estimates can approximate real human gait.
2. Multi-factor evaluation across joint type, BMI, and limb side, as the proposed approach is validated across three joints (hip, knee, ankle), four BMI categories, and bilateral limb conditions.
3. Identification of joint-specific and phase-dependent limitations of velocity-based modelling, based on the distinct error mechanisms for each joint.
4. Translation of modeling results into control-oriented design guidelines for the personalization of rehabilitation robot gait references using the Picobot system.

The remainder of this paper is organized as follows: Section 2 describes the data collection protocol, gait pattern generation procedure, and similarity metrics used. Section 3 presents the results of the gait pattern comparison across joints, BMI groups, and limb sides. Section 4 discusses the findings in the context of personalized rehabilitation robot control, and Section 5 concludes the paper.

2 METHODS

This section describes the three main stages of the methodology, as shown in Figure 1. First is data preparation, reusing the gait dataset from [15]. Second is gait pattern generation, in which estimated angular velocities from the NN-15 model are combined with real phase-specific timing and initial joint positions to reconstruct lower limb joint angle trajectories. Lastly, the research conducted similarity analysis between the estimated and real trajectories using multiple quantitative metrics.

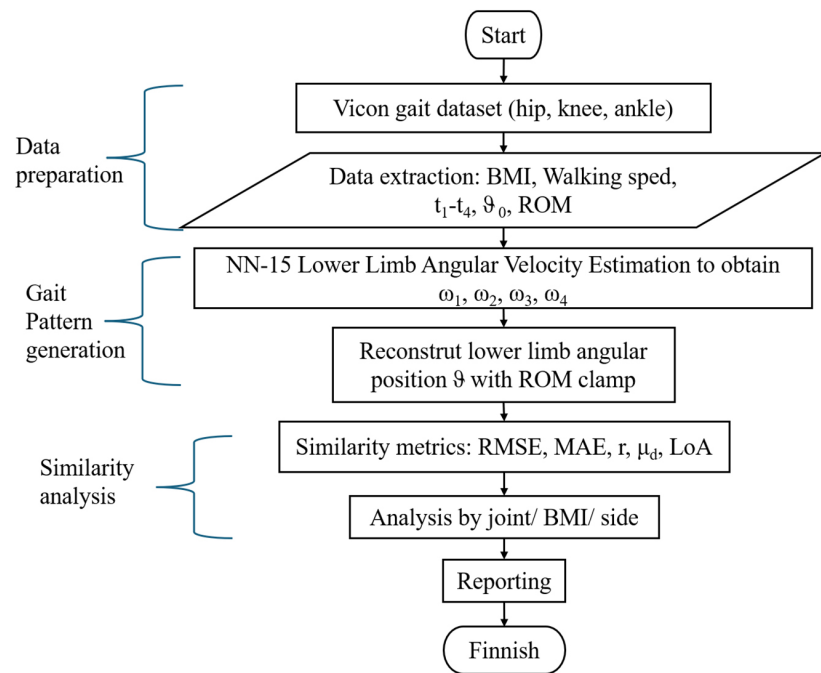


Fig. 1. Research flowchart

2.1 Participants

The gait data used in this study comprises two groups. The first group consists of 424 gait cycles from 24 healthy participants whose data was used to develop the NN-15 angular velocity model in the previous study [15]. Because these subjects contributed to model training, this group represents an in-sample evaluation that assesses how well the generated gait patterns match the real trajectories of the development cohort. The second group consists of 131 gait cycles from eight additional participants (two per BMI category: U, N, Ov, and Ob), each contributing 13–18 gait cycles. These eight participants were not involved in the development of the NN-15 model in any capacity, and their data was completely unseen during model training and validation. This independent test cohort therefore constitutes a subject-independent test set that evaluates the model's ability to generalize to new individuals.

All data collection protocol, participant characteristics, and ethical approval are detailed therein. Ethical clearance was obtained from the Health Research Ethics Committee of RSUD Haji Sukolilo, Surabaya, East Java Province, Indonesia (Approval No. 445/103/KOM.ETIK/2024, dated May 31, 2024). Gait data were collected from 32 healthy adults aged 25–40 years spanning all four BMI categories: U with $\text{BMI} \leq 18.5 \text{ kg/m}^2$, N with $18.6 \leq \text{BMI} \leq 23.9 \text{ kg/m}^2$, Ov with $24.0 \leq \text{BMI} \leq 27.9 \text{ kg/m}^2$, and Ob with $\text{BMI} \geq 28.0 \text{ kg/m}^2$. Gait data were recorded with a Vicon optical motion capture system with 16 reflective markers placed on standard anatomical landmarks. Joint angle time-series were obtained using the embedded plug-in gait in Vicon Nexus software for the hip, knee, and ankle of both left and right limbs. Details of the marker placement and segment are explained in previous research [15]. Each participant performed six overground walking trials at preferred speed. Gait cycles were segmented into four phases consistent with the Picobot system [17]: P1–P4. The following parameters were extracted per gait cycle: BMI and walking speed of

each participant; duration of each phase (t_1, t_2, t_3, t_4); initial joint angular position (θ_0) measured by Vicon at the start of each cycle; and joint ROM per cycle.

2.2 Gait pattern generations

The gait pattern generation converts phase-averaged angular velocity estimates from the NN-15 model into reconstructed joint angle trajectories using real gait phase durations and initial joint positions from the Vicon dataset. The procedure is applied independently for each gait cycle trial, each joint (ankle, knee, hip), and each limb side (left, right), as follows.

Initially, the angular velocity is estimated via the developed NN-15 model. For each gait cycle, the participant's BMI (x_1) and self-selected walking speed (x_2) are input to the NN-15 model. The model outputs four phase-averaged angular velocity references, $\omega_1, \omega_2, \omega_3$, and ω_4 (in °/s), for Phases 1–4, for each of the three joints (hip, knee, and ankle). The NN-15 architecture consists of a min–max input normalization layer, 15 hidden layers with hyperbolic tangent sigmoid activation, and a linear output layer trained using the Levenberg–Marquardt algorithm. Full architectural details and trained weight matrices are reported in [15].

The reconstructed joint angle $\theta(t)$ is built phase-by-phase, starting from the real initial angular position θ_0 . For each phase $k \in \{1, 2, 3, 4\}$, the joint angle at the end of that phase is computed as in Equation 1

$$\theta_k = \theta_{k-1} + \omega_k \cdot t_k, \quad (1)$$

where θ_{k-1} is the angle at the end of the previous phase (with θ_0 the Vicon-measured initial angle), ω_k is the NN-15 estimated angular velocity for phase k (°/s), and t_k is the real measured duration of phase k (s). Real phase durations from the Vicon data are used deliberately instead of estimated durations to isolate the contribution of angular velocity accuracy to pattern fidelity, independently of any phase timing errors. Then, to ensure the generated trajectory remains physiologically plausible, a ROM constraint is applied at each update step. If the updated angle exceeds the observed ROM boundary for that joint (as measured by Vicon), it is clamped and held constant for the remainder of the phase, as in Equation 2 and Equation 3

$$\theta_k = \min(\theta_{k-1} + \omega_k \cdot t_k, ROMmax), \text{ if } \omega_k > 0, \quad (2)$$

$$\theta_k = \max(\theta_{k-1} + \omega_k \cdot t_k, ROMmin), \text{ if } \omega_k < 0, \quad (3)$$

where $ROMmax$ and $ROMmin$ are the maximum and minimum joint angles within the gait cycle of the real trajectories. This models the Picobot behavior of holding joint position once maximum displacement is reached, preventing overshoot beyond the natural ROM. Those steps are repeated independently for every gait cycle trial in the dataset, for each joint (ankle, knee, and hip), and for each limb side (left and right). This yields a complete paired set of generated and real joint angle trajectories for similarity analysis. The number of valid trials per BMI group and limb side is summarized in Table 1, where H is height, BW is body weight, M is male, and F is female.

Table 1. The data demographic used in this study

BMI (Kg/m ²)	H (cm)	BW (Kg)	M (n)	F (n)	Left (n)	Right (n)	Mean Cycle (s)	
							Left	Right
U	162.1 ± 8.96	47.00 ± 4.70	3	1	47	47	1.35 ± 0.16	1.33 ± 0.15
N	157.62 ± 7.87	57.4 ± 7.87	5	5	63	65	1.31 ± 0.19	1.29 ± 0.17
Ov	158.68 ± 4.56	77.76 ± 14.38	5	5	55	57	1.38 ± 0.17	1.40 ± 0.17
Ob	162.03 ± 9.23	90.48 ± 14.22	3	5	113	107	1.31 ± 0.14	1.31 ± 0.15
Total/Mean	160.10 ± 7.76	68.16 ± 20.23	15	17	278	276	1.33 ± 0.16	1.33 ± 0.165

2.3 Missing data handling

The Vicon data contained two types of missing values. Trailing missing values arise from natural variation in gait cycle duration and are preserved, as they represent valid differences in cycle length rather than measurement errors. Scattered internal missing values caused by transient marker occlusion were filled using linear interpolation within the valid data range of each trial. This approach is appropriate for the smooth and continuous nature of joint angle signals [22]. Additionally, a small number of hip angle records contained angle wrapping artifacts (values outside the physiologically plausible range of approximately -35° to $+50^\circ$) caused by angle wrapping artifacts beyond $\pm 180^\circ$ from the Vicon pipeline. These were corrected by applying the corresponding $\pm 180^\circ$ or $\pm 360^\circ$ offset, verified by visual inspection of the corrected trajectories before analysis.

2.4 Similarity metrics

Four complementary metrics quantify the similarity between generated and real trajectories, computed per trial at valid (non-missing) time points and then averaged within each joint $\times$ BMI group $\times$ limb side combination. The first metric is RMSE, which measures overall angular deviation magnitude, as in

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{\theta}_i - \theta_i)^2}, \quad (4)$$

where N is the number of valid time points, $\hat{\theta}_i$ is generated angular position and θ_i is the actual angular position. RMSE is reported in degrees ($^\circ$). The second parameter is MAE, which is the average absolute angular deviation, less sensitive to large outlier differences than RMSE. The MAE is calculated using equation 5

$$MAE = \frac{1}{N} \sum_{i=1}^N |\hat{\theta}_i - \theta_i|. \quad (5)$$

Pearson Correlation Coefficient (r) is the next parameter, as shown in Equation (6), which measures the shape correspondence between generated and real trajectories independently of absolute magnitude.

$$r = \frac{\sum_{i=1}^N (\hat{\theta}_i - \bar{\hat{\theta}})(\theta_i - \bar{\theta})}{\sqrt{\sum_{i=1}^N (\hat{\theta}_i - \bar{\hat{\theta}})^2 \sum_{i=1}^N (\theta_i - \bar{\theta})^2}}, \quad (6)$$

where $\bar{\theta}$ is the average of the actual angular position and $\bar{\hat{\theta}}$ is the average of the generated angular position. Pearson correlation values are interpreted following established guidelines for gait biomechanics: $r < 0.40$ as poor, $r = 0.40\text{--}0.74$ as modest, and $r > 0.75$ as excellent agreement [12]. For context, state-of-the-art deep learning joint angle estimation methods report r values of 0.97–0.99 for hip and knee trajectories [13], while the simpler angular velocity integration approach of this study is expected to yield more moderate but clinically meaningful correlation values. Lastly, Bland–Altman analysis is conducted. This method is a clinical standard for comparing two measurement methods [23]. The bias μ_d and 95% Limits of Agreement (LoA) are computed as shown in Equation 7 and Equation 8.

$$\mu_d = \frac{1}{N} \sum_{i=1}^N \hat{\theta}_i - \theta_i, \quad (7)$$

$$LoA = \mu_d \pm 1.96\sigma_d, \quad (8)$$

where σ_d is the standard deviation of pointwise differences. A narrow LoA indicates high agreement. Bland–Altman analysis is applied, pooling all valid time-point pairs within each joint $\times$ BMI $\times$ side combination.

Lastly, to assess whether estimation accuracy differs significantly between left and right limbs, the Shapiro–Wilk test was first applied to assess the normality of each distribution. If both limbs were normally distributed ($p > 0.05$), an independent-samples Welch’s t -test was used; otherwise, the Mann–Whitney U test was applied. A significance threshold of $\alpha = 0.05$ was adopted. Results are reported as mean $\pm$ SD, with significance indicated by markers: *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$), and ns (not significant). The research expects that the estimation model can keep its accuracy for both limbs since the input—phase durations, initial angle, and ROM—come from each corresponding limb instead of a neighbor limb.

3 RESULTS

3.1 Gait pattern similarity across joints, BMI groups, and limb sides

Table 2 summarizes the complete similarity metrics of the development cohort, while Table 3 shows the similarity metrics of the independent cohort. Figure 2 shows the corresponding mean real and estimated trajectories over the normalized gait cycle for all six joint–side combinations across the four BMI groups. The trajectories are also grouped into phases: P1 (0–12%), P2 (12–50%), P3 (50–62%), and P4 (62–100%). The pattern of the trajectories across the joints is fine, but only the ankle trajectory of the U-independent cohort seems off. In phase 4, the estimated trajectory goes down instead of going up. This is because the NN-15 estimates the ankle ω_4 for the unseen data to be a negative value, pointing out the limitation of the model for wider generalization.

Across all conditions on the development cohort data, the hip joint demonstrated the highest agreement, with Pearson r ranging from 0.85 (right U) to 0.93 (left N) and relatively low RMSE from $5.09 \pm 2.03^\circ$ (right Ov) to $8.42 \pm 3.62^\circ$ (right Ob). The ankle joint showed moderate agreement, with r from 0.67 (left Ob) to 0.81 (left Ov) and RMSE from $6.17 \pm 1.54^\circ$ (right Ov) to $10.76 \pm 3.89^\circ$ (right U). The knee joint had moderate correlation and the highest absolute error of the three joints, with r from 0.71 (right N) to 0.83 (right Ov) and RMSE from $9.28 \pm 2.42^\circ$ (left U) to $15.31 \pm 3.31^\circ$ (right N). These results

indicate that reconstruction accuracy is strongly dependent on joint kinematic complexity, with simpler motion patterns, such as the hip joint, yielding greater fidelity. The independent cohort data supports the findings, where the hip joint shows the highest agreement, with the highest Pearson r of 0.94, compared to the ankle and knee trajectories estimation, with the highest Pearson r of 0.47 and 0.40, respectively.

Regarding BMI group effects, the Ov group consistently achieved good performance at the hip and ankle for both development and independent cohorts, showing the lowest RMSE and highest r for those joints. The Ob BMI group of the independent cohort yielded the highest knee RMSE and MAE despite generally stable gait. Development cohort data shows different patterns where the N group shows the highest knee RMSE and MAE instead, which indicate different accuracy between seen and unseen data. The Ob group of the independent cohort showed the highest variability, particularly at the left knee ($\text{RMSE} = 23.80 \pm 5.39^\circ$). Meanwhile, the U development cohort shows the highest variability at the right knee ($\text{RMSE} 15.31 \pm 3.31$). Overall, these results confirm that BMI influences not only gait kinematics but also the predictability of joint motion, directly affecting reconstruction accuracy. The BMI influences are also different between development and independent cohort data.

Table 2. Gait metrics similarity metrics on the development cohort

Joint	Side	BMI	n	RMSE $\pm$ SD ($^\circ$)	MAE $\pm$ SD ($^\circ$)	r	Bias ($^\circ$)	95% LoA ($^\circ$)
Ankle	Left	U	33	7.91 ± 4.09	6.73 ± 3.92	0.77	-4.48	[-19.01, 10.06]
		N	45	7.88 ± 1.69	5.93 ± 1.45	0.72	-2.40	[-17.52, 12.72]
		Ov	38	6.53 ± 2.12	5.17 ± 1.79	0.81	-3.35	[-15.49, 8.80]
		Ob	97	7.73 ± 2.87	6.09 ± 2.55	0.67	-4.00	[-18.12, 10.12]
	Right	U	34	10.76 ± 3.89	9.20 ± 3.64	0.69	-6.25	[-24.49, 11.98]
		N	47	6.27 ± 1.59	4.69 ± 1.36	0.74	-1.85	[-13.86, 10.16]
		Ov	39	6.17 ± 1.54	4.80 ± 1.32	0.79	-2.91	[-13.95, 8.13]
		Ob	91	6.39 ± 2.35	5.14 ± 2.10	0.76	-2.51	[-14.93, 9.91]
Knee	Left	U	33	9.28 ± 2.42	6.80 ± 1.41	0.75	-0.32	[-18.85, 18.21]
		N	45	14.73 ± 3.27	10.99 ± 2.98	0.71	-0.48	[-29.61, 28.65]
		Ov	38	12.62 ± 2.36	8.12 ± 1.01	0.80	-3.95	[-28.10, 20.21]
		Ob	97	10.62 ± 3.73	7.92 ± 2.58	0.73	-0.60	[-22.74, 21.54]
	Right	U	34	13.77 ± 2.57	9.14 ± 1.95	0.78	-3.82	[-30.19, 22.55]
		N	47	15.31 ± 3.31	11.35 ± 3.56	0.71	-0.82	[-30.93, 29.28]
		Ov	39	11.51 ± 2.59	7.95 ± 2.22	0.83	-2.03	[-25.19, 21.13]
		Ob	91	11.01 ± 2.76	7.50 ± 1.75	0.82	-3.61	[-24.60, 17.37]
Hip	Left	U	33	8.27 ± 1.15	6.94 ± 0.77	0.90	0.88	[-15.25, 17.02]
		N	45	6.80 ± 1.42	4.99 ± 0.88	0.93	-1.20	[-14.64, 12.24]
		Ov	38	5.91 ± 2.32	4.19 ± 1.39	0.89	-2.22	[-14.31, 9.88]
		Ob	97	8.05 ± 2.93	6.51 ± 2.40	0.90	2.45	[-13.74, 18.65]
	Right	U	34	8.06 ± 2.13	5.85 ± 1.49	0.85	-2.57	[-17.85, 12.71]
		N	47	7.12 ± 1.32	5.14 ± 1.07	0.92	-1.92	[-15.54, 11.70]
		Ov	39	5.09 ± 2.03	3.67 ± 1.23	0.92	-1.67	[-12.44, 9.10]
		Ob	91	8.42 ± 3.62	6.53 ± 3.14	0.89	1.46	[-16.37, 19.29]

3.2 Bland–Altman analysis

Tables 2 and 3 also summarize the Bland–Altman analysis, and Figure 3 presents the Bland–Altman plots for all three joints and four BMI groups (left and right combined). The Bland–Altman plots for all joints were mostly homoscedastic, confirming that the phase-averaged angular velocity model reconstructs joint angle trajectories with the greatest consistency across individual gait cycles. A consistent negative bias was observed across nearly all ankle conditions (range: -8.15° to -1.85°), indicating systematic underestimation of ankle angles except for independent cohort data with a bias of 2.28. The 95% LoA was widest for the left U ankle of the independent cohort ($[-28.48^\circ, +13.12^\circ]$) and narrowest for the right Ov ankle of the development cohort ($[-13.95^\circ, +8.13^\circ]$). For the knee, bias was near zero for most conditions (range: -3.95° to -0.32°), indicating no systematic directional error on the development cohort. But the independent cohort data shows the knee is mostly overestimated, with the largest bias on the left Ob (12.66). The 95% LoA were markedly wide (up to $[-39.52^\circ, +33.62^\circ]$ for the right Ov of the independent cohort), reflecting substantial point-wise variability. For the hip, biases were small (range: -2.82° to $+6.48^\circ$) with no consistent directional tendency for either development or independent cohort. The LoA were substantially narrower ($[-8.80^\circ, +8.28^\circ]$ to $[-17.85^\circ, +12.71^\circ]$).

Table 3. Gait metrics similarity metrics on an independent cohort

Joint	Side	BMI	n	RMSE $\pm$ SD ($^\circ$)	MAE $\pm$ SD ($^\circ$)	r	Bias ($^\circ$)	95% LoA ($^\circ$)
Ankle	Left	U	14	12.39 $\pm$ 3.01	9.23 $\pm$ 2.63	0.37	-7.68	$[-28.48, 13.12]$
		N	18	9.31 $\pm$ 1.32	6.39 $\pm$ 1.25	0.36	-4.88	$[-20.71, 10.94]$
		Ov	17	11.68 $\pm$ 3.89	9.34 $\pm$ 3.44	0.34	-8.15	$[-26.47, 10.17]$
		Ob	16	9.06 $\pm$ 1.08	7.20 $\pm$ 1.05	0.21	2.28	$[-14.96, 19.52]$
	Right	U	13	10.52 $\pm$ 4.44	7.65 $\pm$ 3.60	0.47	-5.19	$[-25.90, 15.52]$
		N	18	8.88 $\pm$ 1.90	6.44 $\pm$ 1.57	0.46	-5.15	$[-19.52, 9.23]$
		Ov	18	10.30 $\pm$ 2.15	7.99 $\pm$ 1.54	0.23	-6.52	$[-22.81, 9.76]$
		Ob	16	10.52 $\pm$ 2.10	8.54 $\pm$ 2.08	0.19	-0.34	$[-21.22, 20.55]$
Knee	Left	U	14	15.62 $\pm$ 4.85	12.55 $\pm$ 4.62	0.32	2.47	$[-28.28, 33.22]$
		N	18	14.89 $\pm$ 3.38	13.32 $\pm$ 3.27	0.40	7.89	$[-18.06, 33.84]$
		Ov	17	16.77 $\pm$ 6.46	12.19 $\pm$ 4.83	0.28	-3.98	$[-38.67, 30.71]$
		Ob	16	23.80 $\pm$ 5.39	18.90 $\pm$ 4.35	0.15	12.66	$[-27.29, 52.61]$
	Right	U	13	14.80 $\pm$ 3.10	11.14 $\pm$ 2.20	0.40	0.25	$[-28.98, 29.49]$
		N	18	16.44 $\pm$ 2.93	13.44 $\pm$ 3.18	0.40	5.36	$[-25.28, 36.00]$
		Ov	18	18.35 $\pm$ 4.20	13.73 $\pm$ 3.43	0.35	-2.95	$[-39.52, 33.62]$
		Ob	16	22.00 $\pm$ 4.37	17.48 $\pm$ 3.61	0.24	10.60	$[-27.32, 48.52]$
Hip	Left	U	14	5.18 $\pm$ 2.19	4.33 $\pm$ 1.88	0.94	-1.90	$[-11.97, 8.17]$
		N	18	5.81 $\pm$ 1.00	4.75 $\pm$ 0.93	0.91	1.03	$[-10.34, 12.41]$
		Ov	17	4.24 $\pm$ 0.90	3.21 $\pm$ 0.76	0.94	-0.26	$[-8.80, 8.28]$
		Ob	16	8.36 $\pm$ 2.14	6.66 $\pm$ 2.05	0.93	6.48	$[-5.02, 17.98]$
	Right	U	13	6.01 $\pm$ 2.48	4.95 $\pm$ 2.18	0.93	-2.82	$[-13.82, 8.18]$
		N	18	6.62 $\pm$ 1.19	5.59 $\pm$ 0.98	0.90	0.57	$[-12.67, 13.81]$
		Ov	18	5.41 $\pm$ 1.07	4.03 $\pm$ 0.86	0.90	-0.56	$[-11.35, 10.22]$
		Ob	16	7.28 $\pm$ 2.71	5.47 $\pm$ 1.96	0.82	4.53	$[-8.19, 17.24]$

3.3 Left-right limb comparison

Figure 4 presents the left–right comparison of RMSE, MAE, and Pearson r for each joint and BMI group in both cohorts. The development cohort shows that the estimation accuracy is balanced between significant and not significant, which are 6 to 6. Mostly, the ankle estimation accuracy differs significantly, such as in the U ($p = 0.046$), N ($p < 0.001$), and Ob groups ($p < 0.001$). The hip has the most similar accuracy between the right and left limb trajectories, where the Ov group has significantly better RMSE on the right side ($p < 0.05$). Meanwhile, the knee significantly differs in the U and Ov groups. The left knee is significantly better ($p < 0.001$) in the U group and is significantly worse ($p < 0.05$) in the Ov group.

Independent cohort data shows contrary behavior. Most of the accuracy is not significantly different between left and right, where 9 out of 12 has $p > 0.05$. Although it has a relatively higher RMSE than the hip joint estimation, the knee estimation keeps its inter-limb accuracy very good throughout the BMI groups. Differently, the hip of the independent cohort has a significant inter-limb accuracy difference on the N ($p < 0.05$) and Ov groups ($p < 0.01$). The estimation model does not distinguish between limb sides, where it uses the same angular velocity reference for both limbs. Therefore, natural inter-limb kinematic variation, such as the (t_1-t_4) , the initial joint angular position (θ_0), and ROM can lead to different estimation accuracy between the left and right knees. Here, the result shows that the proposed estimation model can be used for both right and left limbs, where the inter-limb estimation accuracy difference is not significant (15 out of 24) across BMI and joint.

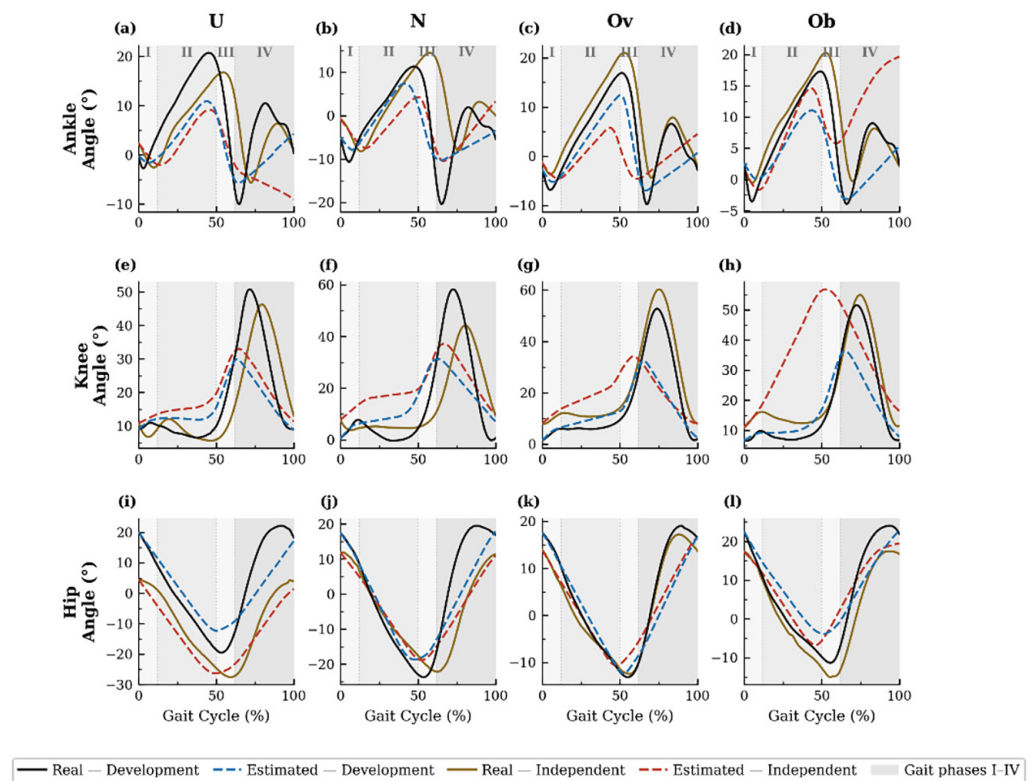


Fig. 2. Estimated trajectories over the normalized gait cycle for all six joint–side combinations across the four BMI groups

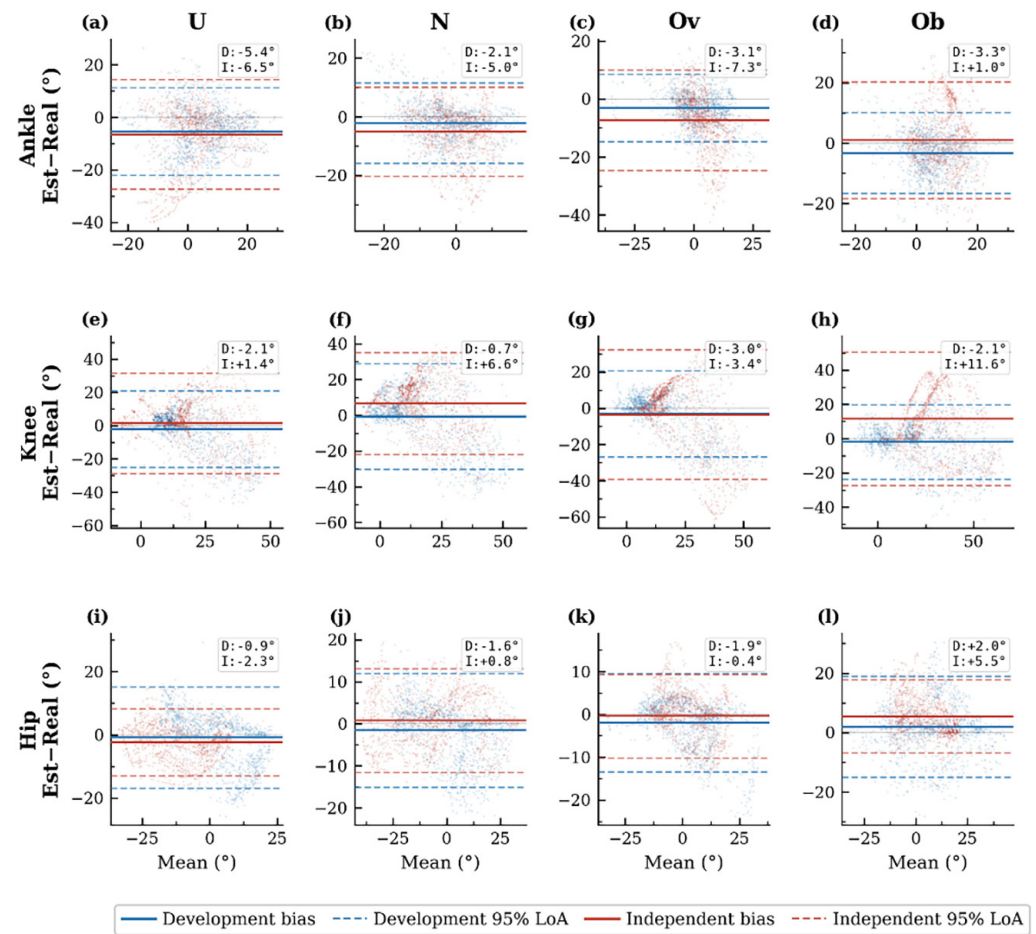


Fig. 3. Bland Altman analysis plot: estimated versus real

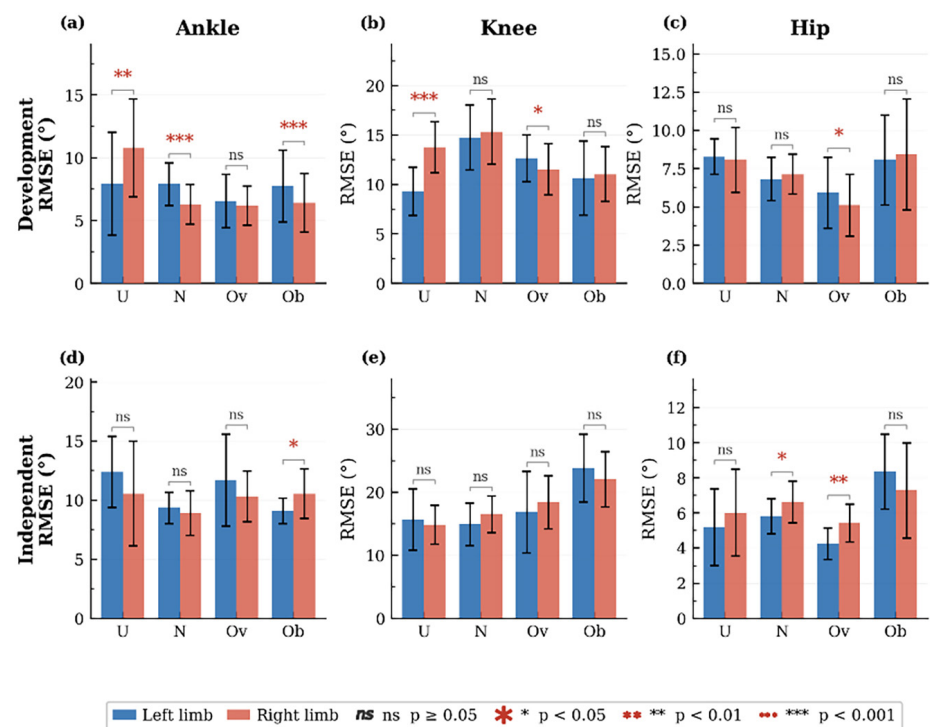


Fig. 4. Left vs. Right estimation accuracy by joint, BMI, and cohort

4 DISCUSSION

4.1 Comparison with related gait reference generation methods

The proposed framework occupies a distinct niche in the landscape of gait reference generation methods. Most existing approaches model the joint angle trajectory directly as a function of kinematic or sensor inputs. Semwal et al. [10] proposed an LSTM-CNN architecture trained on 42 healthy subjects walking at eight different treadmill speeds, achieving $R^2 > 0.90$ for hip and knee angle reconstruction. Parametric regression methods using walking speed, gender, age, and BMI as predictors have also been shown to reconstruct lower limb sagittal kinematics with errors within one standard deviation of normative waveforms across 54 participants [24]. Speed-dependent key-event regression for robotic gait support demonstrated that joint angle trajectories can be estimated from walking speed and body height alone across a wide speed range (0.5–5 km/h) [13]. A parametric 3D gait generation approach using walking speed and body height has also been demonstrated for robot-assisted rehabilitation with strong kinematic shape correspondence [12]. These methods achieve high shape fidelity but require either real-time sensor data, multi-variable anthropometric measurements, or large training datasets.

In contrast, the present framework operates from only two inputs (BMI and walking speed) and produces not a continuous waveform but a phase-averaged angular velocity integrated over the real phase duration. This fundamental difference results in a less accurate but substantially simpler model. The Pearson r values obtained here (0.15–0.94 across joints and conditions) are lower than those reported by full trajectory estimation methods [10], [24], but the comparison is not strictly equivalent: the proposed method requires no pre-session anthropometric measurement beyond BMI and no waveform-level model training. Moissenet et al. [24] reported that a mismatch in walking speed, age, sex, or BMI can introduce errors exceeding 5° in sagittal lower limb kinematics, which directly motivates the BMI-stratified personalization approach adopted here. The LSTM-based single-IMU method of Park et al. [25] achieved RMSE below 7° and $R^2 > 0.74$ for all three joints during overground walking, representing a relevant benchmark. The hip RMSE (4.24 – 8.42°) and Pearson R (0.82 – 0.94) reported in this study are comparable to or better than this benchmark. It is also better than other IMU-based kinematic estimation literature that reports hip joint correlation coefficients of 0.60 – 0.88 for overground walking [26], [27]. The NN-15 framework achieves hip pattern fidelity comparable to sensor-based methods despite requiring no real-time measurement.

The ankle has moderate agreement with RMSE values in the range of 6.17 – 12.39° for both development and independent cohorts. IMU-based methods without explicit angle waveform training report ankle RMSE in the range of 2 – 7° for level walking [26], [28], while EMG-based estimation with LSTM achieves an RMSE of approximately 9° [29]. The ankle's complex two-directional reversal pattern across the four gait phases (plantarflexion in P1, dorsiflexion in P2, plantarflexion for push-off in P3, and dorsiflexion for foot clearance in P4) places greater demands on phase-averaged velocity accuracy than the simpler hip trajectory, since the sign of the angular velocity changes between nearly every phase transition.

The knee joint has the highest error compared to other joints. The RMSE is high, ranging from 9.28° to 15.31° , yet the Pearson r (0.710 – 0.825) is moderate in the development cohort. For reference, knee angle RMSE values of 9.24° (absolute) have been reported for IMU-based PCA methods [30] and approximately 9° for EMG-based LSTM estimation [29], while a single-IMU LSTM approach achieved RMSE

below 7° and $R^2 > 0.74$ in overground walking [25]. The knee RMSE values reported here exceed these benchmarks, which is expected given that the NN-15 model uses no real-time kinematic measurement for knee reconstruction. It does even worse on the independent cohort, where the RMSE ranges from a minimum of 14.80° to 23.80° . The shape is also not preserved with a low Pearson r of 0.15–0.40. The knee RMSE values reported here exceed these benchmarks, which is expected given that the NN-15 model uses no real-time kinematic measurement for knee reconstruction.

Among robot-specific methods, the CLME approach used in some exoskeletons [14] generates trajectories from the contralateral limb but requires at least one functioning limb, making it inapplicable for bilateral impairment. The Gaussian process trajectory approach of Hong et al. [31] produces individualized trajectories from 11 anthropometric variables but imposes a high pre-session measurement burden. Compared to all these approaches, the NN-15 framework trades some accuracy for substantially lower measurement burden, where the trade-off is appropriate for a wearable rehabilitation robot in a crowded clinical setting.

4.2 Phase wise gait pattern similarity

The similarity metrics across the four gait phases are shown in Figure 5. The hip joint has the simplest motion profile and strong agreement, in other words, having the strongest gait pattern similarity across all BMI groups and limb sides. The hip also shows good generalization, where the strong agreement is also true for both development and independent cohorts. The Pearson r consistently exceeds 0.81, and the RMSE is as low as $4.24 \pm 0.90^\circ$ in the Ov group. This is directly attributable to the biomechanical simplicity of hip motion during the gait cycle. The hip undergoes a predominantly unidirectional motion pattern: extension during P1 and P2 and flexion during P3 and P4 [32], [33]. This single-reversal trajectory is highly amenable to reconstruction from phase-averaged angular velocity estimates, since the direction of motion is consistent within each phase and the transition between extension and flexion aligns naturally with the four-phase gait segmentation of the Picobot system.

The phase-wise analysis in Figure 5 confirms a consistent and monotonically increasing error pattern across all BMI groups, both development and independent cohort. P1 yielded the lowest RMSE (0.97 – 3.64° across groups) with acceptable to strong r (0.63–0.99 across groups), while P4 produced the highest RMSE (6.22 – 10.96° across groups) with high r (0.86–0.97 across groups). A notable anomaly was observed in P3 (heel off to toe off). Pearson r dropped sharply for the Ov ($r = 0.56$) and Ob ($r = 0.23$) of the development cohort. Pearson r is even worse on the independent cohort group across BMI, where the range is -0.39 to 0.09 . Negative correlations mean the model estimates different directions of angular velocity. This phase marks the onset of hip flexion, which may follow a less linear and more complex trajectory than the phase-averaged velocity model assumes. Less linearity is possible due to altered pelvis mechanics, trunk lean compensation, or reduced hip flexor power associated with higher body mass [6]. The actual trajectory changes to the positive direction may also happen at the end of P2, where the angular velocity estimation is in the negative direction; thus, explaining the negative correlation.

The ankle joint shows error patterns that varied similarly to the hip error pattern across both gait phases and BMI groups. In the development cohort, the ankle joint followed a phase-wise accuracy pattern broadly similar to that of the hip, with the estimation performing well in the early cycle and degrading toward the end. Averaged across BMI groups, Phase 1 showed the lowest error (average RMSE = 3.12°),

and the mid-cycle phases retained strong shape correspondence, with Phase 2 and Phase 3 reaching Pearson r of 0.88 and 0.86, respectively, comparable to the hip in the same cohort. As with the hip, the largest errors appeared in the terminal phases, with Phase 3 and Phase 4 RMSE rising to 9.05° and 8.42° . This indicates that, when evaluated on the same subjects used for model development, the ankle reconstruction captured the overall sagittal motion pattern with acceptable fidelity across most of the gait cycle.

However, this favorable pattern did not transfer to the independent cohort. When the model was tested on completely unseen subjects, the ankle similarity dropped sharply, particularly in the shape-based metric. Averaged across BMI groups, Phase 3, which has rapid plantarflexion push-off [12], exhibited the worst similarity of all phases, with RMSE increasing to 15.75° . Pearson r is also collapsing to -0.10 , indicating that the estimated push-off trajectory no longer followed the real motion on new individuals. Phase 1 ($r = 0.50$) and Phase 4 ($r = 0.11$) also performed poorly, mirroring the low correlations already observed in the development cohort for these phases. This is expected and biomechanically interpretable. During P4, the ankle is free from ground contact, and the dorsiflexion trajectory varies considerably across individuals in both timing and magnitude [26], making it the most challenging phase to reconstruct from a scalar phase-averaged velocity.

In contrast, Phase 2 retained an appropriate level of similarity even on unseen subjects (RMSE = 6.73° , $r = 0.864$), remaining the most reliable phase for the ankle. A likely explanation is that Phase 2 corresponds to the most stable segment of ankle motion, during which the joint moves consistently in a single direction (progressive dorsiflexion as the tibia advances over the planted foot) from the beginning to the end of the phase. This monotonic, low-variability motion is well matched to a single phase-averaged angular velocity, allowing it to generalize. Meanwhile, the more dynamic and direction-changing Phase 3 and Phase 4 estimation could not match the real trajectory well. Future iterations should consider different gait phase schemes to estimate the angular joint velocity.

The knee joint showed a different phase-wise behavior from the ankle and hip. Averaged across BMI groups in the development cohort, the error was smallest in Phase 1 (RMSE = 2.23°) and grew steadily toward the end of the cycle, reaching its maximum in Phase 4 (RMSE = 17.62°) during swing, where the knee undergoes its largest flexion. A distinctive feature appeared in Phase 2, where the Pearson r was very low ($r = 0.195$) despite a modest RMSE of 5.83° . This indicates that the knee trajectory shape was poorly captured during mid-stance, even though the absolute error remained small. The reason is that the knee stays close to full extension during Phase 2 and moves very little, so the real angular velocity is near zero. The phase-averaged velocity model assigns a small but non-zero velocity, producing a gradually drifting trajectory that does not follow the near-flat real motion, which lowers the correlation while keeping the RMSE small. Phase 3 and Phase 4 retained strong shape correspondence ($r = 0.901$ and 0.806), confirming that the model captured the direction of knee flexion even where the magnitude was underestimated.

In the independent cohort, the knee accuracy dropped across all phases. Averaged across BMI groups, Phase 4 remained the largest source of error (RMSE = 19.09°), and Phase 3 also rose sharply (RMSE = 21.37°). More importantly, the near-zero Phase 2 correlation persisted on unseen subjects ($r = -0.03$), confirming that the poor mid-stance shape agreement is not a cohort-specific artifact but a consistent limitation of the phase-averaged velocity approach for the knee. Phase 1 remained the most reliable phase (RMSE = 4.30°). Phase 3, which

had shown strong shape correspondence in the development cohort ($r = 0.901$), dropped to $r = 0.330$ on unseen subjects, indicating that the earlier high correlation did not generalize. Zhang et al. [34] similarly reported that the largest estimation error in knee exoskeleton control occurred during phases of rapid angular change, such as in P3 and P4, while error was smallest during the stable mid-distance period, consistent with the low P1 error observed here. But, since phase 2 has a near-zero correlation in both cohorts, this study recommends holding the knee at its initial position during the early stance phases rather than driving it with a velocity reference, reserving active velocity control for the later phases where the knee genuinely moves.

Overall, the similarity metrics are acceptable throughout the gait phases if the current and previous gait phases have the same directions. This is expected from the nature of the model, which reconstructs each phase from a single phase-averaged angular velocity. When the current phase keeps the same direction as the preceding one, the estimated velocity carries the correct sign and the trajectory follows the real motion, as seen in the ankle Phase 2, the knee Phase 3, and the hip Phases 1, 2, and 4, where the Pearson r remained high. But if the opposite happened, then there is a risk of inappropriate estimation, such as positive angular velocity instead of negative angular velocity, which lowers the correlation even when the absolute error stays small. This is visible in the hip Phase 3 and the ankle Phase 4, both of which follow a direction reversal. A second, related case occurs when the joint moves very little within a phase, such as the knee during Phase 2, where the joint stays near full extension. In this situation the real angular velocity is close to zero, but the model still assigns a small non-zero velocity, producing a drifting trajectory with a low correlation despite a small RMSE. These two situations: (1) direction reversal and (2) near-zero motion—account for the phases where the estimation is least reliable. In the independent cohort the same pattern held and became more pronounced, with the reversal-affected ankle Phase 3 showing the sharpest drop in correlation. This indicates that the direction of motion within and between phases, rather than the BMI group or the specific joint, is the primary factor governing the reliability of the phase-averaged velocity estimation.

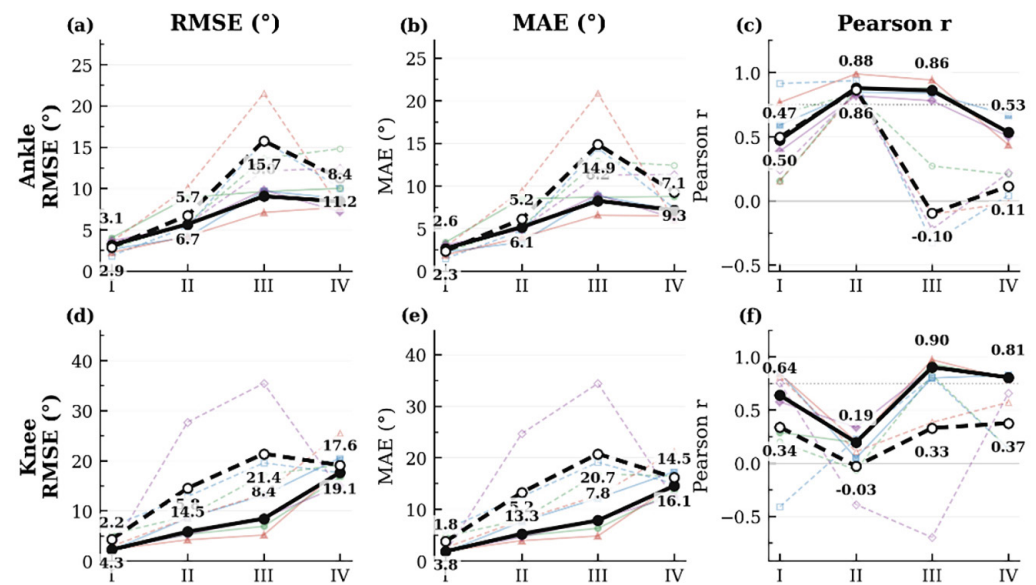


Fig. 5. (Continued)

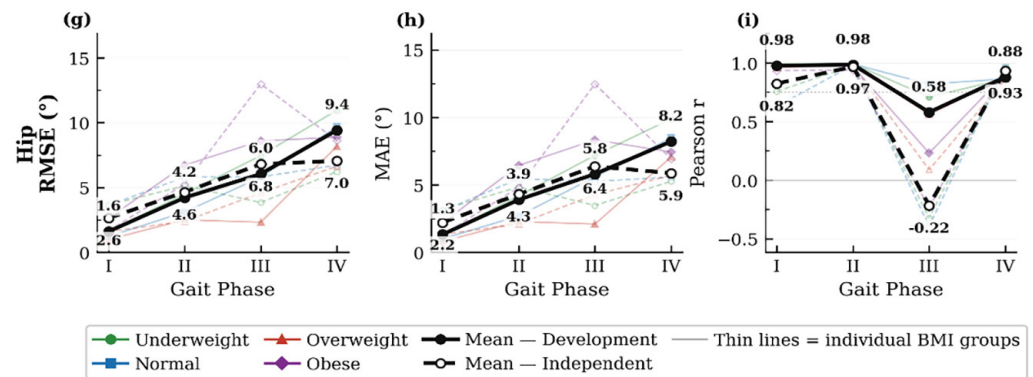


Fig. 5. Phase-wise gait pattern similarity by joint and BMI—Development vs. Independent cohort

4.3 BMI group effects and clinical relevance of personalization

The overweight group consistently achieved the best hip and ankle agreement, consistent with the lower within-group angular velocity variance found in the previous research [15]. This reflects the kinematic regularity of Ov's gait: Valeria et al. [19] demonstrated that young Ov adults show specific but consistent gait adaptations, including altered hip and knee angles, while Malek et al. [6] showed that BMI significantly influences sagittal ankle kinematics and knee dynamics. The regularity of these BMI-specific adaptations is precisely what makes BMI a valuable personalization variable, where the NN-15 model learns these systematic deviations and applies them to generate group-appropriate references. In this case, the references are joint angular velocity at certain gait phases.

This work is closely related to Moissenet et al. [24], who demonstrated using multiple regression that walking speed, gender, age, and BMI together predict lower limb sagittal kinematics with errors within one standard deviation of normative waveforms. Their finding that a mismatch in BMI alone can introduce errors exceeding 5° in sagittal kinematics directly supports the personalization rationale of this study: using a patient's own BMI as the model input, rather than a group average, reduces this mismatch error. The hip RMSE values reported here (4.24–8.42°) are in the same order as the BMI-mismatch prediction errors in [24], suggesting that the NN-15 personalization reduces but does not fully eliminate this source of error.

The U group showed the highest estimation variability, consistent with the faster and more variable gait associated with lower body mass [19]. The small U sample (two participants) further limited the model's exposure to within-group diversity. The Ob group maintained moderate but stable performance. Although obesity is associated with altered knee and ankle biomechanics, including reduced knee flexion and reduced ankle ROM [5], the Ob group's consistency within this dataset (188 gait cycles from 6 participants) suggests that the NN-15 model can represent this group reliably given sufficient training data.

4.4 Comparison of estimation accuracy between left and right limbs

By design, the NN-15 model produces a symmetrical motion reference for the left and right limbs. The model uses only body parameters, such as BMI and walking speed, as inputs. Obviously, they do not distinguish between limb sides and therefore generate an identical set of phase-averaged angular velocity references (ω_1 – ω_4).

for both limbs. As a result, the reconstructed gait trajectories for the left and right limbs are largely similar in shape, where 15/24 non-significant differences across BMI, joint, and cohort group are found. The minor differences that do arise between sides originate not from the velocity estimates themselves but from the limb-specific timing and initial conditions used during reconstruction: the measured duration of each gait phase (t_1 – t_4), the initial joint angular position (θ_0), and the joint ROM can differ slightly between the left and right limbs even within the same gait cycle. Since the joint angle is reconstructed by integrating the shared velocity over these limb-specific durations, small differences in phase duration or initial position translate into modest differences in the resulting trajectory. Consequently, the model produces more or less symmetrical gait references, with only minor side-to-side variation attributable to natural differences in gait timing between limbs.

This design characteristic is reflected in the results. The differences in estimation accuracy between the left and right limbs were not significant in many joint and BMI group combinations. Most notably, estimation accuracy at the hip was comparable across both limbs in all BMI groups. Where significant differences did appear (primarily at the ankle and knee in certain BMI groups), they cannot be attributed to the model, since the model applies the same velocity reference to both sides; rather, they reflect the natural inter-limb kinematic variation present in the real gait data, which a symmetric model is inherently unable to reproduce. Such natural left–right variation is well documented even in healthy individuals [35], [36], arising from individual strategy to accommodate functional differences between the dominant and non-dominant limbs in their contributions to support and propulsion. Because the present framework cannot account for this natural variation, future work should investigate extending the model to differentiate between the left and right limbs. For instance, introducing limb side and limb-dominance as an additional model input would be meaningful to better capture the inherent inter-limb differences. This extension would be particularly valuable for post-stroke rehabilitation, where pronounced and clinically meaningful gait asymmetry between the affected and unaffected limbs is a defining feature that a symmetric reference model cannot represent.

4.5 Implications for Picobot and clinical translation

The results collectively define a health population joint-specific deployment strategy for the NN-15 framework in Picobot. The working principle of Picobot is shown in Figure 6. The system identifies the gait phase using a force-sensing resistor beneath the insole. Picobot then moves accordingly with phase-averaged angular velocity references ($\omega_1, \omega_2, \omega_3, \omega_4$) using a BLDC motor equipped with a rotary encoder located at each joint. For instance, if the system detects the current gait phase is phase 2, then it will move the joint with the respective ω_2 . Positive and negative values correspond to the direction of the flexion. The initial joint angle is the current angle measured using the encoder in the beginning of each cycle. Gait phase durations are not measured because it is the consequence of each gait cycle detected. The joint ROM is measured before the training using the rotary encoder. Firstly, the user uses the Picobot. Then, they do positive and negative flexion as much as they can according to their own current joint ROM. This is especially useful for adjusting the gait control, which depends on patient recovery progress (an early-stage patient might have less joint ROM than a mid-stage patient). This will also capture the inter-limb capabilities where one limb might have larger ROM than the other.

Implementing the current gait pattern generator using the Picobot system should consider the error tracking performance. Previous studies report no exact tolerable threshold. Despite that, the acceptable level of error may depend on the rehabilitation phase and patient condition. Early-stage rehabilitation may tolerate slightly higher errors if the focus is on passive mobilization, while advanced stages may require greater precision for active or resistive exercises [37]. One study on upper limbs reports that tracking error below 10° is preferable [38]. Another study reports that knee flexion tracking error between 4.47° to 13.72° is acceptable depending on the assistance mode [39]. Meanwhile, the tracking error of the proposed method reaching 15° for the knee flexion, which raises a concern as it could compromise the effectiveness of rehabilitation by deviating from the intended therapeutic trajectory. Precise trajectory tracking is critical for ensuring proper joint alignment, muscle activation, and neuromotor recovery [38].

Improvement of the proposed method is urgent for future work because the proposed method only measures the joint angle and no other parameters like muscle activation or trunk stability as control feedback. For hip control, the framework can serve as a stand-alone personalized velocity reference across all BMI groups and both limbs. For ankle control, the framework provides reasonable stance-phase references but should incorporate a reduced-gain or ROM-limiting mode during P4 to account for swing-phase variability or use a different gait phase scheme. For knee control, implementing a position hold during P1 and P2 and reserving velocity-driven control for P3 and P4 would substantially reduce the largest avoidable error. These modifications constitute a hybrid control strategy: (1) position hold during near-stationary phases and (2) velocity-driven motion during active displacement phases. Hopefully the modifications will better reflect the phase-specific biomechanical role of each joint.

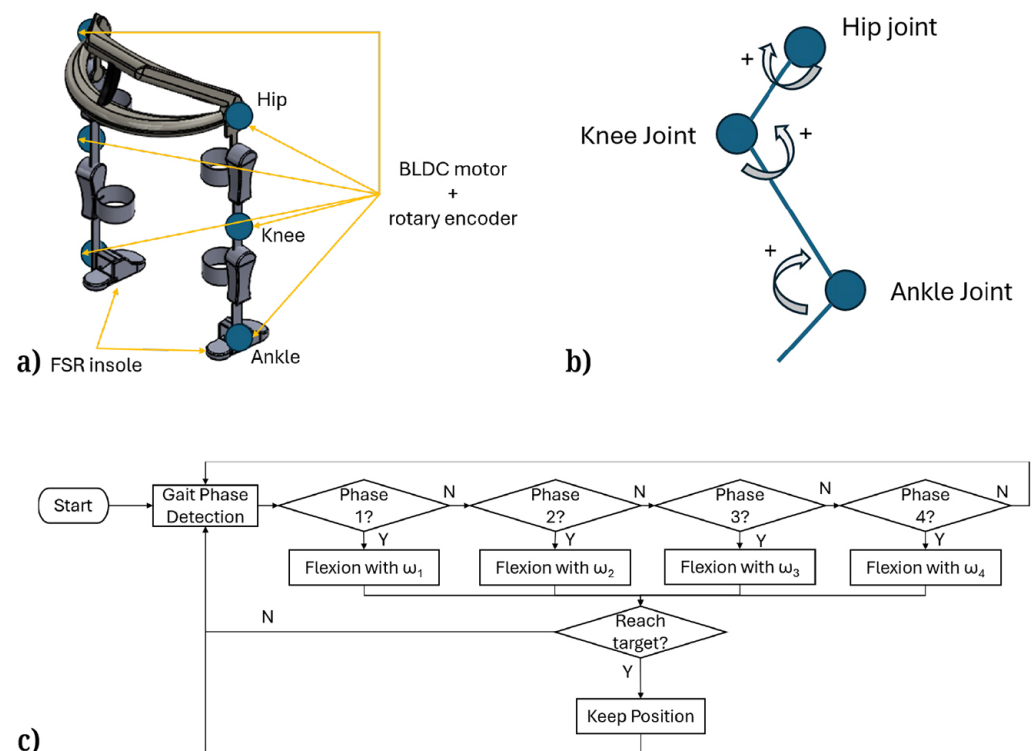


Fig. 6. Working principle of Picobot to perform gait movement for training purposes: (a) hardware setup; (b) joint flexion direction; (c) overall gait control algorithm

A key practical advantage of this framework is that it requires no pre-session anthropometric measurement beyond BMI and joint ROM. Walking speed can be estimated from IMUs already integrated in Picobot or preset for treadmill-based training [40]. This simplicity positions the framework as a strong candidate for high-throughput clinical rehabilitation settings. The BMI-based personalization addresses a documented clinical problem, which is the error introduced by applying normative gait references across diverse body compositions [24], without the complexity of full trajectory modeling. By doing this, the patient can train to follow the gait movement of the healthy population, which is represented by the phase-average joint velocity reference. Therefore, future work should make an effort in validating the impact of using the proposed method in the Picobot system for post-stroke patient recovery.

The proposed method also can facilitate patient recovery progress by calibrating the joint ROM according to the subject joint ROM capability. It is also worth noting that the proposed method tracking error is always inside the joint ROM. Meaning overextension is out of the table. Meticulous calibration of the joint ROM is important to be done before using the Picobot system with the proposed gait pattern generation method to ensure no over-extension. On the contrary, the less extension due to the tracking error given by the Picobot system might decrease the effectiveness of the training, which is a subject for future studies.

Future work should also validate the framework on post-stroke participants, evaluate performance across a range of walking speeds, and explore incorporating additional inputs (cadence, leg length) to improve ankle and knee accuracy. Real-time adaptation, for instance by using the first few strides to refine the reference based on observed kinematics via a lightweight IMU feedback loop, could progressively reduce the residual estimation error during each rehabilitation session. Updating the neural network using more health population data is also suggested in the future to refine the estimation tracking error.

4.6 Limitations

Several limitations should be considered. First, only healthy adults at preferred walking speed were tested. Applicability to post-stroke patients with pathological gait, reduced ROM, and pronounced asymmetry has not been validated. The generated references represent the target healthy trajectory for rehabilitation of the patient, but not the patient's current gait. Second, only preferred walking speed was evaluated; performance across controlled speeds remains untested. Third, real Vicon-measured phase durations were used in reconstruction to isolate the contribution of velocity accuracy; in actual Picobot deployment, phase durations are determined by real-time foot contact events and may differ from healthy adult norms, introducing additional timing errors not captured here. Additionally, the phase-wise RMSE analysis employed approximate gait cycle boundaries from standard literature [32], [33] rather than trial-specific foot contact timings, which represents a further simplification.

The measured joint trajectories in Figure 2 show a relatively large dispersion (Tables 2 and 3), even within BMI groups. This dispersion comes from the data itself, not the estimation model. Each BMI group is small (two to eight participants), so a single atypical walker widens the standard-deviation band. All trials used a self-selected preferred speed, and sagittal knee and ankle kinematics are speed-dependent [13], [41], which adds further variability. Marker placement also

introduces uncertainty at the hip and knee joint centers, where different operators might place the marker slightly differently. Time normalization to 0–100% can also introduce minor variability across trials. The same factors explain the clustered points in some Bland–Altman plots, where individual subjects appear as separate clusters due to the small group size. Larger and more homogeneous cohorts with controlled walking speeds would reduce this dispersion in future work.

5 CONCLUSION

Unlike prior studies that focus on maximizing reconstruction accuracy, this work emphasizes the trade-off between accuracy and system simplicity, which is critical for real-world deployment in wearable rehabilitation robotics. This study evaluated the gait pattern similarity between lower limb joint angle trajectories generated from a BMI- and walking-speed-based angular velocity model (NN-15) from a previous study [15] and real Vicon-measured trajectories across 424 gait cycles from a development cohort (24 subjects) and 131 gait cycles from an independent cohort of unseen 8 subjects. The hip joint achieved the strongest agreement ($r = 0.82$ – 0.94 , $RMSE = 4.24$ – 8.42°) owing to its simple unidirectional motion pattern (extension in stance, flexion in swing), while the ankle showed moderate agreement ($r = 0.19$ – 0.81 , $RMSE = 6.17$ – 12.39°) with the largest error in the swing phase due to highly variable dorsiflexion, and the knee exhibited the highest error ($r = 0.15$ – 0.83 , $RMSE = 9.28$ – 23.80°) driven by near-zero angular velocity during stance and a non-linear trajectory during swing. The Ov BMI group demonstrated the best overall performance at the hip and ankle, while the U group showed the highest variability. The Bland–Altman plots for all joints show a homoscedastic pattern, indicating consistency of the phase-averaged angular velocity model across individual gait cycles. The model was also able to serve both limbs despite producing only a single phase-averaged angular velocity per phase for both sides, as the left and right estimation accuracy did not differ significantly in most joint and BMI combinations.

Based on these findings, it is evident that the compact angular velocity NN-15 model can reproduce physiologically plausible gait patterns without complex anthropometric measurement. Also, while the NN-15 framework is recommended as a personalized hip joint reference for Picobot without modification, room for improvement is still available. Adopting a different gait phase scheme is advised for ankle control, and a position-hold strategy during Phases 1 and 2 is proposed for the knee to eliminate avoidable stance-phase error. Future work also should validate the framework on post-stroke patients, especially regarding the impact of using the Picobot system with the proposed gait control strategy. Extend evaluation across multiple walking speeds, and a more homogenous cohort is also the case for the future.

6 ACKNOWLEDGMENT

The authors express their gratitude towards the Indonesia Endowment Fund for Education Agency - National Research Innovation and Agency (LPDP - BRIN) for their support through Grant 70/IV/KS/07/2024 and Grant 223/SAM4/PPM/2024. The authors also wish to thank Summit Features Sdn. Bhd. for providing research equipment support, specifically the Vicon motion capture system.

7 REFERENCES

- [1] T. Thayabaranathan *et al.*, “Global stroke statistics 2022,” *International Journal of Stroke*, vol. 17, no. 9, pp. 946–956, 2022. <https://doi.org/10.1177/17474930221123175>
- [2] A. Kusec *et al.*, “Long-term psychological outcomes following stroke: The OX-CHRONIC study,” *BMC Neurol.*, vol. 23, no. 1, Art. no. 426, 2023. <https://doi.org/10.1186/s12883-023-03463-5>
- [3] R. Algahtani, R. Gasemaltayeb, Z. Binsiddiq, M. Almatrafi, S. Felimban, and R. Alsaud, “Therapeutic interventions for the non-motor strokes sequelae: An overview,” *Egyptian Journal of Neurology, Psychiatry and Neurosurgery*, vol. 61, no. 1, Art. no. 38, 2025. <https://doi.org/10.1186/s41983-025-00969-2>
- [4] H. Nedergård, M. Sandlund, C. K. Häger, and S. Palmcrantz, “Users’ experiences of intensive robotic-assisted gait training post-stroke—A push forward or feeling pushed around?” *Disabil. Rehabil.*, vol. 45, no. 23, pp. 3861–3868, 2023. <https://doi.org/10.1080/09638288.2022.2140848>
- [5] P. Capodaglio *et al.*, “Effect of obesity on knee and ankle biomechanics during walking,” *Sensors*, vol. 21, no. 21, Art. no. 7114, 2021. <https://doi.org/10.3390/s21217114>
- [6] M. Adouni, F. Alkhatib, R. Hajji, and T. R. Faisal, “Effects of overweight and obesity on lower limb walking characteristics from joint kinematics to muscle activations,” *Gait Posture*, vol. 113, pp. 337–344, 2024. <https://doi.org/10.1016/j.gaitpost.2024.06.024>
- [7] T. Van Crieking, W. Saeys, S. Truijen, L. Vereeck, L. H. Sloot, and A. Hallemans, “A full-body motion capture gait dataset of 138 able-bodied adults across the life span and 50 stroke survivors,” *Sci. Data*, vol. 10, no. 1, Art. no. 852, 2023. <https://doi.org/10.1038/s41597-023-02767-y>
- [8] R. Ni’mah, D. Adiputra, H. N. Fadhillah, M. A. M. Shapie, and M. H. A. Hassim, “Understanding normative gait spatio-temporal variability: A multi-factor analysis of age, gender, and BMI,” *Gait Posture*, vol. 212, pp. 4–5, 2025. <https://doi.org/10.1016/j.gaitpost.2025.07.010>
- [9] R. R. Rizkika, H. N. Fadhillah, T. Mustaqim, and R. Ni’Mah, “Development of a document-based gait system with interactive visualisation for clinical analysis,” *Jurnal RESTI*, vol. 9, no. 3, pp. 554–563, 2025. <https://doi.org/10.29207/resti.v9i3.6451>
- [10] V. B. Semwal, R. Jain, P. Maheshwari, and S. Khatwani, “Gait reference trajectory generation at different walking speeds using LSTM and CNN,” *Multimed. Tools Appl.*, vol. 82, no. 21, pp. 33401–33419, 2023. <https://doi.org/10.1007/s11042-023-14733-2>
- [11] F. Wang *et al.*, “Estimation of lower limb joint angles and joint moments during different locomotive activities using the inertial measurement units and a hybrid deep learning model,” *Sensors*, vol. 23, no. 22, Art. no. 9039, 2023. <https://doi.org/10.3390/s23229039>
- [12] D. Shi, W. Zhang, X. Ding, and L. Sun, “Parametric generation of three-dimensional gait for robot-assisted rehabilitation,” *Biol. Open*, vol. 9, no. 3, 2020. <https://doi.org/10.1242/bio.047332>
- [13] B. Koopman, E. H. F. van Asseldonk, and H. Van der Kooij, “Speed-dependent reference joint trajectory generation for robotic gait support,” *J. Biomech.*, vol. 47, no. 6, pp. 1447–1458, 2014. <https://doi.org/10.1016/j.jbiomech.2014.01.037>
- [14] H. Vallery, E. H. F. Van Asseldonk, M. Buss, and H. Van Der Kooij, “Reference trajectory generation for rehabilitation robots: Complementary limb motion estimation,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 17, no. 1, pp. 23–30, 2009. <https://doi.org/10.1109/TNSRE.2008.2008278>
- [15] D. Adiputra *et al.*, “Estimation of lower limb joint angular velocity from BMI and walking speed using regression and neural network models for personalized gait control,” *IEEE Access*, vol. 13, pp. 196247–196260, 2025. <https://doi.org/10.1109/ACCESS.2025.3633220>

- [16] D. Adiputra, M. A. A. Rahman, Ubaidillah, and S. A. Mazlan, "Improving passive ankle foot orthosis system using estimated ankle velocity reference," *IEEE Access*, vol. 8, pp. 194780–194794, 2020. <https://doi.org/10.1109/ACCESS.2020.3033852>
- [17] D. Adiputra, U. Asfari, Ubaidillah, M. A. Abdul Rahman, and A. M. Harun, "Immediate effect evaluation of a robotic ankle–foot orthosis with customized algorithm for a foot drop patient: A quantitative and qualitative case report," *Int. J. Environ. Res. Public Health*, vol. 20, no. 4, Art. no. 3745, 2023. <https://doi.org/10.3390/ijerph20043745>
- [18] D. Kim, C. L. Lewis, and S. V. Gill, "Effects of obesity and foot arch height on gait mechanics: A cross-sectional study," *PLoS One*, vol. 16, no. 11, Art. no. e0260398, 2021. <https://doi.org/10.1371/journal.pone.0260398>
- [19] V. Rosso, V. Agostini, R. Takeda, S. Tadano, and L. Gastaldi, "Influence of BMI on gait characteristics of young adults: 3D evaluation using inertial sensors," *Sensors (Switzerland)*, vol. 19, no. 19, Art. no. 4221, 2019. <https://doi.org/10.3390/s19194221>
- [20] S. L. Molitor, K. E. Zelik, and K. A. McDonald, "Lower-limb dominance does not explain subject-specific foot kinematic asymmetries observed during walking and running," *J. Biomech.*, vol. 162, Art. no. 111877, 2024. <https://doi.org/10.1016/j.jbiomech.2023.111877>
- [21] L. Vismara *et al.*, "Brain asymmetry and its effects on gait strategies in hemiplegic patients: New rehabilitative conceptions," *Brain Sci.*, vol. 12, no. 6, Art. no. 798, 2022. <https://doi.org/10.3390/brainsci12060798>
- [22] L. Mobbs, V. Fernando, R. D. Fonseka, P. Natarajan, M. Maharaj, and R. J. Mobbs, "Normative database of spatiotemporal gait metrics across age groups: An observational case–control study," *Sensors*, vol. 25, no. 2, Art. no. 581, 2025. <https://doi.org/10.3390/s25020581>
- [23] P. Griffiths and T. Murrells, "Reliability assessment and approaches to determining agreement between measurements: Classic methods paper," *International Journal of Nursing Studies*, vol. 47, no. 8, pp. 937–938, 2010. <https://doi.org/10.1016/j.ijnurstu.2010.03.004>
- [24] F. Moissenet, F. Leboeuf, and S. Armand, "Lower limb sagittal gait kinematics can be predicted based on walking speed, gender, age and BMI," *Sci. Rep.*, vol. 9, no. 1, Art. no. 9510, 2019. <https://doi.org/10.1038/s41598-019-45397-4>
- [25] J. Sung *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*, vol. 22, no. 1, Art. no. 53, 2022. <https://doi.org/10.3390/s22010053>
- [26] J. Lebleu, T. Gosseye, C. Detrembleur, P. Mahaudens, O. Cartiaux, and M. Penta, "Lower limb kinematics using inertial sensors during locomotion: Accuracy and reproducibility of joint angle calculations with different sensor-to-segment calibrations," *Sensors*, vol. 20, no. 3, Art. no. 715, 2020. <https://doi.org/10.3390/s20030715>
- [27] M. Al Borno *et al.*, "OpenSense: An open-source toolbox for inertial-measurement-unit-based measurement of lower extremity kinematics over long durations," *J. Neuroeng. Rehabil.*, vol. 19, no. 1, Art. no. 22, 2022. <https://doi.org/10.1186/s12984-022-01001-x>
- [28] C. Jiang, Y. Yang, H. Mao, D. Yang, and W. Wang, "Effects of dynamic IMU-to-segment misalignment error on 3-DOF Knee angle estimation in walking and running," *Sensors*, vol. 22, no. 22, Art. no. 9009, 2022. <https://doi.org/10.3390/s22229009>
- [29] X. Ma, Y. Liu, Q. Song, and C. Wang, "Continuous estimation of knee joint angle based on surface electromyography using a long short-term memory neural network and time-advanced feature," *Sensors*, vol. 20, no. 17, pp. 1–18, 2020. <https://doi.org/10.3390/s20174966>
- [30] T. McGrath, R. Fineman, and L. Stirling, "An auto-calibrating knee flexion-extension axis estimator using principal component analysis with inertial sensors," *Sensors (Switzerland)*, vol. 18, no. 6, Art. no. 1882, 2018. <https://doi.org/10.3390/s18061882>

- [31] J. Hong, C. Chun, S. J. Kim, and F. C. Park, "Gaussian process trajectory learning and synthesis of individualized gait motions," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 6, pp. 1236–1245, 2019. <https://doi.org/10.1109/TNSRE.2019.2914095>
- [32] R. Baker, *Measuring Walking: A Handbook of Clinical Gait Analysis*. London: Mac Keith Press, 2013.
- [33] M. Patil, M. S. Kulkarni, A. Sinha, and R. R. Ghorpade, "Studies on biomechanics of human ankle joint, joint forces foot pressure assessment during gait," *Trends Biomater. Artif. Organs*, vol. 38, no. 3, pp. 153–158, 2024. <https://doi.org/10.5281/zenodo.14826276>
- [34] Z. Zhang, X. Cai, M. Zhang, W. Chen, Y. Chen, and P. Wang, "Real-time gait intention recognition for active control of unilateral knee exoskeleton," *Appl. Bionics Biomech.*, vol. 2024, no. 1, Art. no. 9426782, 2024. <https://doi.org/10.1155/2024/9426782>
- [35] P. G. Arauz *et al.*, "Spine and lower body symmetry during treadmill walking in healthy individuals—In-vivo 3-dimensional kinematic analysis," *PLoS One*, vol. 17, no. 10, Art. no. e0275174, 2022. <https://doi.org/10.1371/journal.pone.0275174>
- [36] E. Bergamini, A. Cereatti, and G. Pavei, "Walking symmetry is speed and index dependent," *Sci. Rep.*, vol. 14, no. 1, Art. no. 19548, 2024. <https://doi.org/10.1038/s41598-024-69461-w>
- [37] E. Barquín-Santos *et al.*, "Early implementation of MAK robotic device in total knee arthroplasty rehabilitation: A proof-of-concept study," *Physiotherapy Research International*, vol. 29, no. 4, Art. no. e2134, 2024. <https://doi.org/10.1002/pri.2134>
- [38] A. Goncalves, H. Mendonca, M. F. Silva, and C. D. Rocha, "Design and control of an electro-mechanical human-robotic manipulator's interface for upper-limb rehabilitation," *IEEE Access*, vol. 14, pp. 59142–59157, 2026. <https://doi.org/10.1109/ACCESS.2026.3684722>
- [39] D. Mosconi, Y. Moreno, and A. Siqueira, "Exploring human–exoskeleton interaction dynamics: An in-depth analysis of knee flexion–extension performance across varied robot assistance–resistance configurations," *Sensors*, vol. 24, no. 8, Art. no. 2645, 2024. <https://doi.org/10.3390/s24082645>
- [40] S. Byun, H. J. Lee, J. W. Han, J. S. Kim, E. Choi, and K. W. Kim, "Walking-speed estimation using a single inertial measurement unit for the older adults," *PLoS ONE*, vol. 14, no. 12, Art. no. e0227075, 2019. <https://doi.org/10.1371/journal.pone.0227075>
- [41] Y. Liu, H. An, H. Ma, and Q. Wei, "Online walking speed estimation based on gait phase and kinematic model for intelligent lower-limb prosthesis," *Applied Sciences (Switzerland)*, vol. 13, no. 3, Art. no. 1893, 2023. <https://doi.org/10.3390/app13031893>

8 AUTHORS

Dimas Adiputra is an Assistant Professor at the Electrical Engineering Department, Telkom University Surabaya, Indonesia. He is also affiliated with the Center of Excellence for Motion Technology for Safety Health and Wellness, Telkom University, Surabaya, Indonesia. His research interests are in control engineering applications for a gait robot (E-mail: dimasze@telkomuniversity.ac.id).

Helisyah Nur Fadhillah is a Lecturer at the Mathematics Department, Institut Teknologi Sepuluh Nopember. She is also affiliated with the Center of Excellence for Motion Technology for Safety Health and Wellness, Telkom University, Surabaya, Indonesia. Her research focuses on decentralized control systems, data assimilation, and smart system applications (E-mail: helisyah.fadhillah@its.ac.id).

Rifdatun Ni'mah is a Lecturer at the Data Science Department, Telkom University Surabaya, Indonesia. She is also affiliated with the Center of Excellence for Motion Technology for Safety Health and Wellness, Telkom University, Surabaya, Indonesia. Her academic interests are rooted in mathematical modeling, data analysis, and applied sciences (E-mail: rifdatun@telkomuniversity.ac.id).

Kadek Heri Sanjaya is a researcher at the Research Centre for Smart Mechatronics, National Research and Innovation Agency (BRIN) of Indonesia. His research interests cover the intersection of industrial design, human factors, biomechanics, and physiology (E-mail: kade001@brin.go.id).

Kok Swee Sim is currently a Professor with the Faculty of Engineering and Technology, Multimedia University, Malaysia. He was a recipient of the TM Kristal Award and multiple World Summit on the Information Society (WSIS) Prizes, in 2017–2021 (E-mail: sksbg2022@gmail.com).

Nur Khozin is a specialist in Physical Medicine and Rehabilitation and a faculty member at the Faculty of Medicine, Universitas Negeri Surabaya, Indonesia (E-mail: nurkhozin@unesa.ac.id).