

Article

An Analytical Model of Inertial Gait Parameters for the Development of Robotic Exoskeletons for Lower-Limb Rehabilitation

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Abstract

Robotic lower-limb exoskeletons are an increasingly important tool in the rehabilitation of patients with motor impairments, and their effectiveness depends on how faithfully the device reproduces the natural gait pattern. Inertial measurement units (IMUs) are widely used to acquire body-worn kinematic data for gait monitoring, but compact, interpretable models linking IMU-derived hip- and knee-flexion features to gait phase under exoskeleton-assisted conditions are still lacking. We collected gait data from two independent experiments: Experiment 1, 20 healthy adults (10 M, 10 F; 22.2 ± 1.9 years) walking freely on level ground, stairs and a ramp with seven Noraxon IMUs; and Experiment 2, six healthy adults (4 M, 2 F; 31.0 ± 8.9 years) walking with and without the Exowalk (HR-02) over-ground exoskeleton with five IMUs. Eight bilateral hip- and knee-flexion features were extracted, and a binary logistic-regression model with stance/swing as the dependent variable was fitted on Experiment 1 and externally cross-validated on Experiment 2. The model classified gait phases with an accuracy of 90.83% (sensitivity 87.50%, specificity 92.50%, positive predictive value 85.37%) on Experiment 1. External validation retained 91.7% accuracy during free walking but dropped to 41.7% under Exowalk-assisted walking, indicating that the device alters the inertial signature of gait. The findings identify swing-phase hip flexion and the minimum swing-phase knee flexion as the kinematic descriptors most predictive of gait phase, and provide quantitative design and control targets for next-generation IMU-instrumented lower-limb rehabilitation exoskeletons.

Keywords: lower-limb exoskeleton; inertial measurement unit; gait analysis; logistic regression; rehabilitation robotics; wearable sensing; hip flexion; knee flexion; machine learning

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1. Introduction

Motor impairment resulting from musculoskeletal injury, stroke, traumatic brain injury, multiple sclerosis or Parkinson's disease compromises independent ambulation and imposes a substantial burden on patients, caregivers and health-care systems [1,2]. Restoring the ability to walk is therefore a central goal of neurorehabilitation. Among the tools that have emerged over the past two decades, lower-limb exoskeletons occupy a

particularly prominent place: they provide repeatable, task-specific gait training, reduce the physical effort required of therapists, and can extend functional walking time both in the clinic and in the community [3–6].

Modern lower-limb exoskeletons are generally classified into treadmill-based, walking-plate and overground systems [2,4]. Regardless of architecture, the device must reproduce the patient's intended gait pattern while remaining safe, lightweight and energetically efficient. Achieving this trade-off requires accurate quantitative knowledge of the kinematic and kinetic parameters that characterise human walking, in particular at the hip and knee joints, which contribute the largest share of mechanical work during overground locomotion [7,8]. Several groups have demonstrated that exoskeletons that explicitly couple hip and knee assistance can reduce metabolic cost by 4% to 50%, depending on architecture, control strategy and population [8–10]. Hip-only and knee-only designs, while simpler, are often unable to reproduce the full kinematic envelope of natural gait, particularly in patients with severe lower-limb impairment [11,12].

Inertial measurement units (IMUs) have become the de facto standard for ambulatory gait monitoring because of their portability, low cost and ability to record joint angles, angular velocities and segment orientations outside of laboratory settings [13,14]. A wide range of analytical approaches has been applied to IMU data to recognise gait phase, intended movement and walking environment, ranging from threshold-based heuristics to deep neural networks [15–21]. Logistic regression remains attractive in this context because it produces an interpretable, parsimonious model in which the weight assigned to each kinematic feature can be directly inspected by the device designer, in contrast with the typically opaque mappings learnt by deeper architectures [22,23].

Despite this rich literature, two gaps remain. First, most analytical models reported to date are validated on a single dataset that is, by construction, similar to the training data; their robustness to a change in walking condition is rarely tested. Second, the explicit identification of the inertial features that drive gait-phase classification—and that should therefore be prioritised in exoskeleton design—is seldom reported. The present study addresses both gaps. We develop a binary logistic-regression model that classifies stance and swing phases from a small set of hip- and knee-flexion features extracted from IMU signals, and we externally cross-validate that model on a second, independently acquired dataset comprising both free walking and Exowalk-assisted walking. The objective is two-fold: (i) to quantify the extent to which a model trained on natural gait generalises to exoskeleton-assisted gait, and (ii) to identify the kinematic descriptors with the greatest classification weight, which can serve as design targets for next-generation lower-limb rehabilitation exoskeletons. The contribution of this work is therefore not the introduction of a new classifier, logistic regression is deliberately chosen for its transparency, but the explicit, quantitative identification of which hip- and knee-flexion descriptors carry the greatest discriminative weight and by how much. Although the directional observation that an exoskeleton alters natural gait is itself well established, the present study converts that qualitative expectation into interpretable, numerically weighted kinematic targets that a black-box model cannot expose, and demonstrates the magnitude of the resulting performance loss under a controlled within-subject comparison.

2. Materials and Methods

2.1. Human Gait and the Gait Cycle

Human gait is a cyclic motor task defined by alternating periods of foot contact with and clearance from the ground. A single gait cycle is conventionally bounded by two successive heel strikes of the same foot and is partitioned into a stance phase (approximately 60% of the cycle) and a swing phase (approximately 40%) [13,24,25]. Stance is itself subdivided into heel strike, loading response, mid-stance, terminal stance and pre-swing, while

swing comprises toe-off, mid-swing and terminal swing (Figure 1). In patients with motor impairment, the temporal and spatial parameters of this cycle—step length, step width, cadence and walking speed—are typically altered, and a major objective of rehabilitation is to restore the cycle to a pattern as close as possible to that of unimpaired walking.

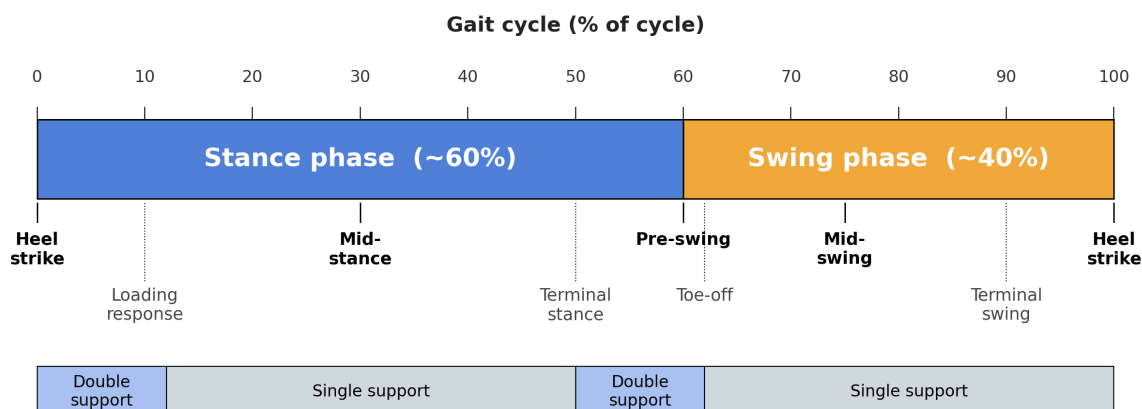


Figure 1. Schematic representation of the normal human gait cycle, partitioned into a stance phase (~60% of the cycle) and a swing phase (~40%). The eight sub-phases (heel strike, loading response, mid-stance, terminal stance, pre-swing, toe-off, mid-swing and terminal swing) and the alternation between double- and single-support intervals are indicated.

2.2. Inertial-Sensor-Based Gait Recognition

Gait-recognition performance depends primarily on the quality of the features extracted from the raw IMU signals. Threshold-based methods are simple to implement but tend to lack generality, while machine-learning models can capture more complex relationships at the cost of interpretability [16–21]. Table 1 summarises representative IMU-based gait-recognition methods reported in recent years; classification accuracies typically range between 92% and 99%, but the comparison across studies is hampered by differences in protocol, sensor placement and walking conditions.

Table 1. Representative inertial-sensor-based gait-recognition methods reported in the literature.

Algorithm	Sensor Type	Wearable	Processing	Task	Accuracy	Ref.
Hidden Markov model	IMU	Yes	Post hoc	Phase recognition	91.88%	[16]
Exponentially-delayed FCNN	IMU + FSR	Yes	Post hoc	Phase recognition	97.9 ± 0.1%	[17]
Deep convolutional NN	IMU	Yes	Post hoc	Phase recognition	97%	[18]
Gaussian mixture model	IMU	Yes	Post hoc	Behaviour recognition	95.75–99.33%	[19]
Individualised gait-pattern generation	Motion-capture	Yes	Real-time	Behaviour recognition	>97%	[20]

2.3. Lower-Limb Exoskeleton Design Considerations

Exoskeletons can be broadly divided into passive and active devices [6,26]. Passive systems store and release elastic or potential energy to redirect the user's own muscle effort and cannot inject net mechanical work, which limits their use during tasks that raise the body's centre of mass. Active devices contain motorised actuators and can therefore provide concentric work, at the cost of increased mass, complexity and energy requirements. A typical lower-limb exoskeleton comprises four functional subsystems: actuators, a perception system, a control system and a load-bearing mechanical structure [2,27]. Electric DC motors are most commonly used because they are quieter and easier to control than pneumatic or hydraulic actuators, although their power-to-mass ratio is comparatively low [28]. The perception system includes kinematic sensors (typically IMUs and electronic goniometers), kinetic sensors (strain gauges, piezoelectric force transducers) and optionally electromyo-

graphic or electroencephalographic sensors that provide direct measurements of muscle or neural activity [14]. Mechanical structures must be light yet sturdy and must follow the anatomical alignment of the segments they assist, to avoid joint misalignment that would otherwise reduce comfort and elicit compensatory movements [29].

2.4. Experiment 1—Free Walking Without an Exoskeleton

2.4.1. Participants

Twenty healthy adults (10 men, 10 women; mean age 22.2 ± 1.9 years) with no self-reported neurological or musculoskeletal disorder participated in Experiment 1. All participants provided written informed consent before data collection.

2.4.2. Instrumentation

Gait was recorded with seven Noraxon Ultium Motion IMUs (Noraxon USA Inc., Scottsdale, AZ, USA), each combining a tri-axial accelerometer (range ± 16 g) and a tri-axial gyroscope (range $\pm 2000^\circ/\text{s}$) sampled at 200 Hz. Sensors were attached to the pelvis, both thighs, both shanks and both feet using the manufacturer's elastic straps following the placement scheme shown in Figure 2a. Joint angles were reconstructed in real time by the Noraxon MyoMotion software, (MR3) which uses a sensor-fusion algorithm to estimate segment orientations in a Cartesian reference frame and to derive lower-limb joint angles, including hip and knee flexion/extension. Stance and swing phases were obtained from gait events, initial foot contact (heel strike) and toe-off, detected automatically by the Noraxon MyoMotion gait-analysis module, which identifies these events from the foot- and shank-mounted IMUs. The interval from heel strike to the subsequent toe-off of the same limb was labelled stance, and the interval from toe-off to the following heel strike was labelled swing. These software-derived gait events, rather than the logistic-regression model itself, defined the phase boundaries used as the ground-truth labels; the model was never used to determine the phase windows from which its own predictors were computed.

2.4.3. Protocol

Each participant performed three over-ground walking tasks at a self-selected speed: (i) level walking on a 10-m straight corridor, (ii) stair ascent and descent on a five-step staircase, and (iii) ascent and descent of an open ramp. The tasks were performed in random order with two-minute rests between tasks to minimise fatigue. The diversity of the walking conditions was intentional, as it provided a wider range of hip and knee kinematics and thus a more demanding validation set for the proposed model.

2.5. Experiment 2—Walking with and Without the Exowalk Exoskeleton

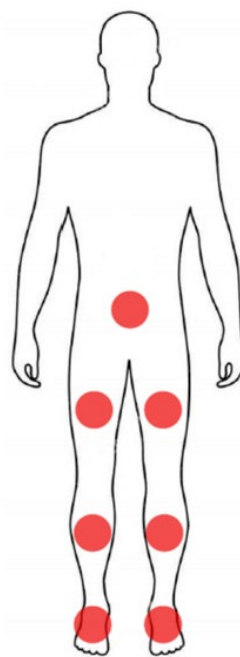
2.5.1. Participants

Six healthy adults (4 men, 2 women; mean age 31.0 ± 8.9 years) with no self-reported neurological or musculoskeletal disorder participated in Experiment 2. All participants provided written informed consent.

2.5.2. Instrumentation

Walking with the exoskeleton was performed with the Exowalk (HR-02, HMM Co. Ltd., Daejeon, Republic of Korea), a robotic over-ground gait-training device of dimensions $1180 \times 980 \times 1350$ mm and a mass of 230 kg (Figure 2b). The Exowalk drives the user's lower limbs through pre-programmed sagittal-plane trajectories using a pair of electric motors at the hip and knee; walking speed and step length can be adjusted in software. Five Noraxon Ultium Motion IMUs (pelvis, both thighs and both shanks) were used to record the participants' kinematics during walking with and without the exoskel-

eton; the foot sensors of the seven-sensor configuration of Experiment 1 were omitted because the participants' feet were strapped to the Exowalk footplates. The MyoMotion processing pipeline was identical to that used in Experiment 1. Because the foot sensors were unavailable in this five-IMU configuration, gait events for Experiment 2 were derived from the sagittal-plane angular-velocity profile of the shank segments, a standard and well-validated alternative for delineating stance and swing when foot-mounted sensors are absent. The same event definitions (heel strike to toe-off as stance; toe-off to the next heel strike as swing) were applied in both the with- and without-exoskeleton trials, so that any change in classification performance between the two conditions cannot be attributed to a change in the labelling procedure.



(a)



(b)

Figure 2. Experimental setup. (a) IMU sensor placement used in Experiment 1: seven Noraxon Ul-tium IMUs were attached to the pelvis, both thighs, both shanks and both feet. For Experiment 2 a reduced five-IMU configuration was used (foot sensors omitted because the participants' feet were strapped to the Exowalk footplates). (b) Representative view of a participant walking with the Exowalk (HR-02) robotic over-ground exoskeleton during Experiment 2.

2.5.3. Protocol

Each participant completed two 50-m straight-line walking trials. In the first trial the participant walked at a self-selected speed without the exoskeleton; in the second trial the participant walked the same distance while strapped into the Exowalk. The order of the two trials was counterbalanced between participants. A two-minute seated rest was provided between trials. Throughout each trial, the five IMUs recorded the participants' lower-limb kinematics and the resulting signals were visualised in the Noraxon (MR 4.2026.2) software for quality control.

2.6. Feature Extraction

From each gait cycle, eight statistical features were computed bilaterally from the hip- and knee-flexion angle traces. It is important to note that the stance- and swing-phase windows over which these descriptors are evaluated were fixed beforehand by the inde-

pendent gait-event detection described in Section 2.4.2, not by the classifier. Quantities such as the mean swing-phase hip flexion are therefore summary statistics of a phase window whose boundaries are already known from the heel-strike/toe-off events; they are not derived from the model output, so no circularity is introduced. The logistic-regression model then learns how strongly each such descriptor distinguishes a stance window from a swing window, which is what makes the descriptor weights interpretable as design targets. The eight features are:

1. range of hip flexion during the swing phase (range_swing_hip_flexion);
2. mean hip flexion during the stance phase (mean_stance_hip_flexion);
3. mean hip flexion during the swing phase (mean_swing_hip_flexion);
4. minimum knee flexion during the swing phase (min_swing_knee_flexion);
5. minimum knee flexion over the entire cycle (min_total_knee_flexion);
6. range of knee flexion during the stance phase (range_stance_knee_flexion);
7. mean knee flexion during the stance phase (mean_stance_knee_flexion);
8. mean knee flexion during the swing phase (mean_swing_knee_flexion).

Suffixes _LT and _RT denote left- and right-leg features, respectively. The eight features describe the amplitude and central tendency of the hip and knee angle during the two main sub-phases of the gait cycle and have been associated with rehabilitation outcomes in previous work [15,16,22]. Figure 3 illustrates the extraction of the hip-flexion swing-phase trace from one participant in Experiment 1.

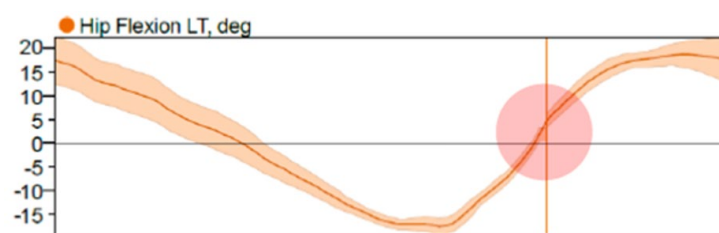


Figure 3. Example hip-flexion trace (degrees) recorded by an IMU during a single gait cycle of a representative participant in Experiment 1. The shaded region marks the swing phase from which the swing-phase features (range, mean and minimum hip flexion) are extracted.

2.7. Logistic-Regression Model and Validation

A binary logistic-regression model was fitted to the Experiment 1 dataset. The dependent variable was the gait phase, coded as 0 for stance and 1 for swing. The candidate independent variables comprised the sixteen bilateral predictors obtained by computing each of the eight hip- and knee-flexion features for both the left and the right leg. A backward stepwise procedure based on the Wald statistic was used to remove predictors that did not contribute significantly, so that the final model retained the eight predictors reported in Equation (6). This selection explains why eight, rather than sixteen, terms appear in the fitted equation. The model returns the log-odds of swing versus stance, y , as a linear combination of the features:

$$y = \beta_0 + \sum_i \beta_i x_i, \quad (1)$$

with the probability of swing given by the logistic transform $P(\text{swing} | x) = 1/(1 + \exp(-y))$. The model was fitted using the maximum-likelihood algorithm implemented in IBM SPSS Statistics v.27 (IBM Corp., Armonk, NY, USA). Goodness of model fit was assessed by the Cox & Snell and Nagelkerke pseudo- R^2 statistics [17–19]. Classification performance was characterised by accuracy (A), sensitivity (S_n), specificity (S_p) and positive predictive value (PPV):

$$A = (TP + TN)/(TP + TN + FP + FN), \quad (2)$$

$$S_n = TP/(TP + FN), \quad (3)$$

$$S_p = TN/(TN + FP), \quad (4)$$

$$PPV = TP/(TP + FP), \quad (5)$$

where TP, TN, FP and FN denote, respectively, the numbers of true-positive, true-negative, false-positive and false-negative classifications, with swing taken as the positive class. The model fitted to the Experiment 1 dataset was then applied without retraining to the Experiment 2 dataset to obtain a participant-wise external cross-validation. Per-participant accuracy was computed separately for stance and swing and for the two walking conditions (with and without the Exowalk). In the model-development stage, one sample corresponds to a single gait-phase observation, the feature vector of one stance interval or one swing interval, obtained for a given participant performing a specific walking task with a given leg; samples were pooled across the twenty participants and the three walking tasks, yielding the 120 observations (80 stance and 40 swing) summarised in Table 2. It should further be emphasised that, in Experiment 2, the same six participants instrumented with the identical five-IMU configuration were tested both with and without the exoskeleton. This paired, within-subject design means that the contrast between the two Experiment 2 conditions isolates the effect of the device itself, because sensor count, participant group and recording protocol are held constant across the comparison. The cross-experiment transfer from Experiment 1 (seven IMUs) is used only to establish the model, not to attribute the performance change to the device. The full analysis workflow is summarised in Figure 4.

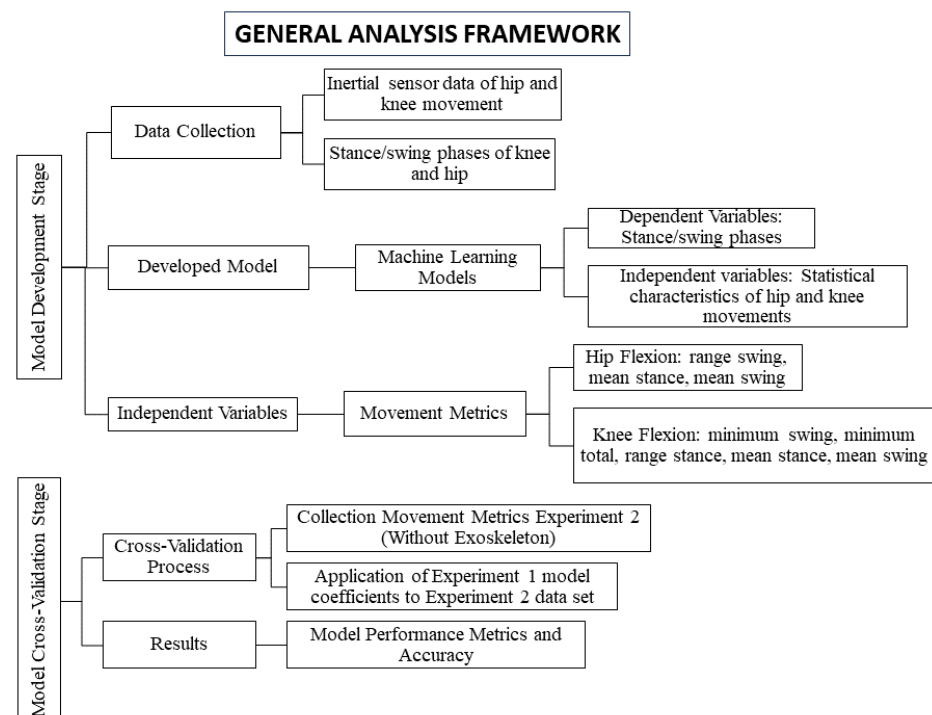


Figure 4. Schematic workflow of the analysis. In the model-development stage, statistical descriptors of hip- and knee-flexion are extracted from IMU recordings of Experiment 1 and used as independent variables in a binary logistic-regression model whose dependent variable is gait phase (stance/swing). In the cross-validation stage, the resulting model coefficients are applied to the Experiment 2 dataset without retraining and the classification accuracy is evaluated per participant and per condition (with vs. without exoskeleton).

Table 2. Classification (confusion) matrix produced by the logistic-regression model on the Experiment 1 dataset. Each sample is a single gait-phase observation (the feature vector of one stance or one swing interval) for a given participant, walking task and leg, pooled across the twenty participants and three tasks (80 stance and 40 swing observations, 120 in total).

		Predicted Stance (0)	Predicted Swing (1)	Total
Observed	Stance (0)	74	6	80
	Swing (1)	5	35	40
Total		79	41	120

3. Results

3.1. Model Development on the Experiment 1 Dataset

All eight hip- and knee-flexion features contributed significantly to the fitted model. These eight predictors are the ones retained by the backward stepwise selection from the sixteen bilateral candidates. The remaining eight candidates did not reach significance and were dropped, which is why Equation (6) contains eight rather than sixteen terms (seven left-leg terms and one right-leg term). The resulting log-odds equation is given in Equation (6):

$$y = -7.357 - 0.398 \cdot \text{range_swing_hip_flexion_LT} - 0.967 \cdot \text{mean_stance_hip_flexion_LT} + 1.075 \cdot \text{mean_swing_hip_flexion_LT} + 2.063 \cdot \text{min_swing_knee_flexion_LT} + 1.794 \cdot \text{min_total_knee_flexion_LT} - 0.193 \cdot \text{range_stance_knee_flexion_LT} - 0.375 \cdot \text{mean_stance_knee_flexion_LT} + 0.447 \cdot \text{mean_swing_knee_flexion_RT}, \quad (6)$$

Confusion-matrix statistics on the Experiment 1 dataset are reported in Table 2. The model correctly classified 74 of 80 stance samples and 35 of 40 swing samples, giving an overall accuracy of 90.83%. Sensitivity, specificity and positive predictive value, defined relative to the swing class, were 87.50%, 92.50% and 85.37%, respectively (Table 3). Goodness of fit was Cox & Snell $R^2 = 0.59$ and Nagelkerke $R^2 = 0.82$, indicating that the eight inertial features jointly explain a large fraction of the variance in gait-phase membership [30–32].

Table 3. Performance metrics of the logistic-regression model on the Experiment 1 dataset.

Metric	Value (%)
Sensitivity (S_n)	87.50
Specificity (S_p)	92.50
Positive predictive value (PPV)	85.37
Accuracy (A)	90.83

3.2. External Cross-Validation on the Experiment 2 Dataset

Applying the model derived from Experiment 1 to the independent Experiment 2 dataset revealed a strongly condition-dependent performance (Table 4). For walking without the exoskeleton, the model classified the stance phase (P1) correctly for all six participants (100%) and the swing phase (P2) for five of six participants (83.3%), giving a pooled accuracy of 91.7% across the twelve phase observations, in close agreement with the within-experiment performance reported above. For walking with the Exowalk, accuracy dropped sharply: the stance phase was correct for only three of six participants (50.0%) and the swing phase for only two of six (33.3%), a pooled accuracy of 41.7%. The single figures of 91.7% and 41.7% are therefore pooled (overall) values computed across both phases and all six participants, not phase-specific accuracies; the per-phase results are listed separately in Table 4 to avoid the impression that the same value holds for each phase individually. This contrast indicates that the kinematic signature of human gait, as captured by hip- and knee-flexion features, is preserved when participants change envi-

ronment or walking task but is markedly altered when their lower limbs are coupled to an exoskeletal frame.

Table 4. Per-participant cross-validation of the logistic-regression model on the Experiment 2 dataset. “O” denotes a correct prediction; “X” a misclassification. P1: stance phase; P2: swing phase. “Phase accuracy” is the percentage of the six participants classified correctly within that phase and condition; “Pooled accuracy” is the overall percentage across both phases (twelve observations) for that condition, and is therefore identical under the P1 and P2 columns. The pooled values (41.7% with the Exowalk; 91.7% without) are condition-level averages and do not hold separately for each phase, the per-phase values being 50.0% (stance) and 33.3% (swing) with the device and 100% (stance) and 83.3% (swing) without it.

Participant	With Exo-skeleton—P1	With Exo-skeleton—P2	Without Exo-skeleton—P1	Without Exo-skeleton—P2
1	X	X	O	O
2	O	O	O	X
3	O	X	O	O
4	O	O	O	O
5	X	X	O	O
6	X	X	O	O
Phase accuracy (%)	50.0	33.3	100.0	83.3
Pooled accuracy (%)	41.7	41.7	91.7	91.7

3.3. Comparison with Other Machine-Learning Approaches

Figure 5 contrasts the accuracy achieved by the proposed model in its initial (Experiment 1) and cross-validated (Experiment 2, with exoskeleton) configurations with two reference machine-learning approaches previously applied to similar problems: the support-vector machine for pressure-sensor-based gait recognition reported by Peng et al. (90.2%) [33] and the linear-discriminant-analysis model of Chen et al. for prosthesis-intent classification (99%) [34]. The performance of the proposed model on natural gait is comparable to the support-vector-machine reference, while the substantial drop observed in the exoskeleton-assisted condition is consistent with the broader observation that classifiers trained on natural-gait data tend to generalise poorly to exoskeleton-assisted walking unless device-specific features are incorporated [11,23]. This comparison is qualitative rather than quantitative: the reference studies used different sensing modalities (plantar-pressure sensors and a multi-sensor fusion system), different datasets, different locomotion tasks and different classification objectives, and their accuracies were therefore not obtained on a common benchmark. The values in Figure 5 should accordingly be read as indicative context, not as a like-for-like ranking of the methods; a fair quantitative comparison would require re-implementing each method on the present dataset, which is identified as a direction for future work.

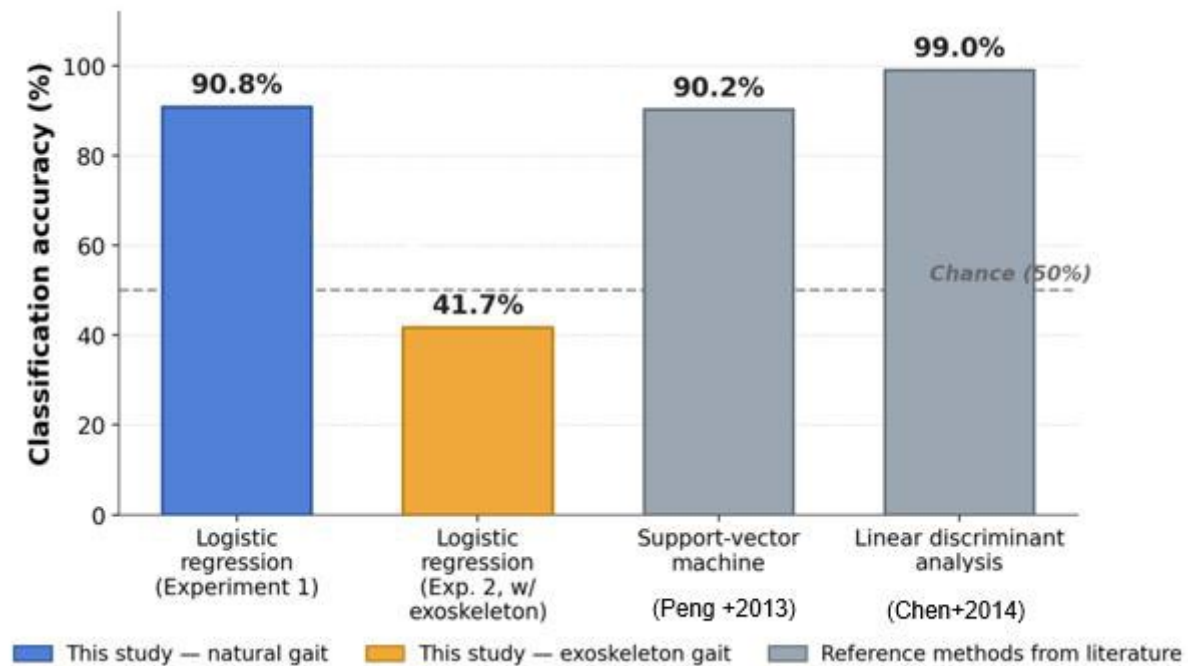


Figure 5. Comparison of classification accuracies of the proposed logistic-regression model on the Experiment 1 (initial) and Experiment 2 (cross-validated, with exoskeleton) datasets against reference machine-learning approaches from the literature: support-vector machine [33] and linear discriminant analysis [34].

4. Discussion

4.1. Interpretation of the Model

Logistic regression yielded an interpretable, parsimonious model that classified stance and swing phases of natural gait with an accuracy of 90.83%, sensitivity of 87.50% and specificity of 92.50% on the Experiment 1 dataset. The Cox & Snell and Nagelkerke pseudo- R^2 values (0.59 and 0.82, respectively) lie well above the conventional thresholds for an acceptable model fit (0.30 and 0.35) [17–19], suggesting that the eight inertial features jointly capture a large share of the variance associated with the stance-to-swing transition. Inspection of the regression coefficients (Equation (6)) reveals that the three features with the largest positive weights are the minimum swing-phase knee flexion of the left leg ($\beta = 2.063$), the minimum total knee flexion of the left leg ($\beta = 1.794$) and the mean swing-phase hip flexion of the left leg ($\beta = 1.075$). The two features with the largest negative weights are the mean stance-phase hip flexion of the left leg ($\beta = -0.967$) and the mean stance-phase knee flexion of the left leg ($\beta = -0.375$). The opposite signs of the stance and swing terms reflect the well-established kinematic pattern in which the knee and hip flex more strongly during swing and more weakly during stance [24]. Importantly, these results identify a small set of bilateral hip- and knee-flexion features that should be prioritised as design and control targets in the development of lower-limb rehabilitation exoskeletons.

4.2. Generalisation to Exoskeleton-Assisted Walking

The most striking finding of the external cross-validation is the contrast between the high accuracy obtained for free walking in Experiment 2 (91.7%) and the marked drop observed when the same participants walked with the Exowalk (41.7%). Because the participants and feature-extraction pipeline were identical across the two conditions, this contrast can be attributed to the kinematic constraints imposed by the device. The Exowalk drives the lower limbs through a pre-programmed sagittal-plane trajectory whose hip- and knee-flexion profiles differ in amplitude, timing and inter-limb coupling from those

of natural gait. As a result, the inertial signatures used by the model are no longer in correspondence with the underlying stance/swing transitions, and classification performance approaches chance level. Several specific mechanisms can be identified for this failure. First, the Exowalk imposes a fixed cadence and a reduced, machine-defined range of knee flexion during swing, so the descriptors that carry the largest weight in Equation (6), the minimum swing-phase knee flexion and the swing-phase hip-flexion amplitude, are compressed toward the values the model associates with stance, driving systematic misclassification. Second, strapping the feet to the footplates suppresses the natural heel-strike and push-off dynamics and therefore the inter-limb timing on which the model implicitly relies. Third, the device enforces a more symmetric and stereotyped inter-limb coupling than free walking, removing the leg-to-leg variability that the bilateral predictors encode. Because the same participants and the identical five-IMU configuration were used with and without the device, these device-induced effects, rather than a change in sensor count, cohort or labelling, are the most plausible explanation for the drop. A residual contribution of the differing walking task (a 50-m straight line in Experiment 2 versus level, stair and ramp walking in Experiment 1) and of the smaller sensor set relative to Experiment 1 cannot be entirely excluded, and is addressed among the limitations below. This observation is in line with recent work showing that controllers tuned on natural-gait data must be re-calibrated when applied to assistive devices, particularly when those devices substantially modify the user's kinematics [23,35,36]. In practical terms, the result implies that analytical models intended to support exoskeleton design or control should either include device-specific covariates—such as actuator torque or joint trajectory—or be retrained on data acquired during exoskeleton use.

4.3. Implications for Exoskeleton Design

Previous work has repeatedly shown that the hip and knee joints together account for the majority of mechanical work generated during over-ground locomotion and that exoskeleton designs that provide coordinated assistance at both joints can reduce metabolic cost by 4% to 50%, depending on population and task [8–10,37]. Hip-only exoskeletons have been shown to improve walking economy in individuals with above-knee amputation [38] and to increase walking distance, reduce sedentary time and enhance gait stability in community-dwelling older adults [39,40]. Hip-knee coupling mechanisms can save more than 20% of the metabolic energy required for walking [11], and dedicated controllers for hip-knee robotic gait training have been developed for both clinical and laboratory environments [41,42]. Powered hip and knee assistance can reduce muscle activation at the hip and ankle during walking [43,44], while passive knee orthoses with active impedance control are particularly beneficial for individuals with spasticity, where damping rather than active actuation is the primary design objective [45,46]. Adaptive control schemes based on neural networks have further been proposed for knee orthoses to improve flexion–extension assistance [47]. From a mechanical perspective, anatomy-aware designs such as the biological-geometry-based knee exoskeleton of Wang et al. [48] and the self-aligning AssistOn-Knee of Celebi et al. [49] illustrate the importance of matching the device's kinematic axes to those of the underlying joint. Model-based assistive-strategy simulations confirm that careful coupling between human and exoskeleton joints is critical for restoring physiological gait [50]. The present study extends these design-oriented findings by quantifying which specific hip- and knee-flexion features carry the strongest classification weight, and therefore which kinematic parameters most need to be reproduced by the device. The findings recommend that priority be given to the swing-phase amplitude of hip flexion and to the swing-phase and overall minima of knee flexion, both of which are typically reduced in patients with motor impairment and which the device's control law should restore.

4.4. Comparison with Related Modelling Approaches

The 90.83% accuracy obtained on natural gait is consistent with the $90.2 \pm 3.8\%$ reported by Cene and Balbinot for logistic-regression-based EMG classification of upper-limb movement [22] and with the support-vector-machine and linear-discriminant-analysis benchmarks of Peng et al. [33] and Chen et al. [34]. More recent deep-learning models can exceed 95% accuracy on similar tasks (Table 1), but they require substantially larger training datasets, are computationally more expensive and, perhaps more importantly, do not return interpretable feature weights. In the context of exoskeleton design—where the model's purpose is not only to classify but also to indicate which kinematic targets the device should pursue—logistic regression therefore offers a favourable trade-off between accuracy and interpretability. It should be acknowledged, however, that the present study does not itself implement and evaluate modern deep-learning baselines such as CNN-based or LSTM-based gait classifiers on the same dataset; the comparison with those approaches is drawn from the literature rather than from a head-to-head experiment on the present data. The deliberately simple model was selected because the goal here is the interpretable identification of design-relevant kinematic features rather than the maximisation of raw classification accuracy, a goal for which a transparent, low-variance estimator is better suited than a high-capacity black-box network trained on only a modest dataset. A direct benchmarking of the proposed model against CNN and LSTM architectures on the present data nonetheless remains an important step and is included in the future-work agenda.

4.5. Limitations

Several limitations should be acknowledged. First, the cross-validation cohort comprised only six participants; the relatively small sample size reflects the time and labour cost of acquiring exoskeleton-assisted gait data in a hospital setting, but it limits the statistical power of the per-participant analysis. Second, only neurologically and musculoskeletally unimpaired adults were recruited, which means that the Exowalk was operated outside its target clinical population. Confirmation of the present findings in patients with stroke, spinal cord injury or other motor impairments is needed before clinical translation. Third, the model relies on a binary stance/swing labelling and on eight pre-selected hip and knee-flexion features; finer phase partitioning and the inclusion of additional kinematic, kinetic or electromyographic features could further improve generalisation to the exoskeleton-assisted condition. Fourth, the validation deliberately transfers a model trained on the seven-IMU Experiment 1 to the five-IMU Experiment 2, and the two experiments also differ in walking task and participant group; the cross-experiment portion of the analysis is therefore subject to domain shift, and it is the paired within-subject with-versus-without-exoskeleton comparison in Experiment 2, rather than the cross-experiment transfer, that provides the cleanest evidence of the device effect. Fifth, the approach uses a conventional logistic-regression classifier and does not, in itself, constitute a methodological advance in classifier design; its value lies in interpretability and in the explicit quantification of design-relevant features, and the absence of a direct, same-dataset benchmark against deep-learning models means that any claim of a practical advantage in raw accuracy remains to be established.

4.6. Future Work

Future research should pursue three directions. (i) Expand the cross-validation cohort, particularly to include patients with neurological or orthopaedic lower-limb impairment and a wider range of exoskeleton designs, including soft exosuits [10] and hip-knee coupled architectures [11]. (ii) Augment the feature set with covariates that explicitly describe the device—such as actuator torque, joint trajectory and assistance level—so that the model can recover its classification performance during exoskeleton-assisted walking.

(iii) Replace the linear logistic-regression model with non-linear machine-learning models (random forests, support-vector machines with non-linear kernels, recurrent or transformer-based deep networks) while preserving interpretability via post-hoc explanation techniques. In particular, convolutional and recurrent gait-classification networks should be implemented and evaluated on the present dataset, so that the proposed interpretable model can be benchmarked against them under identical data, sensor and labelling conditions. Such extensions would move the present analytical framework from a proof-of-concept tool toward a practical aid for the design and individualised tuning of next-generation lower-limb rehabilitation exoskeletons.

5. Conclusions

A binary logistic-regression model based on eight bilateral hip- and knee-flexion features extracted from IMU recordings classified the stance and swing phases of natural gait with an accuracy of 90.83%, a sensitivity of 87.50% and a specificity of 92.50%. External cross-validation on a second, independently acquired dataset confirmed an accuracy of 91.7% during free walking but revealed a substantial drop to 41.7% when participants walked with the Exowalk robotic exoskeleton. The findings indicate that (i) hip- and knee-flexion features extracted from IMU data are reliable descriptors of gait-phase transitions during natural locomotion; (ii) swing-phase hip-flexion amplitude and the minimum knee-flexion angle should be prioritised as design and control targets in lower-limb rehabilitation exoskeletons; and (iii) analytical models intended to support exoskeleton design or control must explicitly account for the kinematic constraints imposed by the device. Beyond their immediate contribution to exoskeleton design, the proposed features and modelling framework can be transferred to other movement-disorder applications and to the development of wearable inertial-sensor systems for ambulatory gait monitoring.

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Abbreviations

The following abbreviations are used in this manuscript:

Abbreviation	Definition
CNN	Convolutional neural network
EEG	Electroencephalography
EMG	Electromyography
FN	False negative
FP	False positive
FSR	Force-sensitive resistor
HMM	Hidden Markov model

IMU	Inertial measurement unit
LDA	Linear discriminant analysis
LR	Logistic regression
ML	Machine learning
PPV	Positive predictive value
SVM	Support-vector machine
TN	True negative
TP	True positive

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