

Article

Preliminary Exploration of a Gait Alteration Index to Detect Abnormal Walking Through a RGB-D Camera and Human Pose Estimation

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Abstract

Quantitative gait analysis is essential for assessing motor function, as altered walking patterns are linked to functional decline and increased fall risk. Although recent advances in markerless motion analysis and human pose estimation enable gait feature extraction from low-cost video systems compared to expensive motion analysis laboratories, clinical translation remains limited by fragmented descriptors or approaches that directly regress clinical scores, often reducing interpretability and generalizability. We propose the Gait Alteration Index (GAI), an interpretable index that quantifies gait abnormality as a functional deviation from typical walking patterns, independently of specific pathologies. The GAI is computed from a small set of gait parameters and integrates three complementary domains: spatio-temporal characteristics, surrogates of dynamic stability, and arm swing behaviour, providing both a global index and domain-specific sub-indices. Preliminary evaluation on a heterogeneous cohort using clinician-derived assessments showed that the GAI captures clinically meaningful gait alterations (Spearman’s $\rho = 0.65$), with the strongest agreement for spatio-temporal features ($\rho = 0.77$). These results suggest that the GAI is a promising low-cost, and interpretable tool for objective gait assessment, screening, and longitudinal monitoring.

Keywords: human pose estimation; gait; Parkinson’s disease; post-stroke; Azure Kinect; machine learning; gait index



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1. Introduction

Gait alterations are prevalent across a wide spectrum of conditions and represent a growing clinical concern in aging societies [1]. Neurological disorders, including both chronic neurodegenerative diseases and acute events such as stroke, are among the most common causes of persistent gait impairment [2]. These alterations have a direct impact on daily functioning and quality of life, particularly in older adults [3]. In this specific group, deviations from typical walking patterns are also frequently observed prior to formal neurological diagnosis, as subclinical motor changes may precede functional decline [4,5].

From a clinical perspective, gait is characterized through a combination of spatio-temporal parameters, balance-related observations, and qualitative evaluation of upper- and lower-limb coordination [6–8]. Integrating these heterogeneous cues into a single judgment of gait quality is inherently subjective and often expressed through coarse ordinal scales, which provide limited resolution [7]. As a result, mild or early-stage gait alterations may not be reliably captured, despite their relevance for fall risk and functional decline [6].

Recent advances in computer vision and markerless human pose estimation (HPE) have enabled the extraction of gait features from RGB or RGB-D videos in unconstrained environments, fostering automatic estimation of clinical gait scores [9]. In Parkinson's disease, several studies have used pose-based representations to regress ordinal clinical scores such as the MDS-UPDRS gait item, reporting moderate agreement with clinician ratings [10–12]. Large-scale benchmarks, such as the recently released CARE-PD [13], further showed that performance strongly depends on the training domain and typically drops in cross-dataset evaluations, while intermediate severity levels remain poorly separated [14]. In addition, the discrete nature of clinical scores constrains resolution and provides limited insight into which specific gait components are altered, reducing interpretability and clinical transparency [15]. While markerless motion analysis addresses scalable data acquisition, it leaves open the question of how gait information should be summarized in a clinically meaningful and generalizable manner. Several gait indices have been proposed, typically relying on laboratory-grade motion capture systems and often tailored to specific pathologies or populations [16]. Well-established indices such as the Gait Deviation Index (GDI) [17] and the Gait Profile Score (GPS) [18] still require marker-based technologies and primarily focus on lower-limb joint kinematics, neglecting relevant aspects such as arm swing and dynamic stability. These limitations, together with cost and infrastructure requirements, restrict applicability in preventive, home-based, and telemedicine-oriented settings. There is therefore a practical need for an index that can be computed from a limited number of interpretable gait parameters, is compatible with low-cost markerless acquisition technologies, and reflects gait abnormality as a functional deviation rather than a disease-specific label.

In this work, we introduce and preliminarily validate the Gait Alteration Index (GAI), a pathology-agnostic measure designed to quantify deviations from typical walking patterns using a compact set of gait parameters extracted from straight-path walking acquired with an RGB-D camera system (Azure Kinect), previously developed within the REHOME project [19]. The GAI integrates information from three complementary domains—spatio-temporal characteristics of lower-limb motion, surrogates of dynamic stability, and arm swing kinematics, providing both an overall index and domain-specific sub-indices. The methodological approach combines markerless 3D skeletal tracking, supervised feature selection, and a geometric formulation based on class centroids to define a bounded and interpretable index. This study is thus designed to answer the following questions in relation to GAI:

- Can gait abnormality be quantified as a continuous functional deviation from typical walking using low-cost markerless RGB-D acquisition?
- Does the proposed index align with clinician-derived gait assessments across heterogeneous populations?

To address these research questions, the rest of the manuscript is organised as follows. Section 2 describes the acquisition system and datasets, the extracted gait parameters, and the feature selection and centroid-based formulation used to define the GAI. Section 3 reports the experimental results and the preliminary validation against clinician-derived assessments. Section 4 discusses the implications of the findings, the interpretability of

the global index and sub-indices, and the limitations of the current evaluation. Section 5 concludes the paper by summarizing the overall work and future directions of research.

2. Materials and Methods

The schematic representation in Figure 1 outlines the key stages of the study. The retrospective datasets employed are described in Section 2.1, along with a brief overview of the dataset creation process. In Phase 1 of the study, (Section 2.2), an optimal subset of features was identified from the AGAIT-SIM dataset using filter-based feature selection methods and a Support Vector Machine (SVM) model. In Phase 2 (Section 2.3), the selected features from Phase 1 were used to design the GAI, which was then evaluated on a dataset of gait profiles (TEST-GAIT) that includes non-pathological (NP) individuals, PD patients, and post-stroke (PS) subjects.

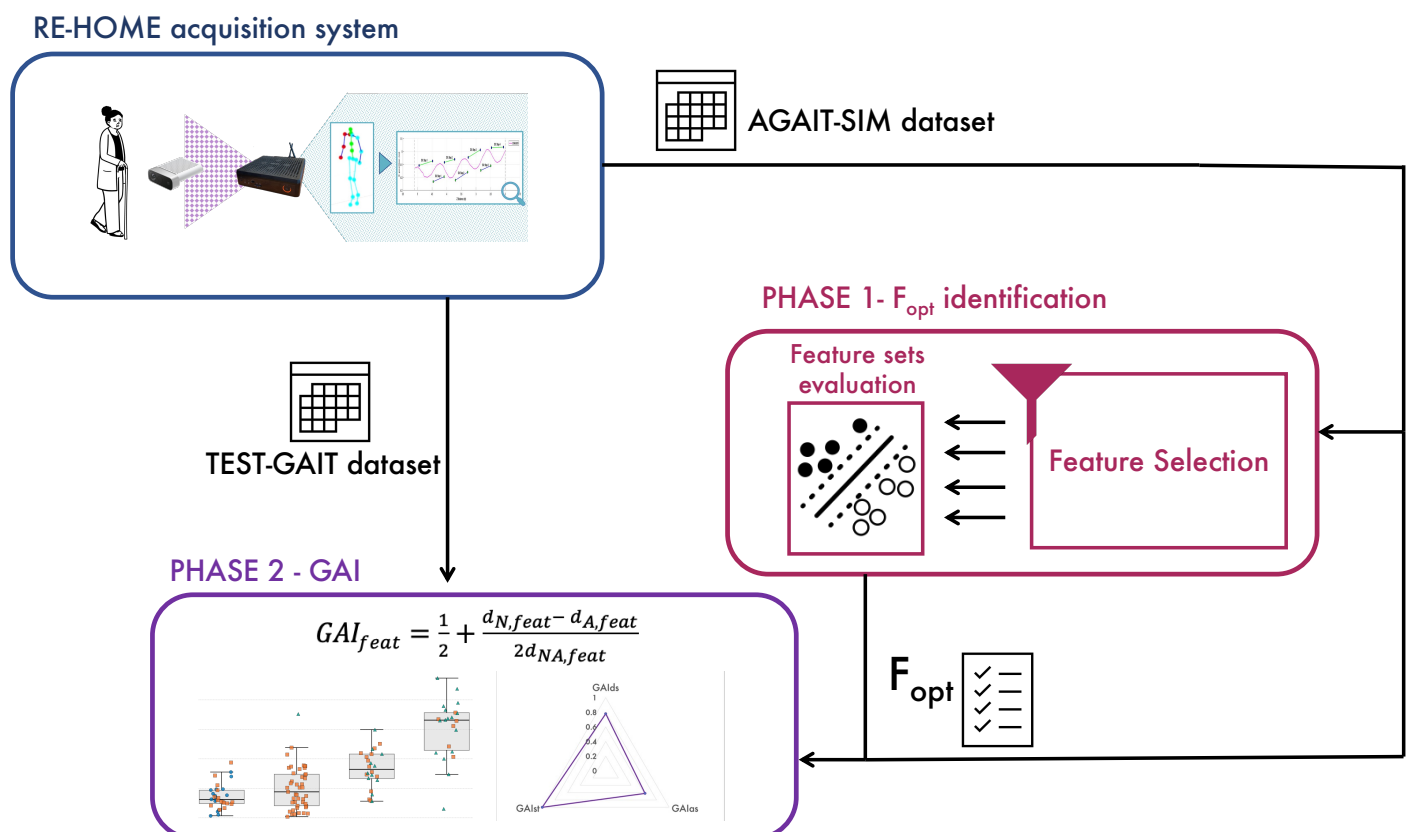


Figure 1. Summary of the study: using the acquisition system proposed for the RE-HOME project, the two datasets employed in this study were collected. In Phase 1 of this study, the optimal gait features for defining the Gait Alteration Index (GAI) are selected using the AGAIT-SIM dataset. In Phase 2, the index is preliminary validated on normal and real pathological walking profiles included in the TEST-GAIT dataset.

2.1. Gait Datasets

This study uses two datasets of gait profiles collected using the acquisition and analysis video system developed for the REHOME project [19]. The acquisition system was based on a single RGB-D sensor (Microsoft Azure Kinect, Microsoft, Redmond, WA, USA) and its proprietary 3D motion tracking algorithm. The collected 3D skeletal models were processed offline using custom scripts written in Matlab R2022b to extract the gait features reported in Tables 1 and 2. These parameters include measures of lower limb mobility, arm swing ability, and dynamic sway of the center of mass during gait. For further information about the feature extraction procedure, refer to the description reported in [20], as the same methodology was replicated in this work.

The first dataset (AGAIT-SIM) includes gait profiles from ten healthy volunteers (average age: 50.2 ± 15.8 ; age range: 45–66; five males and five females) that performed three gait trials characterized by normal and simulations of altered gait patterns [21]. Specifically, normal pace walking sessions (NPS), low-speed and short-step walking sessions (RPS), and dangling walking sessions (DPS) were considered to simulate altered walking patterns typical in elderly and pathological subjects with gait disorders, such as parkinsonian and PS individuals with hemiplegia. For each session, three walking trials were included. According to the acquisition protocol, each subject started 5 m away and walked toward the RGB-D sensor along a straight path. In this way, the subject entered the tracking region, approximately from 4.5 m to 2 m from the RGB-D sensor, fully operational, allowing the correct detection of each step and the estimation of gait parameters. The final AGAIT-SIM dataset contains 30 NPS, 26 RPS, and 28 DPS.

Table 1. Spatiotemporal and Center of Mass (COM) parameters related to gait analysis in this work.

Parameter	Meaning	Unit
$STEP_{LEN}$	Step length ¹	m
$STEP_{WIDTH}$	Step width ¹	m
$STEP_{VEL}$	Step velocity ¹	m/s
$STEP_{TIME}$	Duration of step ¹	s
$STRIDE_{LEN}$	Length of gait cycle ¹	m
$DOUBLE_{SUPP}$	Duration of double support ¹	% of gait cycle
$STANCE_{DUR}$	Duration of stance phase ¹	% of gait cycle
$GAIT_{VEL}$	Gait velocity	m/s
CADENCE	Gait cadence	steps/min
ML_{SWAY}	Mediolateral sway of COM	mm
V_{SWAY}	Vertical sway of COM	mm

¹ Computed separately for left and right legs and then averaged.

The second dataset (TEST-GAIT) contains gait sessions acquired using the proposed system at the Division of Neurology and Neurorehabilitation of San Giuseppe Hospital (Istituto Auxologico Italiano, Piancavallo, Verbania, Italy) and in the facilities of a local patients' association (Associazione Amici Parkinsoniani Piemonte Onlus). The data were collected in an experimental session approved in advance by the local ethics committee according to the Declaration of Helsinki (1964) and its amendments. This dataset contains 79 PD, 28 PS and 16 NP walking trials for a total of 123 samples. The inclusion criteria for PS subjects were: ability to walk 10 m without the assistance of another person or aids, ability to understand the instructions for performing the gait analysis test. The inclusion criteria for PD subjects were: tremor severity ≤ 1 , H&Y score in 1–3 range. The exclusion criteria for both groups were: cognitive impairment with Mini-Mental State Examination (MMSE) $< 27/30$, previous neurosurgical procedures, history of other neurological or musculoskeletal disorders unrelated to stroke and PD. The exclusion criteria did not include age, sex, side dominance, or therapy. NP subjects were recruited among caregivers and clinical personnel of the hospital and the patients' association, excluding subjects with a clinical diagnosis of pathological gait or a history of injuries that may impact gait profiles. This dataset shows different types and degrees of alteration, across two distinct pathological conditions affecting gait. This choice reflects the goal for GAI to measure generic gait alterations rather than disease-specific information. This means that gait alterations could be identified by the GAI also in NP subjects and, for instance, not in parkinsonian subjects whose gait is not yet severely impaired by the disease.

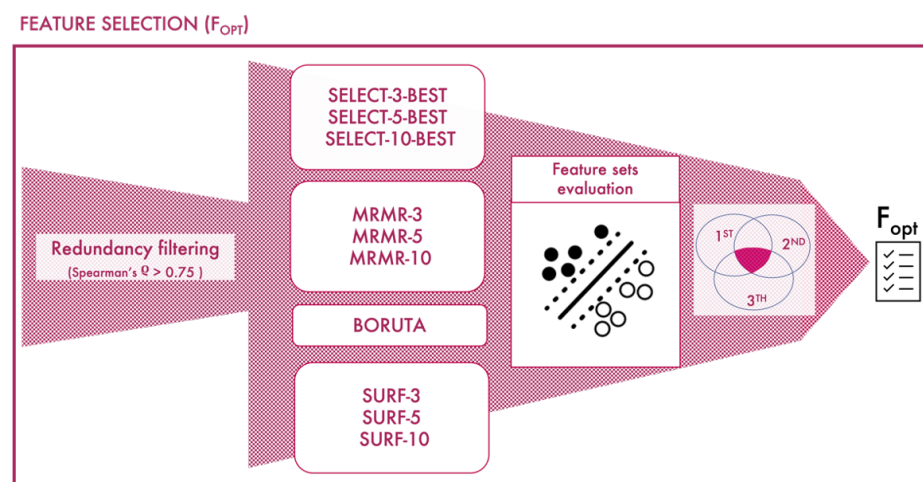
Table 2. Arm swing parameters computed in this work. AP: Antero-posterior, UD: Up-Down, ML: Medio-lateral.

Parameter	Meaning	Unit
$SWAY_ANT_{AP,UD,ML}$	Anterior max arm sway ^{1,2} in AP, UD, ML directions	mm
$SWAY_POS_{AP,UD,ML}$	Posterior max arm sway in AP, UD, ML directions ^{1,2}	mm
$SWAY_RANGE_{AP,UD,ML}$	Range of arm sway in AP, UD, ML directions ^{1,2}	mm
$PATH_{TOT}$	Total distance swung by arm ²	mm
$SWAY_{AREA}$	Area of arm movement (AP–ML) ²	mm ²
$SPEED_{AP}$	Maximum speed on AP ² direction	mm/s
$ANGLE_{ANT}$	Max anterior angle ²	deg
$ANGLE_{POS}$	Max posterior angle ²	deg
$ANGLE_{RANGE}$	Range of arm angle ²	deg
ASA_{ANGLE}	Asymmetry of arm swing angles in anterior direction between arms	%
ASA_{PATH}	Asymmetry of distance swung by arms	%
$ASA_{AP-RANGE}$	Asymmetry of in swing range between arms	%
$SI_{ARM-LEG}$	Synchrony index [20] of arm and opposite leg ²	–
SI_{ARMS}	Synchrony index [20] of arms	–

¹ On AP, ML, and UD directions. ² Computed separately for left and right arm and then averaged.

2.2. Phase 1: Selection of the Optimal Features

The selection of optimal markers of gait alterations was conducted to identify a reduced set of significant gait features. The procedure encompassed several steps, as illustrated in Figure 2: redundancy filtering using correlation; evaluation of several filter-based feature selection approaches; finally the intersection of the best performing candidate sets, to generate the optimal set $\mathcal{F}_{opt}$.

**Figure 2.** Steps for identifying optimal features for GAI calculation: first redundant features are removed using correlation; then, several approaches for feature selection are tested and combined to obtain the optimal feature set $\mathcal{F}_{opt}$.

As a preliminary step to limit redundancy across optimal features, redundancy filtering was applied before any selection method. The procedure consisted of computing pairwise Spearman's correlation ρ between features, identifying pairs having $\rho > 0.75$. Spearman's correlation was selected as it is robust, compared to other variants such as Pearson's correlation, to non-normal distributions, which is the case for most of the gait features in the dataset. For each pair, only the feature with the highest correlation to the class label (NPS, RPS, and DPS) was maintained while removing the other. A priori redundancy removal is essential to prevent the final optimal set from containing only highly

correlated features, which could overshadow other relevant and peculiar aspects, for a more comprehensive evaluation of gait from different viewpoints [22]. Indeed, we expected $\mathcal{F}_{\text{opt}}$ to be composed of a subset of features from each of the three initial groups (spatiotemporal, dynamic stability, and arm swing) since these groups convey different but equally relevant information to identify the alterations in the AGAIT-SIM dataset. Moreover, this preliminary step may improve the redundancy removal power of the subsequent feature selection methods.

Four popular feature selection methods for identifying $\mathcal{F}_{\text{opt}}$ were considered: Select-K-best, using as metric Spearman's correlation to class label [23]; Minimum Redundancy—Maximum Relevance (MRMR) [24]; Boruta [25]; Speeded Up Robust Features (SURF) [26]. While the Boruta algorithm does not require setting any hyperparameter, in the case of Select-K-best, MRMR, and SURF, the number of features K to retain during the selection process was set to values 3, 5, and 10 for preliminary exploration. For the comparison of the methods, as many SVM models as the obtained feature sets were trained and evaluated using bayesian search for identifying SVM optimal hyperparameters (i.e., kernel, cost of misclassification C , degree, γ), combined with nested cross-validation (10 outer splits, 5 inner splits) for overall model evaluation. $\mathcal{F}_{\text{opt}}$, which is then employed in Phase 2, is obtained considering the intersection of the three best-performing feature sets from nested-cross-validation.

2.3. Phase 2: GAI Proposal and Preliminary Validation

Conceptually, the Gait Alteration Index (GAI) is designed to capture gait abnormality as a functional deviation from typical walking by integrating complementary aspects of locomotion. The spatio-temporal domain reflects the efficiency and regularity of lower-limb progression, capturing changes such as reduced gait speed, altered step timing, or shortened steps, which are among the most salient indicators of impaired walking. The dynamic stability domain quantifies surrogates of postural control during gait, reflecting the individual's ability to maintain balance and control the center of mass while moving. Finally, the arm swing domain captures upper-limb contribution and coordination with lower limbs, which are known to be altered in several neurological and age-related conditions and to play a role in balance and gait stability. By combining these three domains, the GAI provides an overall measure of gait alteration that reflects not a single isolated deficit, but the integrated functional impact of multiple interacting gait components, in line with the way clinicians qualitatively assess walking performance [27]. The mathematical definition of GAI is based on the modeling of *Normal* and *Altered* gait sessions from the AGAIT-SIM dataset using the concept of class centroid, as defined in Equation (1):

$$\mathbf{c}_l = \frac{1}{L} \sum_{i=1}^L \mathbf{x}_{i,l}, \quad \mathbf{x}_{i,l}, \mathbf{c}_l \in \mathbb{R}^f \quad (1)$$

where $\mathbf{c}_l$ is the centroid of class l (i.e., Normal N or Altered A), L is the cardinality of such class, and $\mathbf{x}_{i,l}$ is a datapoint (a gait session) belonging to it, represented as a vector whose components correspond to the f optimal features in $\mathcal{F}_{\text{opt}}$. The centroids are computed after *z-score standardization* of $\mathbf{x}_{i,l}$, such that all feature dimensions have comparable scaling. The same *z-score* normalization is applied to the testing data before evaluating the GAI.

Denoting by $\mathbf{c}_N$ the centroid of the Normal class and by $\mathbf{c}_A$ that of the Altered class, these two vectors result from the concatenation of three subvectors, each referring to one of the three feature groups included in the original feature set and then reduced in $\mathcal{F}_{\text{opt}}$, namely spatiotemporal (ST), dynamic stability (DS), and arm swing (AS). For instance, $\mathbf{c}_N$ can be expressed as the concatenation of the subvectors $\mathbf{c}_{N,ST}$, $\mathbf{c}_{N,DS}$, and $\mathbf{c}_{N,AS}$.

Therefore, given a new gait session represented by the vector $\mathbf{g} \in \mathbb{R}^f$ (and its subcomponents $\mathbf{g}_{ST}$, $\mathbf{g}_{DS}$, and $\mathbf{g}_{AS}$), the computation of the GAI starts from the evaluation of three feature-group-specific indices, namely GAI_{ST} , GAI_{DS} , and GAI_{AS} , using Equations (2)–(4):

$$d_{l,feat} = \|\mathbf{g}_{feat} - \mathbf{c}_{l,feat}\| \quad (2)$$

$$d_{NA,feat} = \|\mathbf{c}_{N,feat} - \mathbf{c}_{A,feat}\| \quad (3)$$

$$GAI_{feat} = \frac{1}{2} + \frac{d_{N,feat} - d_{A,feat}}{2 d_{NA,feat}} \quad (4)$$

where *feat* denotes the feature group under consideration (ST, DS, or AS), and *l* indicates the class label of the centroid (either *N* or *A*).

The overall GAI is then computed as the average of the three feature-group-specific indices, as reported in Equation (5):

$$GAI = \frac{GAI_{ST} + GAI_{DS} + GAI_{AS}}{3} \quad (5)$$

As can be inferred from the formulation, the GAI (as well as its feature-group-specific components) always lies in the range $[0, 1]$, thanks to geometric properties of triangles and to the $\frac{1}{2}$ shifting factor included in Equation (4). Values close to 0 correspond to a normal gait pattern, whereas values approaching 1 indicate increasingly altered gait performance.

The proposed GAI definition offers several advantages. First, in addition to evaluating the overall index, it allows identifying which specific gait aspects are most compromised through the analysis of the three feature-group-specific GAIs. Second, the index could potentially be adapted to assign different weights to the three contributions, depending on the pathology or population under analysis. Finally, the computation can be specialized by defining $\mathbf{c}_A$ as the centroid of a specific type of alteration (e.g., RPS or DPS from AGAIT-SIM), thus tailoring the index to quantify the tendency toward a specific gait impairment, such as slowness/reduced step length or trunk instability.

As a preliminary investigation about the informative power of the index with respect to alterations in gait due to pathological impairment, we computed GAI for the subjects in the TEST-GAIT dataset. Weights for the subcomponents were maintained equal, to avoid bias towards specific types of impairment or pathology (e.g., post-stroke subjects may have more markedly disrupted arm swing symmetry). We then compared GAI values with clinical scores assigned to the video in TEST-GAIT by an experienced neurologist, investigating statistically significant correlations (p -value < 0.05). We asked the clinician to assign both an overall Gait score, and three domain-specific scores focusing on: spatio-temporal impairment from lower-limb dynamic (ST score); dynamic stability impairment during walking (DS score); arm swing alteration (AS score). All these scores ranged from 0 (no impairment) to 4 (severe impairment), as typically done for gait assessment in the Unified Parkinson's Disease Rating Scale (UPDRS) [27].

3. Results

The results are organized with respect to the two main phases (Phase 1 and 2) highlighted in Section 2. Phase 1 results report on the selection of the optimal feature set for GAI computations, whereas Phase 2 results highlight validity of GAI with respect to clinical assessment. All the figures were generated using Python 3.10 and the following libraries: `scipy` = 1.15.3, `seaborn` = 0.13.2 and `matplotlib` = 3.10.7.

3.1. Phase 1 Results

Figures 3 and 4 show the Spearman correlation matrices of the investigated features before and after redundancy filtering, respectively, using a threshold set to $\rho > 0.75$. As can be observed, the most significant reduction involves the spatiotemporal parameters, which are largely summarized by the $GAIT_{VEL}$ and $STEP_{WIDTH}$ features. This behaviour can be explained by the fact that alterations in parameters such as $STEP_{LENGTH}$, $DOUBLE_{SUPP}$, or $STEP_{TIME}$ are inevitably reflected in the overall walking velocity during the gait session; therefore, they can be effectively summarized by a single value variation. Conversely, $STEP_{WIDTH}$ shows a weaker correlation with $GAIT_{VEL}$ and has therefore been retained.

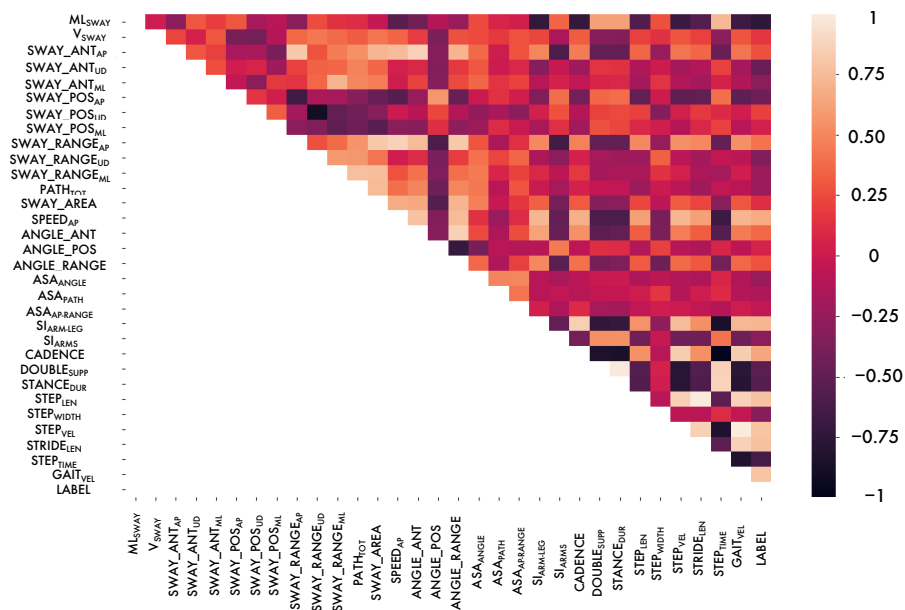


Figure 3. Spearman's correlation matrix of the investigated features before redundancy filtering ($\rho > 0.75$).

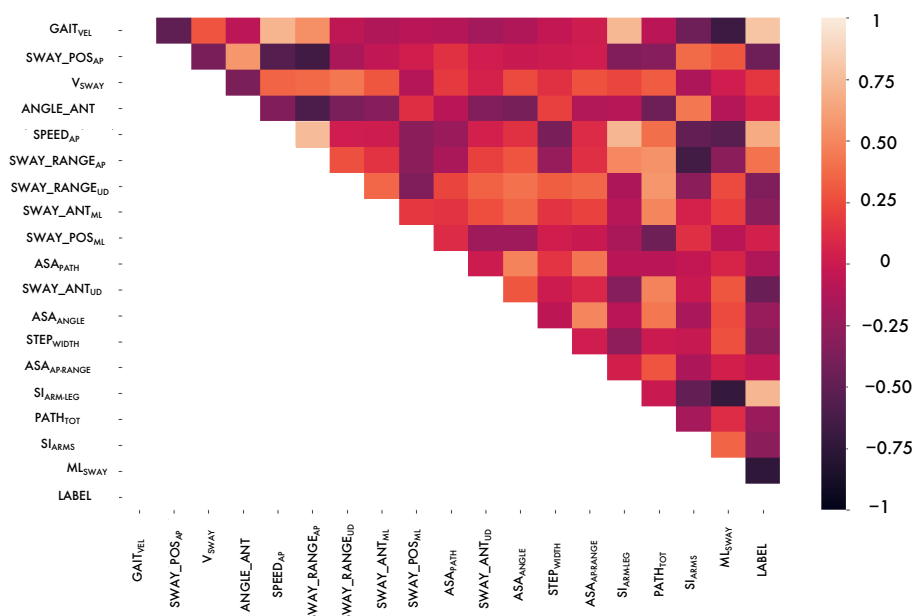


Figure 4. Spearman's correlation matrix of the investigated features after redundancy filtering ($\rho > 0.75$).

Table 3 reports the average accuracy and the corresponding standard deviation for both the multiclass and binary classification problems, obtained using SVM models trained

on the candidate feature sets identified by the selected feature selection methods. The three best-performing feature sets for both classification tasks are identified by BORUTA, MRMR with $K = 10$ (MRMR-10), and SURF with $K = 10$ (SURF-10). These three sets are subsequently intersected to identify the optimal feature set $\mathcal{F}_{\text{opt}}$, composed of the following parameters: GAIT_{VEL} , ML_{SWAY} , V_{SWAY} , $\text{SWAY_RANGE}_{\text{UD}}$, $\text{SI}_{\text{ARM-LEG}}$, $\text{SWAY_ANT}_{\text{UD}}$, and SPEED_{AP} .

As expected, the final optimal dataset includes a reduced combination of features belonging to the three investigated domains: spatiotemporal (ST), dynamic stability (DS), and arm swing (AS). The last row of Table 3 reports the performance of the SVM model trained using $\mathcal{F}_{\text{opt}}$. Overall, all methods require a larger number of features (i.e., 10) to better discriminate between NPS, RPS, and DPS classes in the multiclass problem, whereas the binary classification performance is consistently high (above 90.0%).

Compared to the results reported in [21], where the AGAIT-SYM dataset was originally used for automatic recognition of gait alterations, performance in the multiclass task shows a clear improvement (79.2% versus over 86.0% in the current study). This may stem from the inclusion in this work of arm swing features that were not considered in the original study. A slight degradation in accuracy is observed when using $\mathcal{F}_{\text{opt}}$, which retains 7 features out of the 10 selected by the three best-performing feature selection methods (BORUTA, MRMR-10, SURF-10) on the multiclass-task; however, this reduction is associated to a decrease in standard deviation. This behaviour is desirable, as it suggests improved generalization capability and a reduced risk of overfitting when applied to unseen data.

Table 3. SVM accuracy for feature sets selected by the different methods and for $\mathcal{F}_{\text{opt}}$. Bold entries denote sets used to derive $\mathcal{F}_{\text{opt}}$.

Feature Set	Multiclass Accuracy $\pm$ STD (%)	Binary Accuracy $\pm$ STD (%)
Select-3-Best	69.50 $\pm$ 12.70	95.50 $\pm$ 10.70
Select-5-Best	68.80 $\pm$ 10.60	95.50 $\pm$ 10.40
Select-10-Best	83.80 $\pm$ 10.00	93.60 $\pm$ 9.80
Boruta	86.70 $\pm$ 10.10	94.30 $\pm$ 7.00
MRMR-3	83.60 $\pm$ 10.70	95.70 $\pm$ 9.10
MRMR-5	82.40 $\pm$ 10.60	97.10 $\pm$ 7.00
MRMR-10	86.40 $\pm$ 10.90	97.10 $\pm$ 5.70
SURF-3	73.30 $\pm$ 13.80	95.50 $\pm$ 9.40
SURF-5	82.40 $\pm$ 10.60	95.50 $\pm$ 6.90
SURF-10	86.70 $\pm$ 13.60	97.10 $\pm$ 8.60
$\mathcal{F}_{\text{opt}}$	84.66 $\pm$ 9.10	97.10 $\pm$ 5.70

3.2. Phase 2 Results

This section discusses the results regarding the proposed GAI and its preliminary validation with respect to clinical assessment.

Table 4 reports the median value along 25th and 75th percentiles of the gait parameters in $\mathcal{F}_{\text{opt}}$, across the three groups included in TEST-GAIT dataset. GAIT_{VEL} shows a clear stratification across groups: NP subjects present higher values (median 1.00 m/s), PD subjects show moderately reduced values (0.85 m/s), while PS subjects exhibit a marked reduction (0.44 m/s), consistent with post-stroke motor deficits.

About dynamic stability, for ML_{SWAY} , PS subjects show markedly higher values (114.17 mm) compared to NP (55.22 mm) and PD (60.79 mm), indicating typical lateral instability characteristic of hemiparesis. In addition, V_{SWAY} progressively increases from NP (33.30 mm) to PD (38.75 mm) to PS (45.31 mm), indicating larger postural instability in pathological populations.

Finally, for parameters of arm swing, $SI_{ARM-LEG}$ reveals a progressive reduction in synchronization across upper limbs: NP group maintains high values (0.84), PD group shows a slight reduction (0.81), while PS group presents significantly lower values (0.63) with high variability, reflecting the typical post-stroke asymmetry. Up-down range of overall swing ($SWAY_RANGE_{UD}$) and swing just in the anterior direction with respect to the body ($SWAY_ANT_{UD}$) are reduced in both PD and PS compared to NP, suggesting a rigidity in arm swing, which is confirmed also by the smaller velocity in the antero-posterior direction ($SPEED_{AP}$) for the pathological groups.

These results suggest that the optimal features, despite being originally selected from simulated data, clearly capture variations due to pathological deficit of the investigated domains of impairment.

Table 4. Median and [25th–75th percentiles] of gait parameters, reported for each pathological group.

Parameter	NP	PD	PS
$GAIT_{VEL}$ (m/s)	1.00 [0.95–1.12]	0.85 [0.72–1.02]	0.44 [0.32–0.68]
ML_{SWAY} (mm)	55.22 [52.10–63.15]	60.79 [49.27–72.53]	114.17 [92.11–132.05]
V_{SWAY} (mm)	33.30 [32.38–38.73]	38.75 [28.58–45.25]	45.31 [32.78–57.71]
$SWAY_RANGE_{UD}$ (mm)	72.18 [58.33–82.42]	54.69 [42.95–71.19]	70.92 [62.57–88.40]
$SI_{ARM-LEG}$ (-)	0.84 [0.75–0.91]	0.81 [0.63–0.89]	0.63 [0.27–0.69]
$SWAY_ANT_{UD}$ (mm)	48.66 [40.07–55.16]	33.37 [23.91–44.80]	31.40 [17.52–41.36]
$SPEED_{AP}$ (mm/s)	755.40 [522.96–854.02]	521.86 [335.48–717.51]	396.68 [281.28–489.97]

3.2.1. GAI vs. Clinical Scores

To assess the validity of the GAI and its sub-components computed using gait parameters in $\mathcal{F}_{opt}$, we performed a Spearman correlation analysis between the GAI indices (GAI , GAI_{DS} , GAI_{AS} , GAI_{ST}) and the corresponding clinical scores assigned by the expert clinician (Gait Score, DS score, AS score, ST score) to the videos in TEST-GAIT dataset. Due to the limited number of videos with clinical scores equal to 4, these were merged with score 3 prior to all analyses.

First, we investigated the correlation within the clinical scores, to observe correspondence between axis of impairments and the omnicomprehensive Gait Score. We did the same evaluation also within GAI and its sub-indices. Table 5 presents these results. Regarding the clinical scores, all three subscales showed strong correlations with the total Gait Score, with ST Score exhibiting the highest correspondence ($\rho = 0.854$), followed by DS Score ($\rho = 0.822$), and AS Score ($\rho = 0.704$). The inter-subscale correlations were moderate to strong, ranging from 0.593 (ST vs. AS) to 0.783 (ST vs. DS), indicating that while the subscales capture related aspects of gait impairment, they maintain sufficient independence to provide complementary information.

Table 5. Internal correlation analysis of clinical scores and GAI indices.

Index	Comparison	ρ	<i>p</i> -Value
<i>Clinical Scores—Subscales vs. Total Gait Score</i>			
	ST Score vs. Gait Score	0.854 ***	<0.001
	DS Score vs. Gait Score	0.822 ***	<0.001
	AS Score vs. Gait Score	0.704 ***	<0.001
<i>Clinical Scores—Inter-subscale correlations</i>			
	ST Score vs. DS Score	0.783 ***	<0.001
	ST Score vs. AS Score	0.593 ***	<0.001
	DS Score vs. AS Score	0.673 ***	<0.001
<i>GAI—Subscales vs. Total GAI</i>			
	GAI _{DS} vs. GAI	0.775 ***	<0.001
	GAI _{AS} vs. GAI	0.661 ***	<0.001
	GAI _{ST} vs. GAI	0.884 ***	<0.001
<i>GAI—Inter-subscale correlations</i>			
	GAI _{DS} vs. GAI _{AS}	0.261 **	0.004
	GAI _{DS} vs. GAI _{ST}	0.627 ***	<0.001
	GAI _{AS} vs. GAI _{ST}	0.432 ***	<0.001

*** $p < 0.001$; ** $p < 0.01$.

For the GAI indices, GAI_{ST} demonstrated the strongest correlation with the overall GAI ($\rho = 0.884$), followed by GAI_{DS} ($\rho = 0.775$), and GAI_{AS} ($\rho = 0.661$). This ranking in correlation is thus coherent with the one observed for clinical scales. Notably, the inter-subscale correlations among GAI components were substantially lower than those observed for clinical scores, particularly between GAI_{DS} and GAI_{AS} ($\rho = 0.261$).

Figure 5, instead, presents the correlation matrix between GAI and the clinical scales. All correlations were statistically significant (p -value < 0.05). The overall GAI index demonstrated a strong and significant correlation with the clinical Gait Score ($\rho = 0.653$, $p < 0.001$), confirming the robustness of the proposed index in capturing clinically relevant gait alterations. Notably, the highest correlation was observed between GAI_{ST} and the clinical ST score ($\rho = 0.776$, p -value < 0.001), followed by the correlation between GAI_{ST} and the overall Gait Score ($\rho = 0.772$, p -value < 0.001). An interesting pattern emerged when comparing the sub-indices with their corresponding clinical scores versus the overall Gait Score. While GAI_{ST} showed comparable correlations with both ST score and Gait Score, the GAI_{DS} and GAI_{AS} sub-indices exhibited notably weaker correlations with the overall Gait Score (GAI_{DS}: $\rho = 0.420$; GAI_{AS}: $\rho = 0.321$) compared to GAI_{ST}. This finding corroborates the thesis that the clinician may have placed greater emphasis on spatio-temporal parameters when assigning the overall gait severity score, potentially underweighting balance and arm swing abnormalities in the global clinical assessment, as observed from the internal correlation analysis previously discussed. Furthermore, the high correlation between GAI_{ST} and the clinician's specific scores for dynamic balance and arm swing suggests that an improved gait pattern, as reflected by spatio-temporal parameters and in particular by gait speed, is generally accompanied by enhanced dynamic stability and more effective arm swing. This confirms that while the GAI_{ST} may not optimally capture every single domain (as indicated by lower correlations in certain axes), it represents a robust indicator of overall gait quality, closely linked to the individual's general physical well-being.

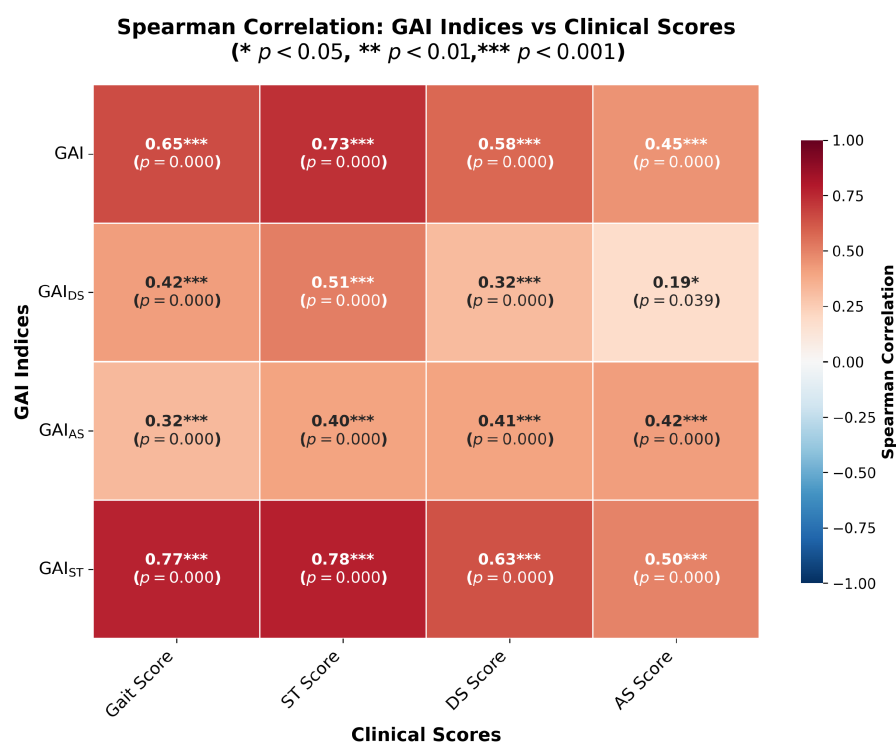


Figure 5. Spearman correlation between GAI indices and clinical scores organized as a matrix. Each cell shows the correlation coefficient with significance level (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) and exact p -value. GAI = overall Gait Assessment Index; GAI_{DS} = Dynamic stability sub-index; GAI_{AS} = Arm Swing sub-index; GAI_{ST} = Spatio-temporal sub-index; ST score = clinical Spatio-temporal score; DS score = clinical Dynamic Stability score; AS score = clinical Arm Swing score.

To further validate the discriminative capacity of the GAI indices, we examined their distribution across the different levels of clinical severity (Gait Score). Figure 6 shows the distribution of the overall GAI index across clinical severity levels. The Kruskal-Wallis test revealed a highly significant difference among groups ($H = 56.89$, p -value = 2.71×10^{-12}). Post-hoc analysis with Dunn's test (Bonferroni-corrected) revealed that groups 0 and 1 (mild impairment) did not differ significantly from each other (p -value = 1.000), while groups 2 and 3 (moderate-to-severe impairment) differed significantly from groups 0 and 1 (all p -values < 0.05). Specifically, the comparison between groups 0 and 2 showed strong significance (p -value < 0.001), as did the extreme comparison between groups 0 and 3 (p -value < 0.001). The comparison between groups 2 and 3 showed a borderline significance (p -value = 0.055).

The overlay of individual data points, color-coded by diagnostic group, reveals distinct patterns across the three populations. NP subjects predominantly clustered in the lower severity scores (0 and 1), exhibiting low GAI values consistent with normal gait patterns. PD patients showed a broader distribution across severity levels, with a notable presence in both mild and moderate impairment categories, reflecting the heterogeneous nature of parkinsonian gait dysfunctions. PS patients were predominantly represented in the higher severity scores (2 and 3), displaying elevated GAI values that capture the more pronounced gait alterations typically observed after cerebrovascular events. This distribution pattern confirms that the GAI effectively captures the different severity profiles characteristic of each clinical population.

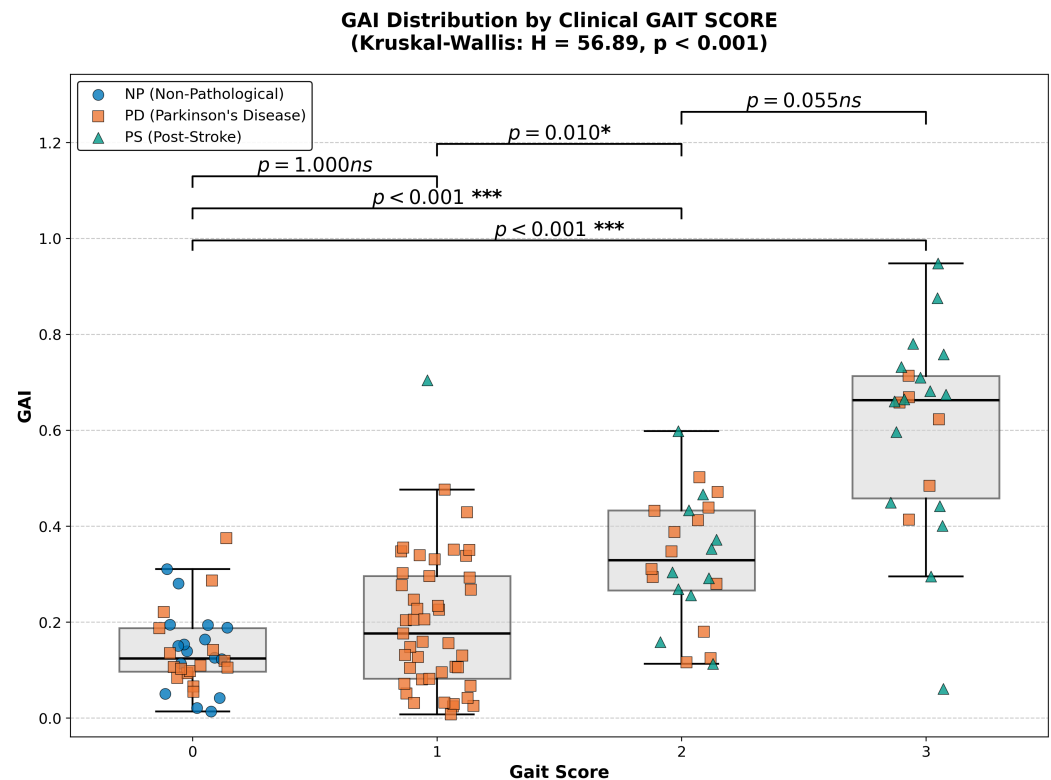


Figure 6. Distribution of GAI across the clinical Gait Score levels. Boxplots show median and interquartile range; individual points are colored by patient group (NP = Non-Pathological; PD = Parkinson's Disease; PS = Post-stroke). Statistical significance from Dunn's post-hoc test with Bonferroni correction is shown (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = not significant).

3.2.2. GAI Sub-Indices vs. Clinical Domains of Impairment

We then examined how each GAI sub-index varied across clinical severity levels, comparing their distribution against both the overall Gait Score and their corresponding domain-specific clinical scores. This side-by-side comparison allows for a direct assessment of whether each sub-index better discriminates severity when evaluated against the global clinical assessment or against its domain-specific clinical counterpart. Figure 7 presents the GAI_{ST} distributions. The spatio-temporal sub-index demonstrated the strongest discriminative power among all indices, with highly significant differences across both the overall Gait Score ($H = 74.00$, $p\text{-value} = 5.93 \times 10^{-16}$) in Figure 7a and the specific ST score ($H = 75.22$, $p\text{-value} = 3.26 \times 10^{-16}$) in Figure 7b. Notably, GAI_{ST} showed significant differences even between adjacent severity levels in both comparisons, with strong discrimination between groups 0 and 2 ($p\text{-value} < 0.001$) and between groups 0 and 3 ($p\text{-value} < 0.001$), confirming the strong alignment between the computed index and clinical evaluation of spatio-temporal gait parameters. Examining the population distribution, PS patients exhibited the highest GAI_{ST} values, consistent with the marked spatio-temporal alterations (reduced gait speed, Table 4) commonly observed in post-stroke. PD patients displayed intermediate values with considerable variability, reflecting the heterogeneous presentation of parkinsonian gait, while NP subjects maintained consistently low GAI_{ST} values across severity levels.

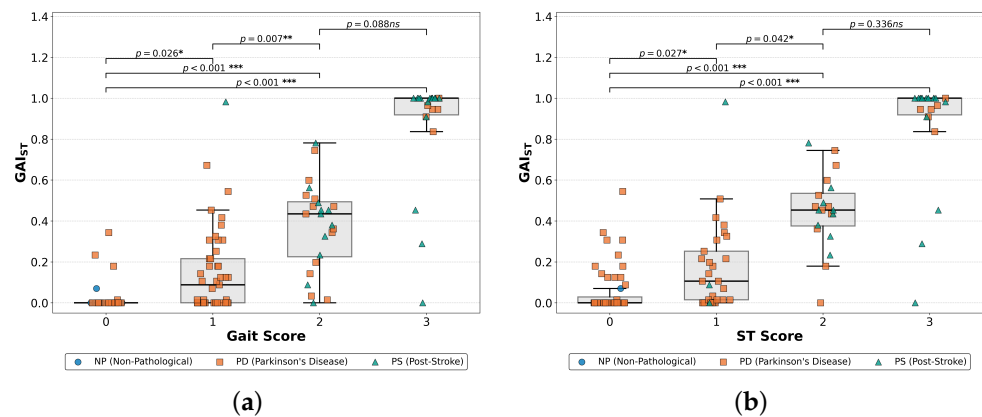


Figure 7. Distribution of GAI_{ST} across clinical severity levels: comparison with the overall Gait Score (a) and the specific ST score (b). Boxplots show median and interquartile range; individual points are colored by patient group (NP = Non-Pathological; PD = Parkinson's Disease; PS = Post-stroke). Statistical significance from Dunn's post-hoc test with Bonferroni correction is shown (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = not significant).

Figure 8 shows the GAI_{DS} distributions. The dynamic stability sub-index exhibited moderate discriminative capacity, with significant overall differences against both Gait Score ($H = 22.97$, p -value = 4.10×10^{-5}) in Figure 8a and DS score ($H = 15.62$, p -value = 1.36×10^{-3}) in Figure 8b. Post-hoc analysis revealed significant differences between groups 0 and 2 (p -value = 0.022 vs. Gait Score; p -value = 0.025 vs. DS score) and between groups 0 and 3 (p -value < 0.001 vs. Gait Score; p -value = 0.030 vs. DS score), while no significant discrimination was observed between adjacent levels. This pattern suggests that postural stability abnormalities become more apparent and consistently detectable by the index only in patients with more advanced gait impairment. The population-specific analysis revealed that PS patients demonstrated the highest GAI_{DS} values, particularly evident at higher severity levels, reflecting the substantial stability deficits characteristic of PS gait. PD patients showed moderate elevation in GAI_{DS} , consistent with the postural instability component of parkinsonian syndrome, while NP subjects maintained low values indicative of preserved balance control.

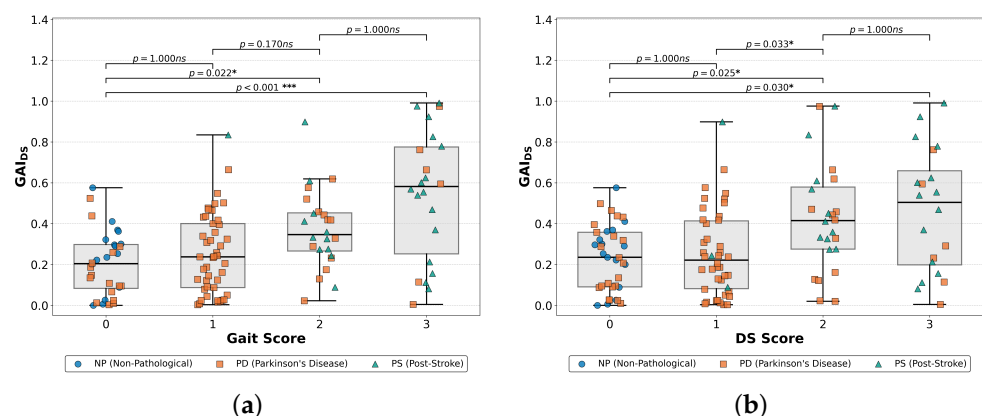


Figure 8. Distribution of GAI_{DS} across clinical severity levels: comparison with the overall Gait Score (a) and the specific DS score (b). Boxplots show median and interquartile range; individual points are colored by patient group (NP = Non-Pathological; PD = Parkinson's Disease; PS = Post-stroke). Statistical significance from Dunn's post-hoc test with Bonferroni correction is shown (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = not significant).

Figure 9 presents the GAI_{AS} distributions. Similar to GAI_{DS} , the arm swing sub-index showed significant overall differences against both Gait Score ($H = 20.83$, $p\text{-value} = 1.14 \times 10^{-4}$) in Figure 9a and AS score ($H = 21.27$, $p\text{-value} = 9.27 \times 10^{-5}$) in Figure 9b. The post-hoc comparisons revealed that GAI_{AS} primarily discriminated between the extreme groups (0 vs. 3: $p\text{-value} = 0.002$ vs. Gait Score; $p\text{-value} < 0.001$ vs. AS score), while the comparison between groups 0 and 2 did not reach significance ($p\text{-value} = 1.000$), and no significant difference was observed between intermediate levels (1 vs. 2: $p\text{-value} = 0.795$). This finding indicates that arm swing abnormalities, unlike balance and spatio-temporal alterations, are most reliably detected only in patients with the most pronounced gait impairment. Interestingly, the population distribution showed that both PD and PS patients exhibited elevated GAI_{AS} values at higher severity levels. NP subjects on average demonstrated low GAI_{AS} values, reflecting preserved and symmetric arm swing during gait.

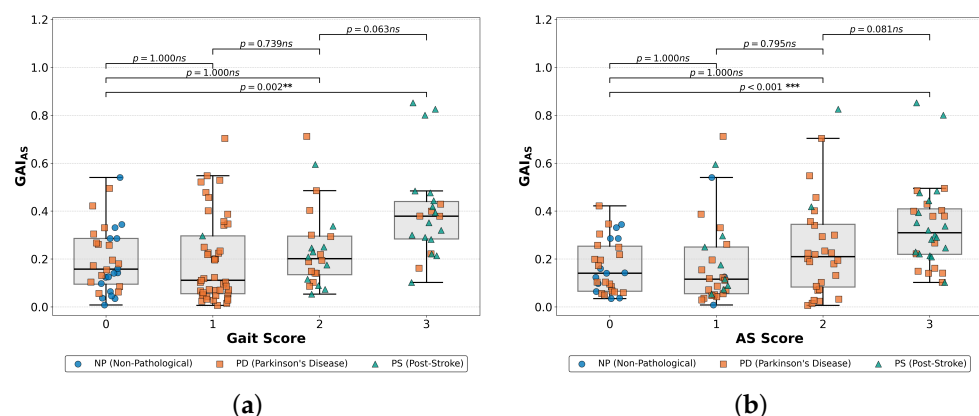


Figure 9. Distribution of GAI_{AS} across clinical severity levels: comparison with the overall Gait Score (a) and the specific AS score (b). Boxplots show median and interquartile range; individual points are colored by patient group (NP = Non-Pathological; PD = Parkinson's Disease; PS = Post-stroke). Statistical significance from Dunn's post-hoc test with Bonferroni correction is shown (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = not significant).

3.2.3. GAI Visualisation

Finally, to further highlight the potentiality of computing GAI as a weighted contribution of the three subcomponents GAI_{DS} , GAI_{ST} , GAI_{AS} , we provide a simultaneous visualisation through radar charts of these values for four interesting cases from TEST-GAIT in Figure 10. The top-left radar chart refers to a NP subject that does not show any kind of gait alteration. In this case, all subcomponents of GAI are small, hence the radar squeezes close to 0. The radar on top-right refers to a parkinsonian gait session that shows specific impairment in dynamic stability, hence GAI_{DS} is significantly larger than the other two indices. The bottom-left radar is again a parkinsonian gait session, but in this case, both dynamic stability and spatiotemporal parameters are altered, whereas normal arm swing is performed by the subject. Finally, the radar chart on the bottom right refers to a PS gait session where all aspects of walking are similarly altered.

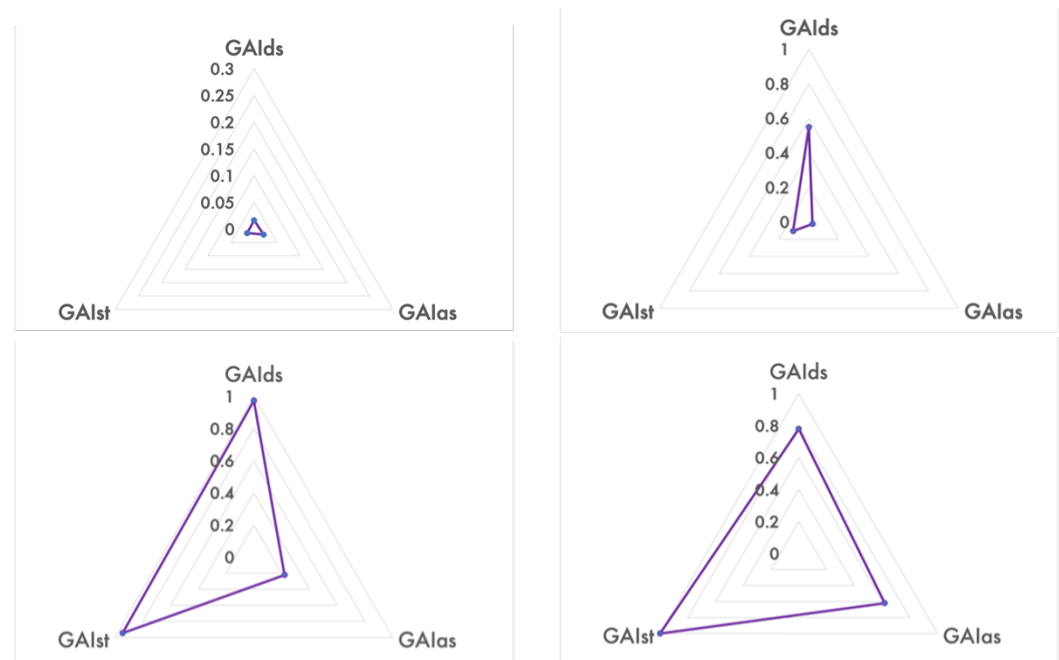


Figure 10. Radar charts of subcomponents of GAI. (**Top-left**): nonpathological subject having a normal gait condition. (**Top-right**): parkinsonian walking trial with problems related only to dynamic stability. (**Bottom-left**): parkinsonian walking trial with both dynamic stability and reduced lower limbs alterations. (**Bottom-right**): post-stroke gait session with altered patterns with respect to all three features group.

4. Discussion

In an aging population, the constant growth in the incidence of disabilities caused by chronic and progressive neurological diseases such as Parkinson's disease (PD), and acute events such as stroke, requires specific and prolonged health treatments. These disability conditions negatively impact several motor functions, among which gait impairment is one of the most disabling since it can result in increased risk of falls, reduced independence in daily-life activities, and general worsening in overall quality of life. New telemedicine solutions investigating gait impairment aim to support objective evaluation of gait quality through emerging technological approaches that could be sufficiently accurate and usable outside traditional hospital settings. However, despite the large number of potential solutions that could enable this monitoring, the field still lacks a summary measure that accounts for the different contributions of the objective parameters, providing clinicians with a single, comprehensive evaluation that is coherent with clinical scales. Despite the effort, machine learning or deep learning models that can accurately distinguish among standard clinical severity levels with a generalizable and cross-dataset-transferable approach are still lacking [13]. This is largely due to the uncertain nature of the clinical labels, as well as the coarse-grained structure of reference scales themselves, which provide limited and often ambiguous severity levels rather than a continuous measure of impairment. Moreover, established indices for measuring gait impairment often rely on high-quality motion capture data to be computed that are disease-specific, rather than generalizable to multiple pathologies.

To overcome these limitations, we proposed the Gait Alterations Index (GAI), a simple yet effective index of gait impairment. This index is computed by exploiting gait parameters from 5-m straight walking sessions recorded through an Azure Kinect device (or any RGB-D camera compatible with Azure Kinect Body Tracking), making it a portable solution for the assessment of gait alterations. To derive and validate GAI, we exploited two previously recorded datasets: the AGAIT-SYM, containing data from non-pathological (NP)

subjects simulating gait alterations, was used to identify relevant markers of impairment to compute the index, and served to define extreme values for healthy and altered gait patterns. The search for relevant and simple biomarkers of gait impairment included: spatio-temporal gait parameters, accounting for motion of the lower limbs; dynamic stability parameters related to the center of mass sway in the vertical and medio-lateral directions; arm swing parameters, including measures of symmetry and coordination between upper and lower limbs. Relevant biomarkers were selected using a combination of a filter approach, removing first the most redundant features (Spearman's $\rho > 0.75$), and a wrapper approach, exploiting an SVM model to identify key factors for the automatic recognition of altered gait profiles.

This analysis summarized spatio-temporal parameters into a single aspect, i.e., the gait velocity. This is reasonable considering that lower limbs parameters show a high degree of correlation among each other [20] and changes in step/stride length or timing inevitably affect velocity. Moreover, gait velocity is a well known indicator of general well-being in older adults [28], as well as one of the main biomarkers of improvement after treatments targeting gait impairment, such as deep brain stimulation [29]. Regarding dynamic stability parameters, both vertical and medio-lateral sway of the center of mass were retained, supporting the idea that observing oscillations in both these directions is necessary to quantify dynamic postural instability. Finally, for arm swing, features considered relevant were those accounting for amplitude and speed of the sway, as well as the lack of synchronicity in upper and lower limbs motion ($SI_{ARM-LEG}$).

The gait profiles defined by these characteristics were clearly different when measured in the TEST-GAIT dataset, across non-pathological (NP) subjects and post-stroke (PS) and parkinsonian patients. The pathological groups reported gait profiles coherent with the expected alterations (Table 4): both groups exhibited reduced gait velocity, more evident instability both in the medio-lateral and vertical directions, especially the PS group, a reduced arm swing amplitude and speed accompanied by compromised synchronicity in limb motion. This latter aspect is especially evident in the PS group, coherently with the typical hemiparesis caused by the stroke event. These gait profiles demonstrate strong consistency with literature findings, particularly in capturing the distinct motor impairments of PD and PS populations through Kinect-based technology [30,31]. The median gait velocity for PD (0.85 m/s) aligns closely with reported averages ranging from 0.61 to 0.83 m/s [31,32], while the lower velocity for PS (0.44 m/s) correctly mirrors the trend of significant speed reduction observed in hemiplegic gait [31,33]. Regarding postural stability, the finding that PS subjects exhibit the highest lateral instability (114.17 mm $Sway_{ML}$) is coherent with previous research works identifying increased body sway and lateral body shifts as primary compensatory strategies for unilateral weakness and abnormal torso tilting [31,33]. Vertical sway values (38.75 mm for PD and 45.31 mm for PS) are highly consistent with ranges from 33 mm to 50 mm reported in the literature [30,31,33], which describe the vertical trajectory of the centre of mass as a reliable indicator of movement efficiency and severity of impairment. For arm swing, parameters in the PD population are coherent with those reported in [20,34] for amplitude in the UD direction ($SWAY_RANGE_{UD}$ median 50.25 mm in [20], 46.6 mm in [34]) and $SI_{ARM-LEG}$ (median value in this work: 0.81, 0.79 in [20]). The speed of arm motion in the AP direction is on average larger (median value in this study: 521.86 mm/s, 365.1 mm/s in [20], 372.2 mm/s in [34]), this may stem from the larger pool of subjects with PD in this work compared to these previous studies, of which the majority spans lower levels of gait impairment according to clinical evaluation, as it can be appreciated in Figure 6.

The validation analyses for the proposed GAI provide converging evidence that the index captures clinically meaningful gait deviations while remaining interpretable through

its sub-domain structure. First, the observed association between the overall GAI and the clinician-derived gait score suggests that aggregating deviations across multiple gait dimensions yields a more stable indicator than relying on a single domain. This is coherent with the practical reality of clinical gait assessment: clinicians implicitly integrate heterogeneous cues (e.g., pace, rhythm, step length regularity, trunk control, arm swing) into an overall impression [27], whereas individual kinematic descriptors may only partially reflect perceived impairment. In this sense, the GAI can be interpreted as a quantitative proxy of a clinician's global impression, with the additional advantage of being continuous rather than discrete. Second, the sub-index analysis supports the design decision to decompose gait abnormality into separable components. The spatio-temporal sub-index showed the strongest alignment with the clinical scores and the clearest separation across gait severity categories. This result is not surprising and can be regarded as a positive confirmation: spatio-temporal alterations (e.g., reduced speed, shortened steps, increased variability) are among the most salient cues for human observers, and they are also among the most robust outputs of contemporary camera-based motion analysis [35,36]. From an implementation standpoint, this means that the GAI retains sensitivity to clinically obvious gait changes while remaining feasible for low-cost deployment.

It is important to note that dynamic stability and arm swing sub-indices exhibited weaker or less consistent agreement with the clinician's video-based ratings. These findings should not be read only as limitations of the proposed approach; rather, they likely reflect a combination of measurement and reference-label constraints, and highlight why a multi-domain index is preferable to a single-domain descriptor. It must be considered that clinical ratings were performed on video, which inherently compresses 3D motion into a 2D representation and may attenuate sway cues. In practice, clinicians can reliably identify gross instability events, but mild-to-moderate 3D imbalance may be difficult to quantify visually, and small changes in trunk motion may not translate into consistent ordinal ratings. Therefore, part of the reduced agreement may reflect the limited observability of stability phenomena in video rather than a true lack of relationship between the extracted stability surrogates and functional balance. Regarding arm swing, this domain is clinically informative but also highly variable in the general population [20]. It is influenced by walking speed, attention/dual-tasking, arm dominance, and compensatory strategies, and it can be altered intentionally or unconsciously (e.g., when subjects focus on the walking task or try to perform well during recording). Moreover, upper-limb pose estimation is particularly susceptible to self-occlusion, clothing, and depth ambiguities, and these issues can degrade the reliability of arm kinematics compared to lower-limb spatio-temporal measures [36] when using HPE technologies. From a biomechanical standpoint, arm swing also interacts with trunk motion and balance control: experimental evidence in PD indicates that constraining arm swing and adding a dual task can worsen trunk control and modify dynamic balance-related measures [37]. In our context, this implies two plausible (and not mutually exclusive) explanations for less optimal arm-swing agreement: the video-based clinical score may be less sensitive to subtle arm-swing deviations (especially when the view is not strictly sagittal and when the arms overlap the torso), and the extracted arm-swing descriptors may capture real variability that is not consistently interpreted as abnormal by the clinician. A key conceptual point in interpreting the validation is that GAI is designed to quantify *gait abnormality* rather than to identify a specific pathology. This is critical when considering individuals categorized as non-pathological based on the absence of a formal diagnosis. The literature shows that neurological gait abnormalities can be present and relatively common even in older community-dwellers without recognized neurological disease [7]. Therefore, cases in which the GAI suggests a deviation while the clinical label is low (or normal) may reflect early/subclinical changes not detected in

routine assessment, non-neurological contributors (e.g., mild musculoskeletal limitations), or limits of the ordinal clinical rating itself.

From a screening and monitoring perspective, this behaviour should not necessarily be interpreted as undesirable: an index that can flag subtle deviations may be clinically useful, provided that its interpretation is carefully framed as a degree of deviation from typical gait rather than the presence of pathology. Recent work has demonstrated that clinically meaningful gait parameters can be extracted from simple videos using HPE and validated against laboratory motion capture, including applications in PD and PS cohorts [38]. In addition, reliability studies on single-camera markerless systems highlight both the potential and the practical constraints required for stable overground measurements (e.g., sufficient trials, proper positioning within the capture volume) [39]. Our contribution is complementary: rather than proposing another parameter set, we introduce a low-cost *indexing layer* that summarizes multi-domain gait deviation into an interpretable score (and sub-scores), explicitly targeting the translational gap between raw kinematic outputs and clinically actionable interpretation. This design choice is aligned with the broader aim of improving accessibility of gait assessment while preserving interpretability and enabling longitudinal tracking.

4.1. Limitations

As a preliminary analysis, this work has several limitations that should be interpreted in light of both the reference standard adopted and the sensing technology employed. A first set of limitations arises from the clinical scoring procedure used as reference. Clinical gait scores were derived from video-based assessments, which may have limited sensitivity to three-dimensional balance phenomena and subtle instabilities. This constraint likely affected agreement particularly for the dynamic stability and arm swing domains, where mild alterations may not be easily observable in standard video recordings. In addition, clinical ratings were provided by a single expert rater; while this choice ensured consistency, it does not allow estimation of inter-rater variability and may introduce subjective bias. A second limitation concerns the study design and sample characteristics. The sample size and the distribution of gait severity levels may limit generalizability across populations and pathological spectra. Larger and more heterogeneous cohorts, as well as repeated acquisitions, are required to assess the robustness and test–retest stability of the GAI in longitudinal and real-world scenarios. Finally, additional limitations stem from the accuracy of markerless pose estimation itself. Although low-cost acquisition improves feasibility, pose estimation reliability is known to depend on factors such as viewpoint, clothing, self-occlusions, and joint type, with reduced accuracy for distal joints and non-sagittal movements [35,36]. These effects may introduce noise in specific gait parameters, particularly those related to upper-limb kinematics, and should be considered when interpreting sub-index behaviour.

4.2. Future Work

Future work should proceed along three main directions. First, strengthen the reference standard: include multi-rater clinical assessments with inter-rater reliability analysis and incorporate a motion-capture benchmark subset to quantify construct validity for each sub-index. Second, translate to RGB-only pipelines: since the GAI definition is parameter-based and computationally lightweight, it is well positioned for porting to RGB-only pose estimation workflows, which have shown a strong promise for clinical gait analysis using simple devices [36,38,39]. Finally, longitudinal and real-world validation: test the GAI sensitivity to change (rehabilitation, disease progression), assess its behaviour in home-like conditions, and investigate whether elevated GAI in non-pathological individuals may pre-

dict future diagnosis, functional decline, or falls, which would support its use as a screening and monitoring tool [6,7]. In this direction, exploring also clinically-informed weighting of the GAI sub indices, as well as sensitivity analysis on the effect of this parameter may provide additional improvement in the correspondence of GAI with impairment caused by specific motor pathologies.

5. Conclusions

The paper proposed a non-invasive telemedicine solution for detecting gait alterations through a Gait Alteration Index. This novel index was defined by exploiting supervised learning approaches and a dataset containing simulated altered gait from non-pathological subjects. Preliminary results indicate that the index, despite being derived from a small pool of humanly simulated data, correlates well with the degree of gait alteration in subjects with Parkinson's disease, post-stroke patients, and non-pathological subjects. Moreover, it can provide insights into which specific features of walking are impaired. This knowledge could support clinicians to optimize rehabilitation strategies and medical treatments targeting specific axes of impairment. In the near future, we are interested in further testing this index to demonstrate its potential across different pathological and clinical scenarios and to assess its clinical validity against standard clinical scales, as well as clinically established, motion-capture-based indices.

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References

1. United Nations Department of Economic and Social Affairs, Population Division. *World Population Ageing 2020—Highlights*; United Nations: New York, NY, USA, 2020; 47p.
2. Béjot, Y.; Yaffe, K. Ageing Population: A Neurological Challenge. *Neuroepidemiology* **2019**, *52*, 76–77. [[CrossRef](#)]
3. Min, K.B.; Min, J.Y. Health-related quality of life is associated with stroke deficits in older adults. *Age Ageing* **2015**, *44*, 700–704. [[CrossRef](#)] [[PubMed](#)]
4. Buckinx, F.; Rolland, Y.; Reginster, J.Y.; Ricour, C.; Petermans, J.; Bruyère, O. Burden of frailty in the elderly population: Perspectives for a public health challenge. *Arch. Public Health* **2015**, *73*, 19. [[CrossRef](#)] [[PubMed](#)]
5. Jin, K.; Simpkins, J.W.; Ji, X.; Leis, M.; Stambler, I. The Critical Need to Promote Research of Aging and Aging-related Diseases to Improve Health and Longevity of the Elderly Population. *Aging Dis.* **2014**, *6*, 1–5. [[CrossRef](#)] [[PubMed](#)]
6. Gade, G.V.; Jørgensen, M.G.; Ryg, J.; Riis, J.; Thomsen, K.; Masud, T.; Andersen, S. Predicting falls in community-dwelling older adults: A systematic review of prognostic models. *BMJ Open* **2021**, *11*, e044170. [[CrossRef](#)]

7. Inzitari, M.; Metti, A.; Rosano, C.; Udina, C.; Pérez, L.M.; Carrizo, G.; Rosso, A.L. Qualitative neurological gait abnormalities, cardiovascular risk factors and functional status in older community-dwellers without neurological diseases: The Healthy Brain Project. *Exp. Gerontol.* **2019**, *124*, 110652. [\[CrossRef\]](#)
8. Siragy, T.; Nantel, J. Quantifying dynamic balance in young, elderly and Parkinson's individuals: A systematic review. *Front. Aging Neurosci.* **2018**, *10*, 387. [\[CrossRef\]](#)
9. Salchow-Hommen, C.; Skrobot, M.; Jochner, M.C.E.; Schauer, T.; Kuhn, A.A.; Wenger, N. Emerging portable technologies for gait analysis in neurological disorders: A review. *Front. Hum. Neurosci.* **2022**, *16*, 768575. [\[CrossRef\]](#)
10. Eguchi, K.; Takigawa, I.; Shirai, S.; Takahashi-Iwata, I.; Matsushima, M.; Kano, T.; Yaguchi, H.; Yabe, I. Gait video-based prediction of unified Parkinson's disease rating scale score: A retrospective study. *BMC Neurol.* **2023**, *23*, 358. [\[CrossRef\]](#)
11. Aşuroğlu, T.; Oğul, H. A deep learning approach for parkinson's disease severity assessment. *Health Technol.* **2022**, *12*, 943–953. [\[CrossRef\]](#)
12. Han, J.; Tian, Z.; Wu, J.; Zhang, K.; Li, S.; Baig, F.; Liu, P.; Vaidyanathan, R.; Morgante, F.; Huo, W. Deep learning-enabled accurate assessment of gait impairments in Parkinson's disease using smartphone videos. *npj Digit. Med.* **2025**, *9*, 98. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Adeli, V.; Klabucar, I.; Rajabi, J.; Filtjens, B.; Mehraban, S.; Wang, D.; Taati, B. CARE-PD: A Multi-Site Anonymized Clinical Dataset for Parkinson's Disease Gait Assessment. *arXiv* **2025**, arXiv:2510.04312.
14. Khan, T.; Zeeshan, A.; Dougherty, M. A novel method for automatic classification of Parkinson gait severity using front-view video analysis. *Technol. Health Care* **2021**, *29*, 643–653. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Deng, D.; Ostrem, J.L.; Nguyen, V.; Cummins, D.D.; Sun, J.; Pathak, A.; Little, S.; Abbasi-Asl, R. Interpretable video-based tracking and quantification of parkinsonism clinical motor states. *npj Park. Dis.* **2024**, *10*, 122. [\[CrossRef\]](#)
16. Gonçalves, S.B.; Lama, S.B.C.; da Silva, M.T. Three decades of gait index development: A comparative review of clinical and research gait indices. *Clin. Biomech.* **2022**, *96*, 105682. [\[CrossRef\]](#)
17. Schwartz, M.H.; Rozumalski, A. The Gait Deviation Index: A new comprehensive index of gait pathology. *Gait Posture* **2008**, *28*, 351–357. [\[CrossRef\]](#)
18. Baker, R.; McGinley, J.L.; Schwartz, M.H.; Beynon, S.; Rozumalski, A.; Graham, H.K.; Tirosh, O. The gait profile score and movement analysis profile. *Gait Posture* **2009**, *30*, 265–269. [\[CrossRef\]](#)
19. Ferraris, C.; Ronga, I.; Pratola, R.; Coppo, G.; Bosso, T.; Falco, S.; Amprimo, G.; Pettiti, G.; Lo Priore, S.; Priano, L.; et al. Usability of the REHOME solution for the telerehabilitation in neurological diseases: Preliminary results on motor and cognitive platforms. *Sensors* **2022**, *22*, 9467. [\[CrossRef\]](#)
20. Ferraris, C.; Amprimo, G.; Masi, G.; Vismara, L.; Cremascoli, R.; Sinagra, S.; Pettiti, G.; Mauro, A.; Priano, L. Evaluation of Arm Swing Features and Asymmetry during Gait in Parkinson's Disease Using the Azure Kinect Sensor. *Sensors* **2022**, *22*, 6282. [\[CrossRef\]](#)
21. Ferraris, C.; Amprimo, G.; Pettiti, G.; Masi, G.; Priano, L. Automatic Detector of Gait Alterations using RGB-D sensor and supervised classifiers: A preliminary study. In *Proceedings of the 2022 IEEE Symposium on Computers and Communications (ISCC)*, Rhodes, Greece, 30 June–3 July 2022; IEEE: New York, NY, USA, 2022; pp. 1–6. [\[CrossRef\]](#)
22. Hall, M.A. Correlation-Based Feature Selection for Machine Learning. Ph.D. Thesis, University of Waikato, Hamilton, New Zealand, 1999.
23. Scikit-Learn Developers. SelectKBest. Available online: https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html (accessed on 27 October 2022).
24. Ding, C.; Peng, H. Minimum Redundancy Feature Selection from Microarray Gene Expression Data. In *Proceedings of the 2003 IEEE Bioinformatics Conference (CSB 2003)*, Stanford, CA, USA, 11–14 August 2003; pp. 523–528. [\[CrossRef\]](#)
25. Kursu, M.B.; Jankowski, A.; Rudnicki, W.R. Boruta—A System for Feature Selection. *Fundam. Informaticae* **2010**, *101*, 271–285. [\[CrossRef\]](#)
26. Bay, H.; Tuytelaars, T.; Van Gool, L. SURF: Speeded Up Robust Features. In *Computer Vision—ECCV 2006, Proceedings of the 9th European Conference on Computer Vision, Graz, Austria, 7–13 May 2006*; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2006; Volume 3951, pp. 404–417. [\[CrossRef\]](#)
27. Goetz, C.G.; Tilley, B.C.; Shaftman, S.R.; Stebbins, G.T.; Fahn, S.; Martinez-Martin, P.; Poewe, W.; Sampaio, C.; Stern, M.B.; Dodel, R.; et al. Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results. *Mov. Disord. Off. J. Mov. Disord. Soc.* **2008**, *23*, 2129–2170. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Studenski, S.; Perera, S.; Patel, K.; Rosano, C.; Faulkner, K.; Inzitari, M.; Brach, J.; Chandler, J.; Cawthon, P.; Connor, E.B.; et al. Gait speed and survival in older adults. *JAMA* **2011**, *305*, 50–58. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Roper, J.A.; Kang, N.; Ben, J.; Cauraugh, J.H.; Okun, M.S.; Hass, C.J. Deep brain stimulation improves gait velocity in Parkinson's disease: A systematic review and meta-analysis. *J. Neurol.* **2016**, *263*, 1195–1203. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Arizpe-Gómez, P.; Harms, K.; Janitzky, K.; Witt, K.; Hein, A. Towards automated self-administered motor status assessment: Validation of a depth camera system for gait feature analysis. *Biomed. Signal Process. Control* **2024**, *87*, 105352. [\[CrossRef\]](#)

31. Cimolin, V.; Vismara, L.; Ferraris, C.; Amprimo, G.; Pettiti, G.; Lopez, R.; Galli, M.; Cremascoli, R.; Sinagra, S.; Mauro, A.; et al. Computation of Gait Parameters in Post Stroke and Parkinson's Disease: A Comparative Study Using RGB-D Sensors and Optoelectronic Systems. *Sensors* **2022**, *22*, 824. [\[CrossRef\]](#)
32. Eltoukhy, M.; Kuenze, C.; Oh, J.; Jacopetti, M.; Wooten, S.; Signorile, J. Microsoft Kinect can distinguish differences in over-ground gait between older persons with and without Parkinson's disease. *Med. Eng. Phys.* **2017**, *44*, 1–7. [\[CrossRef\]](#)
33. Cerfoglio, S.; Ferraris, C.; Vismara, L.; Amprimo, G.; Priano, L.; Bigoni, M.; Galli, M.; Mauro, A.; Cimolin, V. Estimation of gait parameters in healthy and hemiplegic individuals using Azure Kinect: A comparative study with the optoelectronic system. *Front. Bioeng. Biotechnol.* **2024**, *12*, 1449680. [\[CrossRef\]](#)
34. Amprimo, G.; Masi, G.; Priano, L.; Azzaro, C.; Galli, F.; Pettiti, G.; Mauro, A.; Ferraris, C. Assessment Tasks and Virtual Exergames for Remote Monitoring of Parkinson's Disease: An Integrated Approach Based on Azure Kinect. *Sensors* **2022**, *22*, 8173. [\[CrossRef\]](#)
35. Scataglini, S.; Abts, E.; Van Bocxlaer, C.; Van den Bussche, M.; Meletani, S.; Truijen, S. Accuracy, Validity, and Reliability of Markerless Camera-Based 3D Motion Capture Systems versus Marker-Based 3D Motion Capture Systems in Gait Analysis: A Systematic Review and Meta-Analysis. *Sensors* **2024**, *24*, 3686. [\[CrossRef\]](#)
36. Cheng, X.; Jiao, Y.; Meiring, R.M.; Sheng, B.; Zhang, Y. Reliability and validity of current computer vision based motion capture systems in gait analysis: A systematic review. *Gait Posture* **2025**, *120*, 150–160. [\[CrossRef\]](#)
37. Siragy, T.; Nantel, J. Absent Arm Swing and Dual Tasking Decreases Trunk Postural Control and Dynamic Balance in People with Parkinson's Disease. *Front. Neurol.* **2020**, *11*, 213. [\[CrossRef\]](#)
38. Stenum, J.; Hsu, M.M.; Pantelyat, A.Y.; Roemmich, R.T. Clinical gait analysis using video-based pose estimation: Multiple perspectives, clinical populations, and measuring change. *PLoS Digit. Health* **2024**, *3*, e0000467. [\[CrossRef\]](#)
39. Boldo, R.; Di Marco, R.; Martini, E.; Nardon, M.; Bertucco, M.; Bombieri, N. On the reliability of single-camera markerless systems for overground gait monitoring. *Comput. Biol. Med.* **2024**, *171*, 108101. [\[CrossRef\]](#)

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