Gait & Posture

Steps to facilitate the use of clinical gait analysis in stroke patients: Validation of a single 2D RGB Smartphone Video-Based System for Gait Analysis

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Abstract:	Introduction: Clinical gait analysis plays a central role in the rehabilitation of stroke patients. However, practical and technical challenges limit their use in clinical settings. This study aimed to validate SMARTGAIT, a deep learning-based gait analysis system that addresses these limitations. Methods: Eight stroke patients took part in the study at the Human Performance Research Centre of the University of Konstanz. Gait measurements were taken using both the marker-based Vicon motion capture system and the single- smartphone based SMARTGAIT system. We evaluated the agreement for knee, hip and ankle joint angle kinematics and spatiotemporal gait parameters between the two systems. Results: The results demonstrated mostly high levels of agreement between the two systems, with Pearson correlations of 3 0.79 for all lower body angle kinematics in the sagittal plane and 3 0.71 in the frontal plane. RMSE values were ≤ 4.6°. The intraclass correlation coefficients for all derived gait parameters showed good to excellent reliability. Conclusion: The results suggest that SMARTGAIT is a promising tool for gait analysis in stroke, particularly for quantifying gait characteristics in the sagittal plane, most relevant for clinical gait analysis. However, further analyses are required to validate SMARTGAIT in larger samples and its transferability to different types of pathological gait. In conclusion, a single smartphone recording (monocular 2D RGB camera) could make gait analysis more accessible in clinical settings, potentially simplifying the process and making it more feasible for therapists and doctors to use in their day-to-day practice.
Suggested Reviewers:	Gudrun Diermayr, Prof. Dr. Full Professor, SRH Hochschule Heidelberg gudrun.diermayr@srh.de Professor Diermayr is highly recognised in the field of stroke and gait research and would therefore be an ideal reviewer for our publication.
	Itshak Melzer, Prof. Dr. Full Professor, Ben-Gurion University of the Negev itzikm@bgu.ac.il Prof Melzer has extensive knowledge and experience in medical and life sciences

	research, particularly in the areas of ageing, stroke and gait. We would therefore be very grateful if he would review our manuscript.a

Dear Editor,

We are pleased to submit our manuscript describing the validation of a novel markerless smartphone video-based AI motion capture system, 'SmartGait'. We validated this novel tool against a gold-standard Vicon system by assessing lower extremity joint kinematics and spatiotemporal gait parameters in stroke patients. The novel markerless system does not require sensors or markers, is smartphone-based, and requires only one camera to estimate 3D kinematics and gait parameters. The potential applications of SmartGait extend to sports performance analysis, movement rehabilitation, and movement disorder assessment. This study represents a significant advancement in motion capture technology, describing a convenient, portable, and high-precision solution for movement-data assessment.

All authors were fully involved in the study and preparation of the manuscript and the material within has not been and will not be submitted for publication elsewhere.

We would like to express our gratitude for your consideration and best wishes from Konstanz.

Gait Analysis in Stroke

High Accuracy Markerless Motion Capture

Simplifying Gait Assessment in Stroke Rehabilitation

Towards Accessible Gait Analysis

3D Kinematics from 2D Videos

Title Page (with Author Details)

Steps to facilitate the use of clinical gait analysis in stroke patients: Validation of a single 2D RGB Smartphone Video-Based System for Gait Analysis

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Keywords: markerless motion capture; gait analysis, stroke; joint kinematics; RGB camera; human movement analysis

Declaration of interest: Manuel Stein, Daniel Seebacher and Philip Zimmermann are part of Subsequent GmbH which provided the AI-based skeleton reconstruction and analysis tool and were involved in the measurements.

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Introduction: Clinical gait analysis plays a central role in the rehabilitation of stroke patients. However, practical and technical challenges limit their use in clinical settings. This study aimed to validate SMARTGAIT, a deep learning-based gait analysis system that addresses these limitations.

Methods: Eight stroke patients took part in the study at the Human Performance Research Centre of the University of Konstanz. Gait measurements were taken using both the marker-based Vicon motion capture system and the single-smartphone based SMARTGAIT system. We evaluated the agreement for knee, hip and ankle joint angle kinematics and spatiotemporal gait parameters between the two systems.

Results: The results demonstrated mostly high levels of agreement between the two systems, with Pearson correlations of ≥ 0.79 for all lower body angle kinematics in the sagittal plane and ≥ 0.71 in the frontal plane. RMSE values were ≤ 4.6°. The intraclass correlation coefficients for all derived gait parameters showed good to excellent reliability.

Conclusion: The results suggest that SMARTGAIT is a promising tool for gait analysis in stroke, particularly for quantifying gait characteristics in the sagittal plane, most relevant for clinical gait analysis. However, further analyses are required to validate SMARTGAIT in larger samples and its transferability to different types of pathological gait. In conclusion, a single smartphone recording (monocular 2D RGB camera) could make gait analysis more accessible in clinical settings, potentially simplifying the process and making it more feasible for therapists and doctors to use in their day-to-day practice.

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Introduction:

Stroke is the second leading cause of death and disability worldwide, with estimated costs exceeding USD 721 billion (Feigin et al., 2022). The rising occurrence of this condition highlights the need for an effective treatment strategy to enhance the quality of life for those affected and alleviate the burden on the healthcare system. About one-third of stroke survivors do not regain independent walking ability and in those who succeed, gait is mainly characterized by an asymmetrical pattern, with a decreased walking speed and increased stride width and double support phase (Calabro et al., 2021). Gait analysis systems can aid in precise and efficient diagnostics, therapy, and rehabilitation. Both lower extremity joint kinematics and spatiotemporal gait parameters are central to the assessment of the gait pattern in stroke patients and quantifying disease status (Balaban & Tok, 2014). The use of 3D motion for instrumented gait analysis is the gold-standard to examine gait deficits, subsequent rehabilitation and treatment options (Van Criekinge et al., 2023). However, despite the availability of various systems, practical and technical hurdles such as complexity, costliness, and effort required for installation and use have made it difficult for therapists and doctors to use them as a standardized aid (Di Biase et al., 2020; Klöpfer-Krämer et al., 2020; Mohan et al., 2021; Muro-de-la-Herran et al., 2014).

Several deep learning techniques have recently emerged as promising tools for efficiently processing instrumented gait data. This has the potential to address some of the existing problems with current gait analysis methods. A number of studies have explored the use of AI in this area (Iosa et al., 2021; Lau et al., 2009; Lee et al., 2000; Scheffer & Cloete, 2012; Zhou et al., 2020) while others have highlighted the limitations of current methods (Kanko et al., 2021; Verheul et al., 2020;

Wade et al., 2022). To improve the feasibility of measurement, particularly in clinical settings, markerless gait analysis using low-cost equipment such as (smartphone-) RGB cameras (capturing red, green, and blue wavelengths) are on the rise. However, only a few studies have applied their models to the analysis of pathological gait. Horsak et al. (2023) validated a markerless motion capture system (OpenCap) that uses two smartphone cameras and reported Root Mean Squared Error (RMSE) of ≤10.2° for lower extremity joint kinematics during impaired walking, suggesting inaccurate estimation of joint kinematics of pathological gait (Horsak et al., 2023). As healthy individuals imitated gait disorders, the results of Horsak et al.'s study cannot be transferred to the clinical setting. Lonini et al. (2022) compared DeepLabCut as an open-source framework markerless pose estimation against the established GAITRite® system (CIR systems, West Conshohocken, PA, USA) in stroke patients (Lonini et al., 2022). They showed relative errors of 0.7 ± 18% for walking speed and 0.3 ± 5.9% for cadence, highlighting the potential of single-camera markerless pose estimation. However, they were not able to estimate spatial gait parameters with only one camera, as they could not obtain or calculate 3D models from their 2D video sequences. Other studies on markerless gait analysis with stroke patients also used two cameras (Moro et al., 2020) or multiple cameras (Steffensen et al., 2023), which makes the simple transfer to the clinic more difficult. The possibility of analyzing gait in a clinical setting using a single RGB camera (e.g. smartphone) could make it much easier to use in therapy and many patients could benefit from a detailed gait analysis.

In this study, we present SMARTGAIT, a new approach that uses deep learning algorithms to estimate individuals' 3D joint coordinates from a single 2D RGB camera (Barzyk et al., 2024). The SMARTGAIT trajectory reconstruction technique is based on a multi-stage convolutional neural network that estimates the 3D joint coordinates. The objective of this study was to compare the SMARTGAIT motion analysis technique against a gold standard VICON system. The analysis was conducted on hip, knee, and ankle joint angular trajectories in the sagittal and frontal planes during overground walking, as well as spatiotemporal gait parameters in stroke patients presenting pathological gait patterns.

Methods:

Participants:

Eight stroke patients (2 women) aged between 36 and 79 years (M = 59.4, ± 13.7 years), took part in the study at the Human Performance Research Centre (HPRC) of the University of Konstanz. The study protocol adhered to the Declaration of Helsinki for human experimentation and the ethical standards of the University of Konstanz. Each participant provided written informed consent before participating. Participant information and the severity of the stroke and impairment can be found in Table 1.

Table 1 Participant information and severity of the stroke and impairment (n.r. = not reported). The FMA-LE scale is an index used to evaluate sensorimotor impairment in individuals who have suffered a stroke (scores of 0-17 = severe disability, 16-22 = marked disability, 23-28 = moderate disability, 29-33 = mild disability, and 34 = normal). The FAC is a six-point functional walking test that assesses a participant's ability to walk and determines the level of human support needed (from 0 (non-functional) to 5 (independent), the level of mobility is determined by the need for assistance. A score of 4 or higher indicates the ability to walk independently). The 10MWT assesses locomotor capacity by calculating the time it takes one to walk a set distance of 10 m.

Participant	*Age [years]*	*Sex*	*Weight [kg]*	*Height [mm]*	*Time since stroke [months]*	*Paretic bodyside*	*Type of stroke*	*Fugl-Meyer-Lower extremitie*	*Functional Ambulation Categories [FAC]*	*10-meter walk test [10MWT, s]*	*Walking aid*

								s [FMA-LE]			
P01	79	m	71	171	51	right	Ischemic	21	5	n.r.	No
P02	44	m	78	170	1	left	Hemorrhagic	26	4	15.6	No
P03	36	m	76	171	4	right	Hemorrhagic	31	5	7.15	No
P04	62	m	79	170	130	left	Ischemic	20	5	n.r.	No
P05	60	m	80	163	4	right	Hemorrhagic	13	2	41.2	Walking stick and foot lift orthosis
P06	62	f	60	166	4	left	Ischemic	18	3	35.7	Quad stick and foot lift orthosis
P07	61	f	65	160	4	left	Hemorrhagic	19	3	28.55	Quad stick and foot lift orthosis
P08	71	m	93	174	3	left	Hemorrhagic	17	3	20.85	Walking stick and foot lift orthosis

Study Design:

Gait measurements were taken using both the marker-based Vicon reference system and the SMARTGAIT system. The SMARTGAIT videos were recorded at 60 frames per second using a single Google Pixel 6a smartphone. Ten gait trials were conducted on an eight-meter straight stretch. They were instructed to walk at an “every day, normal, and safe pace”. Twelve Vicon T40-S cameras were positioned on the ceiling around the room. Forty-three reflective markers (14 mm) were placed on anatomical landmarks according to the Plug-in Gait Model (Vicon Motion Systems, Oxford Metrics Group Ltd). Similarly, SMARTGAIT extracts 24 anatomical key points skeletal structures from the Smartphone videos, to estimate joint kinematics. To synchronize the systems, the timestamps of the foot contacts during the first gait cycle within the measurement area for both systems were determined. A least-squares fit was then used to determine the temporal offset.

Material and Data Acquisition:

Vicon Motion Capture

The Vicon 3D motion capture system (Oxford Metrics, Oxford, UK) was used, comprising of 12 Vicon-T40S infrared cameras with a sampling rate of 100 Hz and Vicon Nexus software (Version 2.12, Oxford Metrics, Oxford, UK). The system was calibrated before use and small 14mm reflectors were utilized. Kinematics, joint angles and gait parameters were calculated by the system based on the 3D coordinates of reflective markers placed at specific anatomical landmarks on each participant.

SMARTGAIT

The novel system analyzes gait and lower extremity kinematics from videos in two stages. First, a deep learning model identifies people and creates bounding boxes around them in each video frame. These frames are then cropped and resized. The second stage employs another deep learning model to predict key body points (24 in total) for each person in 2D and 3D relative to the camera (Barzyk et al., 2024). This model is robust to challenges like perspective changes, occlusions, and clothing variations, thanks to its use of statistical information about human movement. The resulting 3D skeletal movement data of the participants serves as the basis for further processing and subsequent gait analysis. Next, the data is normalized temporally and spatially in order to be invariant to differences in variables such as frame rate, body size, etc. Afterwards, this normalized data is used to perform a gait cycle detection using a second deep learning model. The detected gait cycles are then used as the basis for assessing the gait parameters of the participants. For example, the stride time is determined on the basis of two consecutive heel strike events, or in our case more generally based on two consecutive foot strike events, to be able to collect data for participants suffering from foot drop paresis or other limitations.

Statistical Analysis:

The agreement between the SMARTGAIT and Vicon systems for measuring angular trajectories in the sagittal plane (i.e. hip flexion/extension, knee flexion/extension, plantar- and dorsiflexion) and frontal plane (i.e. hip abduction/adduction, knee varus/valgus), was quantified using Pearson correlations (r), root mean square error (RMSE), mean average error (MAE), as well as the absolute error in the maximal and minimal joint angles. Pearson's r values ranging from 0.4 to 0.8 are considered to indicate moderate correlation, while values above 0.8 indicate strong correlation. Statistical parametric mapping (SPM) was used to determine significant agreement between the time-continuous measurements of the two systems using a t-test metric ($p<0.05$). To assess the agreement of the spatiotemporal gait parameters (step length, stride length, speed, cadence, stride time, and step time), we calculated intraclass correlation coefficients (ICCs) and the MAEs. ICC values between 0.75 and 0.9 indicate good reliability, and values above 0.9 indicate excellent reliability (Koo & Li, 2016). RMSE ≤ 2° were defined as low and RMSE between 2-5 were defined as acceptable but requiring consideration in data interpretation after clinical gait analysis (McGinley et al., 2009).

Results:

Correlations between Vicon and SMARTGAIT in the sagittal plane were ≥ 0.79 for all angle kinematics (Table 2). The maximum RMSE and MAE values were 4.6° and 3.2° for plantarflexion and dorsiflexion, respectively. In the frontal plane, we observed moderate to high correlations of ≥ 0.71, and the maximum RMSE and MAE were 4.2°/3.0° for hip abduction and adduction. The analysis of the SPM revealed significant correlations between Vicon and SMARTGAIT for angular progressions in all planes (Table 2). Figure 1 illustrates the angular progression in the frontal and sagittal planes of both systems, together with the SPM analysis, for a single participant. The figures for the remaining participants can be found in the appendix.

Table 2 Statistical results for the agreement between the SMARTGAIT and Vicon system (Pearson correlations (r), root mean square error (RMSE), mean absolute error (MAE), absolute error in the maximal (Max_err) and minimal (Min_err) joint angles, as well as statistical parametric mapping (SPM).

Plane	*Movement*	*Pearson's r*	*RMSE [°]*	*MAE [°]*	*Max_err [°]*	*Min_err [°]*	*SPM [p-value]*
Sagittal	Hip flex./ext.	0.95	3.5	2.7	2.6	2.5	0.011
	Knee flex./ext.	0.94	3.7	2.8	2.4	2.9	0.009
	Plantar/Dorsi flex.	0.79	4.6	3.2	2.1	4.5	0.012

Frontal	Hip abd./add.	0.75	4.2	3.0	2.3	2.2	0.009
	Knee var./val.	0.71	3.9	2.9	3.7	2.8	0.008

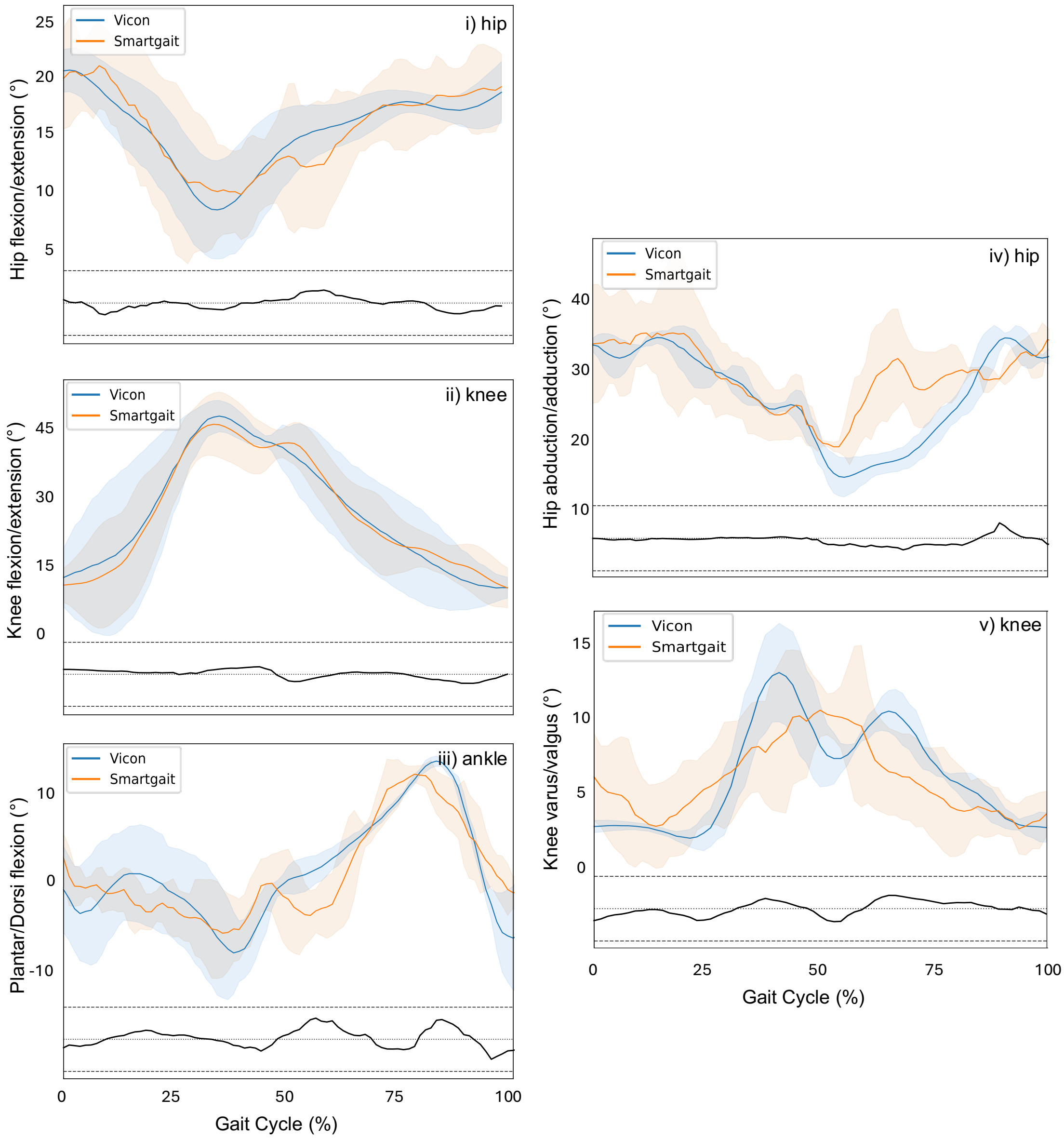

Figure 1 Mean i) hip, ii) knee and iii) ankle angle in the sagittal plane, and mean iv) hip, and v) knee angle in the frontal plane, for participant P01 from ten walks. Zero degrees means full hip and knee extension and neutral ankle position. The grey bar at the bottom of each graph indicates significance (from SPM analysis) as the corresponding t-test statistics in relation to a critical threshold (black dashed lines; p = .05).

The ICCs show good to excellent reliability for all gait parameters (Table 3). The mean speed and cadence were 0.6 ± 0.4 m/s and 75.9 ± 24.7 steps/min for Vicon and 0.6 ± 0.4 m/s and 74.1 ± 26.4 steps/min for SMARTGAIT. The average stride and step times were 1.8 ± 0.7 s and 1.0 ± 0.5 s for Vicon and 1.9 ± 0.8 s and 0.9 ± 0.4 s for SMARTGAIT. In terms of spatial parameters, stride length and step length were 0.8 ± 0.3 m and 0.4 ± 0.1 m for Vicon and 0.8 ± 0.3 m and 0.4 ± 0.1 m for SMARTGAIT, respectively. The mean values for all gait parameters, are presented in the appendix, along with the mean absolute error (MAE).

Table 3 Intraclass Correlation Coefficients (ICCs) for absolute agreement of all spatiotemporal gait parameters between Vicon and SMARTGAIT. Values greater than 0.90 indicate excellent reliability.

Parameters	*ICC Point Estimate*	*Lower 95% CI*	*Upper 95% CI*
Cadence (steps/min)	0.987	0.971	0.994
Stride time (s)	0.982	0.960	0.992
Step time (s)	0.963	0.918	0.984
Speed (m/s)	0.997	0.994	0.999
Stride length (m)	0.985	0.967	0.994
Step length (m)	0.781	0.562	0.899

Discussion:

The present study compared lower extremity kinematics and gait parameters in stroke participants using SMARTGAIT, a novel deep learning-based system for gait analysis, against a gold standard Vicon system. The results demonstrated moderate to high levels of agreement between the two systems, with Pearson correlations of ≥ 0.79 for all lower body angle kinematics in the sagittal plane and ≥ 0.71 in the frontal plane. The correlations found between both systems may suggest that SMARTGAIT has the potential to measure lower extremity angle trajectories during gait cycles with an accuracy that is sufficient for clinical gait analysis, particularly in the sagittal plane. In addition to joint kinematics, the study also evaluated the agreement of spatiotemporal gait parameters between the SMARTGAIT and Vicon systems. The results showed excellent agreement for all parameters (ICCs ≥ 0.96) except for step length (ICC = 0.78). These findings suggest that SMARTGAIT can accurately estimate joint kinematics and spatiotemporal gait parameters, even from videos of a single 2D RGB smartphone camera.

The use of deep learning algorithms in gait analysis has been explored in previous studies (Iosa et al., 2021; Lau et al., 2009; Lee et al., 2000; Scheffer & Cloete, 2012; Zhou et al., 2020), but the application of these techniques to clinical settings has been limited due to practical and technical challenges. The current study addresses these limitations by demonstrating the proof-of-concept of using a single RGB camera for gait analysis.

Angle kinematics:

The majority of motion during normal walking occurs in the sagittal plane, providing useful information, for example, for quantifying the status of neurologic disease (Balaban & Tok, 2014). McGinley et al. (2009) proposed that in the majority of clinical scenarios, errors of 2° or less are likely to be deemed acceptable, as such errors are likely to be too minor to necessitate explicit consideration during data interpretation. Errors between 2° and 5° are also likely to be regarded as reasonable, although they may require consideration in data interpretation. The errors observed in our study fall within the 2° to 5° range, indicating that SMARTGAIT may have clinical value for gait analysis. However, caution is required when interpreting values. This is particularly relevant to the plantar dorsi flexion angle (RMSE 4.6°), which has a relatively small range of motion (ROM), thereby increasing the impact of measurement error.

Although kinematics in clinical gait analysis is predominantly calculated in the sagittal plane, joint angles for the hip and knee joints are frequently reported for the frontal plane (Sandau et al., 2014). The RMSE values were found to be in the range of 2° to 5°, which is comparable to the results of Horsak et al. (2023), who demonstrated RMSE values for hip abduction between 3.7° and 4.8° in three pathological gait patterns. Although the results demonstrate good values throughout the gait cycle, the results cannot be readily generalized. As illustrated in Figure 1v, the novel system encounters significant challenges when calculating rotational movements, such as varus and valgus of the knee. This can lead to complications when analyzing individual sections of the gait cycle.

Horsak et al. (2023) employed two smartphone cameras and OpenCap markerless gait analysis. The healthy participants were instructed to simulate three pathological gait patterns (crouch, circumduction and equinus) under the supervision of a physiotherapist. In general, they observed greater RMSE values for hip flexion (ranging from 5.5° to 7.6°), knee flexion (5.9° to 8.5°), and ankle angle (6.1° to 7.9°) compared to the findings of our study. These findings suggest that the pose estimation algorithms embedded into SMARTGAIT result in higher correlation and lower error rates during marker-based motion capturing than previous approaches, despite the use of fewer cameras (i.e., one vs two cameras). One can hypothesize that the “end-to-end” modelling of the 3D reconstruction within the deep learning model of SMARTGAIT is more robust than the retrospective reconstruction of multiple 2D views of OpenCap.

Moreover, these findings demonstrate particularly high RMSE values for the joint most affected by the pathological gait pattern (crouch = knee flexion, equinus = ankle flexion). It is evident that deep learning algorithms encounter challenges in accurately identifying aberrant gait patterns, as these are not as extensively represented in the data sets upon which the systems are based (Kanko et al., 2021). Nevertheless, this outcome also suggests the potential for these methods to yield enhanced outcomes with the inclusion of further pathological gait data.

SPM analysis:

Average SPM values did not exceed $p \leq 0.05$ for any angle trajectory, indicating agreement between the SMARTGAIT and Vicon system. Few SPM values in individual patients were above the threshold for specific angles (see appendix). This shows that deviations can occur at specific phases of the gait cycle in individual cases, which are more significant. These deviations were not observed more frequently at a specific angle or in a specific patient. Potential causes for these outliers may be, that patients perform special movements due to their stroke, which the deep learning models only recognize to a limited extent. However, these outliers may be fully compensated for, by including additional training data of patients with pathological gait patterns, as discussed above.

Comparison of patients with and without walking aid:

A comparison of the data in Table 3 revealed that patients with a walking aid exhibited a greater incidence of measurement errors (RMSE range: 2.8° - 6.6°) than patients without a walking aid (RMSE range: 2.6° - 5.2°). In patients who were not using a walking aid, all RMSE values were below the 5° threshold deemed suitable for clinical applications (with the exception of one patient, hip abduction/adduction: RMSE: 5.2°). Conversely, 35% of the RMSE values determined with a walking aid were above the threshold value of 5°, with the majority of these values being above the threshold for plantar/dorsiflexion and hip abduction/adduction. The increased occurrence of elevated RMSE values in these patients may be attributed to a number of factors. The use of a walker or the presence of a therapist, particularly on the side facing the camera, can result in increased masking and, on occasion, a lack of contrast between the walker/therapist and the legs or shoes and the background. These factors, in conjunction with the observation that all patients with gait abnormalities exhibited the most aberrant and deviant gait patterns of all patients studied, may account for the observed increase in RSME scores.

Spatiotemporal gait parameters:

We observed excellent ICC values for all gait parameters, except for step length, demonstrating the potential of

SMARTGAIT for measuring spatio-temporal features during walking. Nevertheless, our results also show that there is potential for improvement in the assessment of specific spatial gait parameters. While the assessment of the stride length works well, the accuracy of the step length estimation is limited. This probably has to do with the significant asymmetries in the gait pattern of stroke patients, which are challenging for the SMARTGAIT system to recognize.

Lonini et al. (2022) employed DeepLabCut, an open-source framework for markerless pose estimation, to track five body key points (hip, knee, ankle, heel and toe) in stroke patients. The temporal gait parameters were then compared to those obtained using the GAITRite system as a reference. In contrast to SMARTGAIT, the pre-trained deep learning model was further fine-tuned by manual annotation of the positions of five landmarks on the leg and foot in two frames for each video. Furthermore, videos from both sides were included in the dataset. The systems were thus able to detect the parameters regardless of the presence of assistive devices and other people in the scene.

The mean MAE and SD of speed (-0.02 ± 0.11) were comparable to our results (0.01 ± 0.03 m/s), whereas the MAE of cadence was found to be significantly higher in the present study (1.80 ± 4.27) in comparison to that reported by Lonini and colleagues (-0.25 ± 3.88). Notwithstanding the tendency of both deep learning algorithms to underestimate gait parameters in comparison to the reference systems, according to Lonini et al. (2022), manual input of marker positions is necessary to refine their outcomes. Consequently, SMARTGAIT could offer advantages in terms of ease of use, which would be beneficial for practical application. Furthermore, Lonini et al. (2022) were unable to obtain or calculate three-dimensional models from their two-dimensional video sequences, which precluded the analysis of spatial gait parameters.

Conclusion:

The findings of this study have several implications for clinical practice. Firstly, the use of a single 2D RGB camera for gait analysis could make gait analysis more accessible in clinical settings. This could potentially simplify the process and make it more feasible for therapists and doctors to use in their practice. Secondly, traditional gait analysis systems like Vicon are often expensive and require specialized equipment and trained personnel. In contrast, a system like SMARTGAIT that uses simple smartphone videos could be a more cost-effective solution. Thirdly, the ability to accurately estimate joint kinematics and spatiotemporal gait parameters could aid therapists and doctors in diagnosing and treating conditions like stroke-induced motor deficits. It could also be used to monitor participant progress during rehabilitation. Lastly, the success of the SMARTGAIT system could encourage further research into the application of deep learning algorithms in gait analysis. This could lead to the development of even more accurate and efficient systems in the future.

However, it is important to note that while the correlations were mostly high, there were still some discrepancies between the SMARTGAIT and Vicon systems. These issues may be due to the inherent limitations of estimating 3D joint coordinates from 2D images. Future research could focus on improving the accuracy of these estimations, perhaps by incorporating additional data or refining the deep learning algorithms used. Nonetheless, the lower limb kinematics errors, measured in degrees, were below the clinically desirable threshold of five degrees for all angles (McGinley et al., 2009).

The results of this study suggest that SMARTGAIT is a promising tool for gait analysis in stroke. However, further analyses are required to validate SMARTGAIT in larger samples and its transferability to different forms of pathological gait.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used DeepL in order to spell-check some sentences. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Author contributions

PB, PZ, DS, MS and JS carried out the experiments, designed the study, performed the computations and data analysis and drafted the manuscript. AB helped with the experiments and reviewed the manuscript. MG, MS, and JL contributed to the design of the study and reviewed the manuscript. All authors contributed substantially to the article and approved the submitted version.

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Appendix

Table 4 Statistical results of the comparison between SMARTGAIT and Vicon for each individual patient, including Pearson correlations (r), root mean square error (RMSE), mean absolute error (MAE), as well as statistical parametric mapping (SPM).

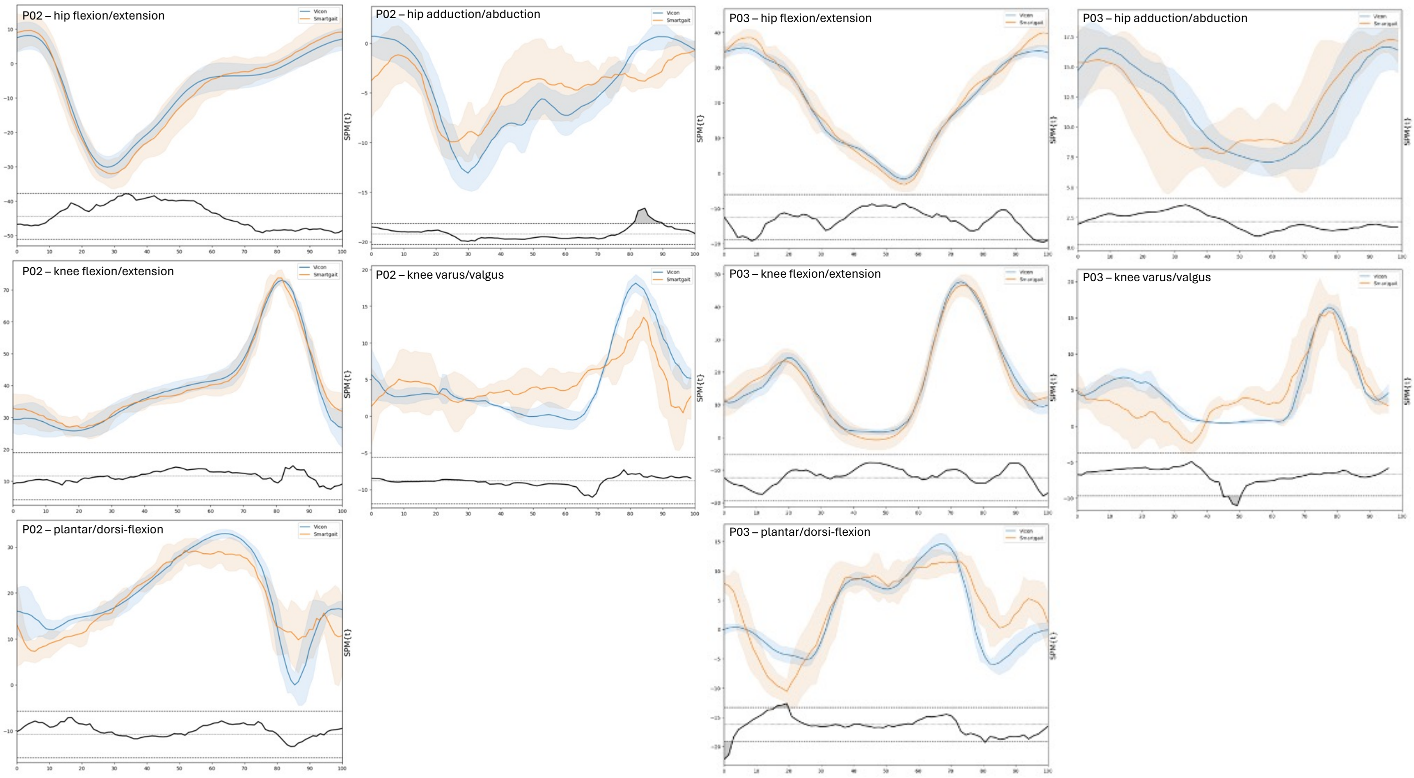
Walking Aid	*Patient*	*Correlation [r]*	*RMSE [°]*	*MAE [°]*	*SPM [p]*	*Correlation [r]*	*RMSE [°]*	*MAE [°]*	*SPM [p]*
		Hip flex./ext.				*Knee flex./ext.*			

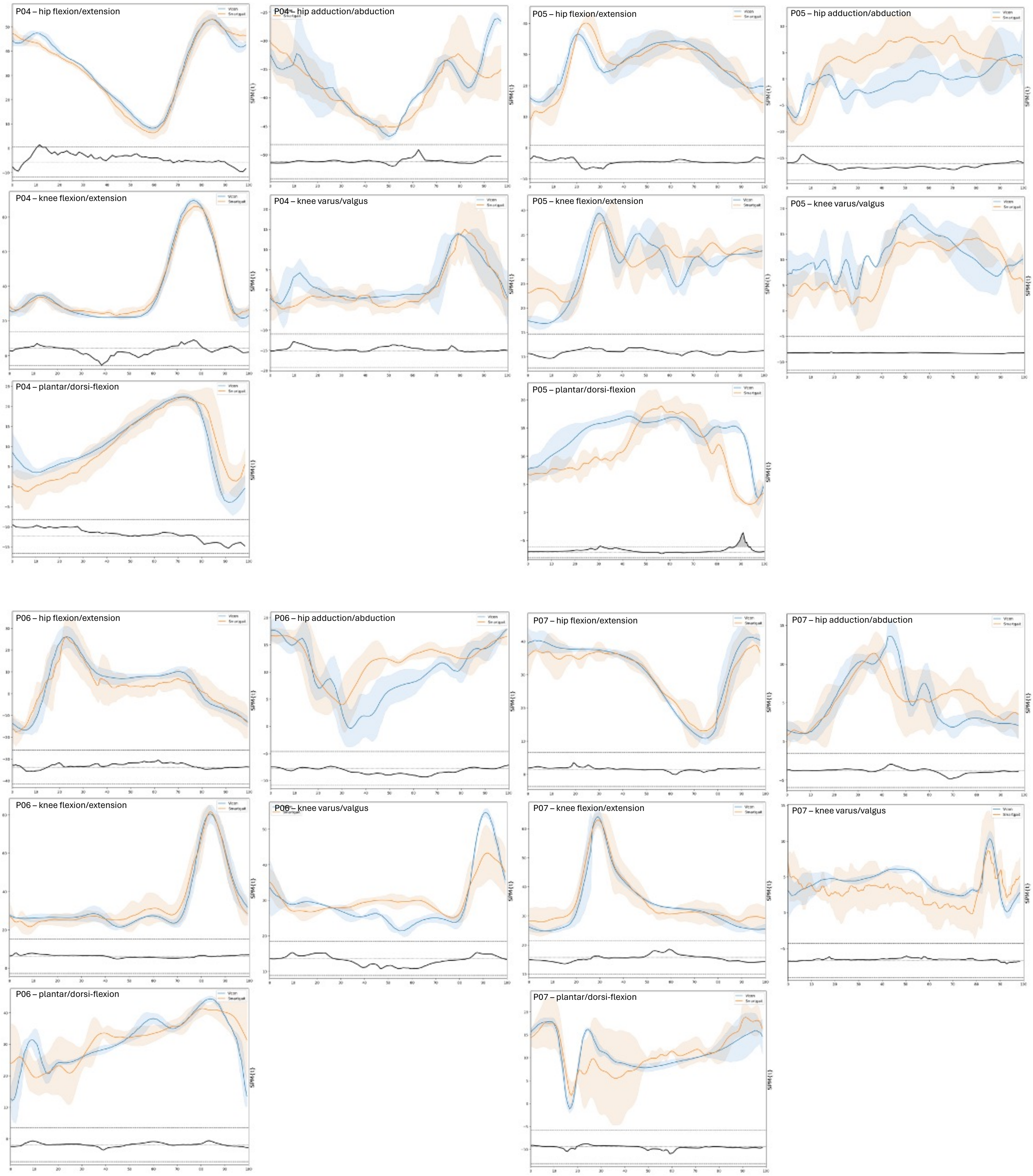
Without walking aid	P01	0.93	3.2	2.5	0.007	0.98	3.2	2.6	0.006
	P02	0.99	2.9	2.2	0.026	0.99	2.6	1.9	0.010
	P03	0.99	3.0	2.4	0.020	0.98	3.0	2.3	0.015
	P04	0.99	2.9	2.1	0.017	0.99	3.2	2.4	0.011
With walking aid	P05	0.88	4.0	3.2	0.006	0.73	4.2	3.2	0.006
	P06	0.92	5.6	4.5	0.007	0.95	5.7	4.0	0.004
	P07	0.96	3.5	2.3	0.004	0.95	3.6	2.7	0.008
	P08	0.97	2.8	2.1	0.004	0.99	3.8	2.8	0.014
		Plantar/Dorsi flex.				*Hip abd./add.*			
Without walking aid	P01	0.76	3.9	2.9	0.012	0.85	5.2	3.8	0.005
	P02	0.90	4.7	3.3	0.014	0.76	3.0	2.2	0.025
	P03	0.77	4.5	3.5	0.022	0.85	2.7	2.2	0.009
	P04	0.89	3.8	2.5	0.016	0.97	3.7	2.4	0.005
With walking aid	P05	0.60	5.5	3.5	0.016	0.36	6.1	4.8	0.010
	P06	0.69	6.6	4.7	0.004	0.65	4.7	3.2	0.009
	P07	0.71	4.2	2.4	0.004	0.69	3.0	1.8	0.005
	P08	0.95	3.4	2.5	0.007	0.86	5.0	3.6	0.004
		Knee var./val.							
Without walking aid	P01	0.70	3.1	2.2	0.009				
	P02	0.68	3.6	2.7	0.008				
	P03	0.78	3.1	2.5	0.014				
	P04	0.84	3.9	3.0	0.006				
With walking aid	P05	0.55	4.9	3.6	0.001				
	P06	0.82	5.3	3.4	0.012				
	P07	0.38	2.8	2.4	0.004				
	P08	0.89	4.3	3.2	0.013				

Table 5 Mean values for all gait parameters for SMARTGAIT and Vicon, together with the mean average error (MAE) between the two systems for each individual patient including cadence (steps/min), stride time (s), step time (s), speed (m/s), stride length (m) and step length (m).

Walking Aid	*Patient*	*Cadence [steps/min]*		*Stride time [s]*		*Step time [s]*		*Speed [m/s]*		*Stride length [m]*		*Step length [m]*	
		SMARTGAIT	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*
	P01	91.5	90.5	1.3	1.3	0.6	0.7	0.7	0.6	0.9	0.9	0.4	0.4

Without walking aid	P02	78.4	79.8	1.5	1.5	0.8	0.8	0.5	0.5	0.7	0.7	0.4	0.4
	P03	112.7	112.4	1.1	1.1	0.5	0.5	1.2	1.2	1.3	1.2	0.6	0.6
	P04	100.1	98.4	1.2	1.2	0.6	0.6	1.0	1.0	1.2	1.2	0.5	0.6
With walking aid	P05	36.2	35.9	3.3	3.4	1.7	1.9	0.2	0.2	0.7	0.7	0.4	0.4
	P06	49.5	50.5	2.4	2.4	1.2	1.4	0.2	0.2	0.5	0.5	0.3	0.3
	P07	42.6	54.0	2.8	2.4	1.4	1.3	0.2	0.2	0.5	0.4	0.3	0.4
	P08	81.4	85.4	1.5	1.4	0.7	0.7	0.5	0.6	0.8	0.8	0.4	0.4
	MAE + SD	1.80	4.27	-0.06	0.15	0.05	0.12	0.01	0.03	-0.02	0.04	0.03	0.07




P04 – hip flexion/extension
P04 – hip adduction/abduction
P05 – hip flexion/extension
P05 – hip adduction/abduction
P04 – knee flexion/extension
P04 – knee varus/valgus
P05 – knee flexion/extension
P05 – knee varus/valgus
P04 – plantar/dorsi-flexion
P05 – plantar/dorsi-flexion
P06 – hip flexion/extension
P06 – hip adduction/abduction
P07 – hip flexion/extension
P07 – hip adduction/abduction
P06 – knee flexion/extension
P06 – knee varus/valgus
P07 – knee flexion/extension
P07 – knee varus/valgus
P06 – plantar/dorsi-flexion
P07 – plantar/dorsi-flexion

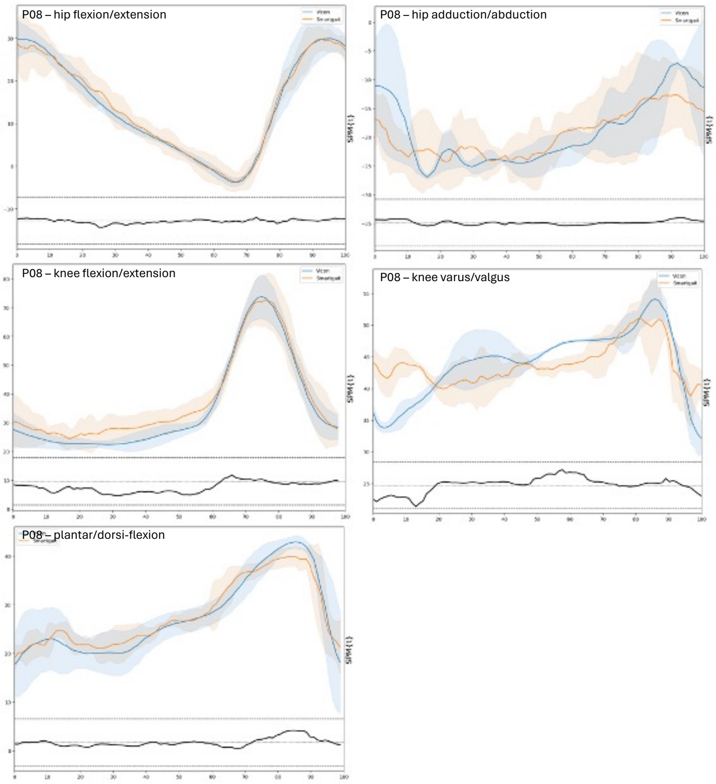

P08 – hip flexion/extension
P08 – hip adduction/abduction
P08 – knee flexion/extension
P08 – knee varus/valgus
P08 – plantar/dorsi-flexion
SPM{t}

Figure1

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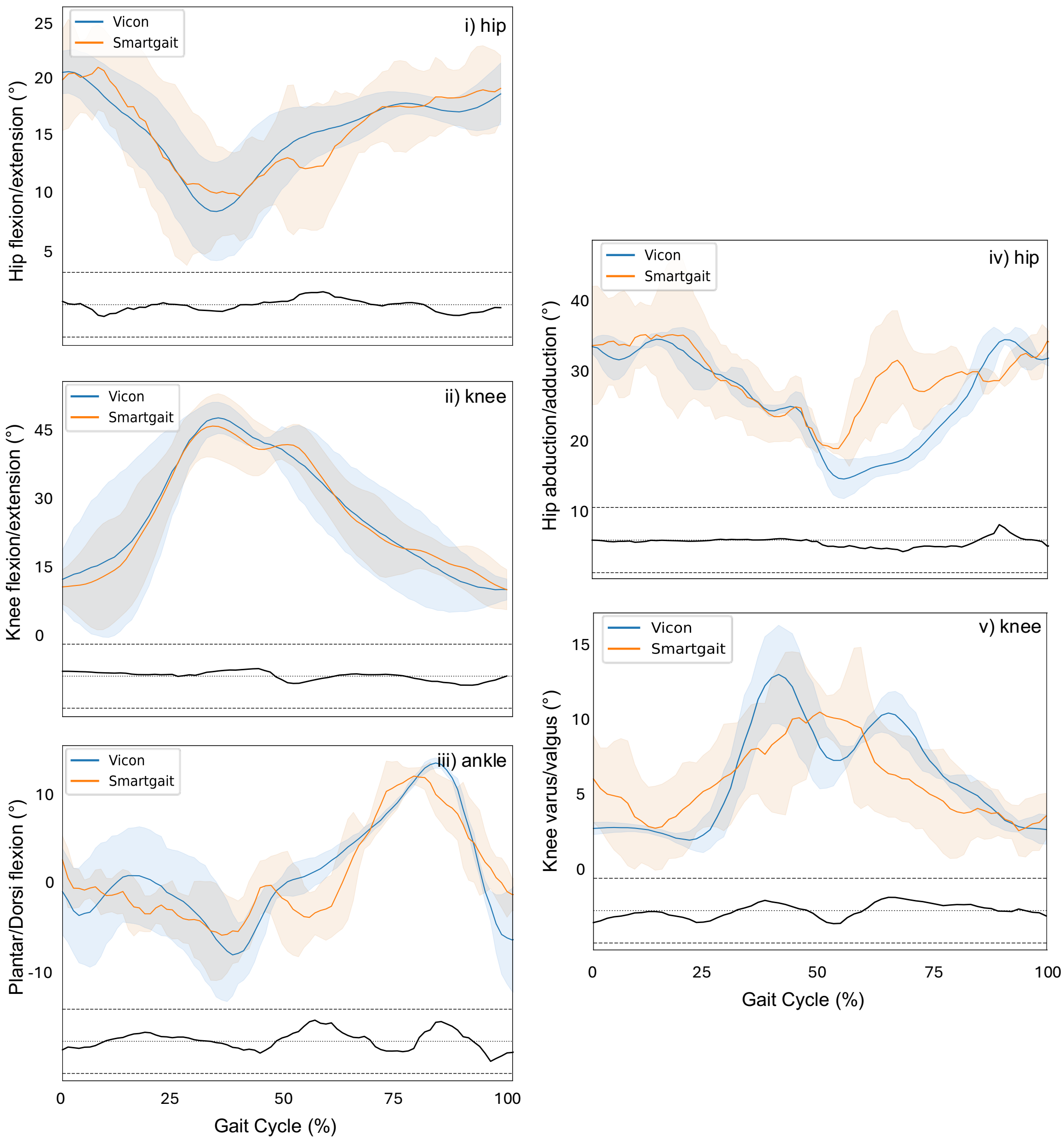
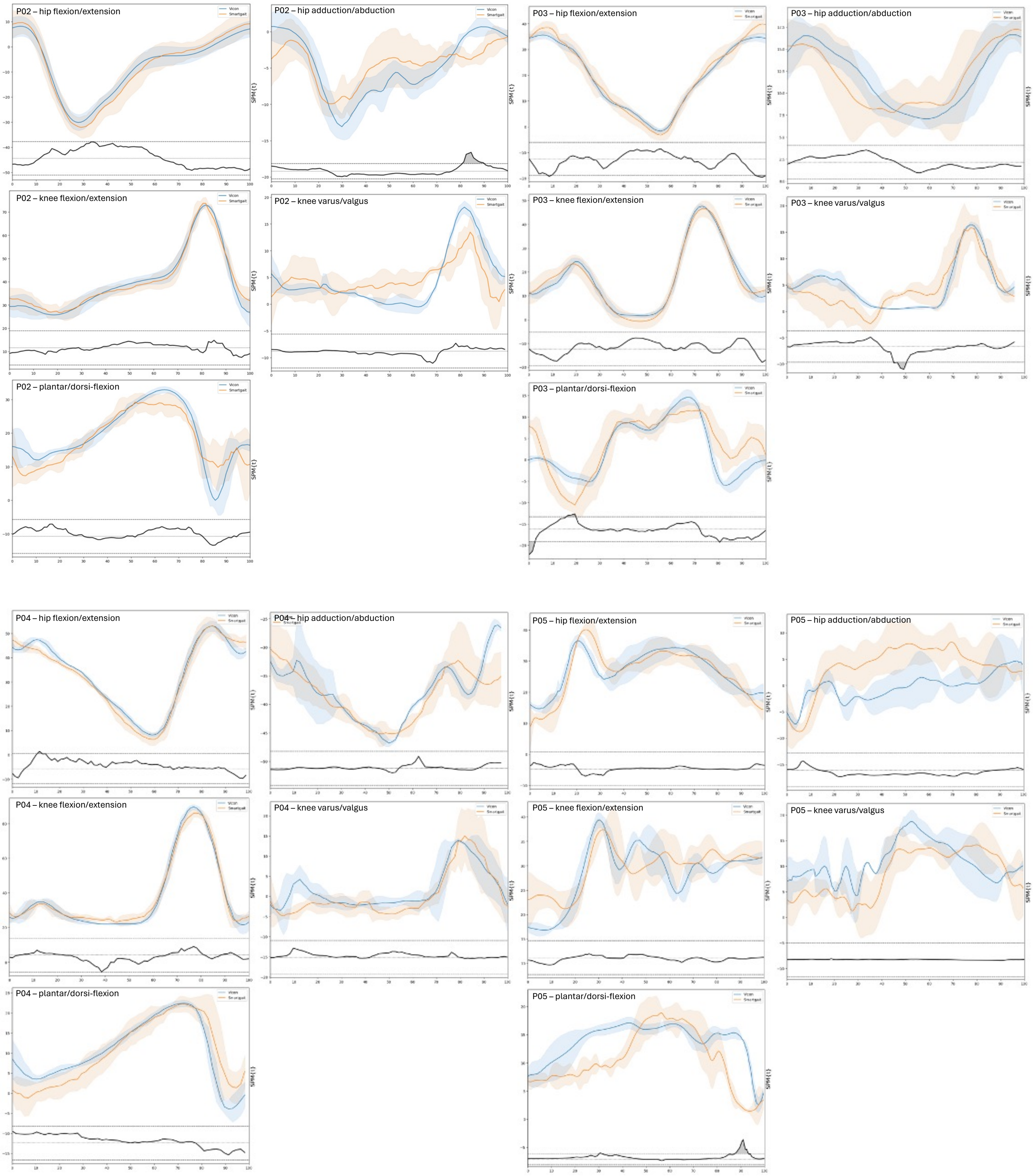
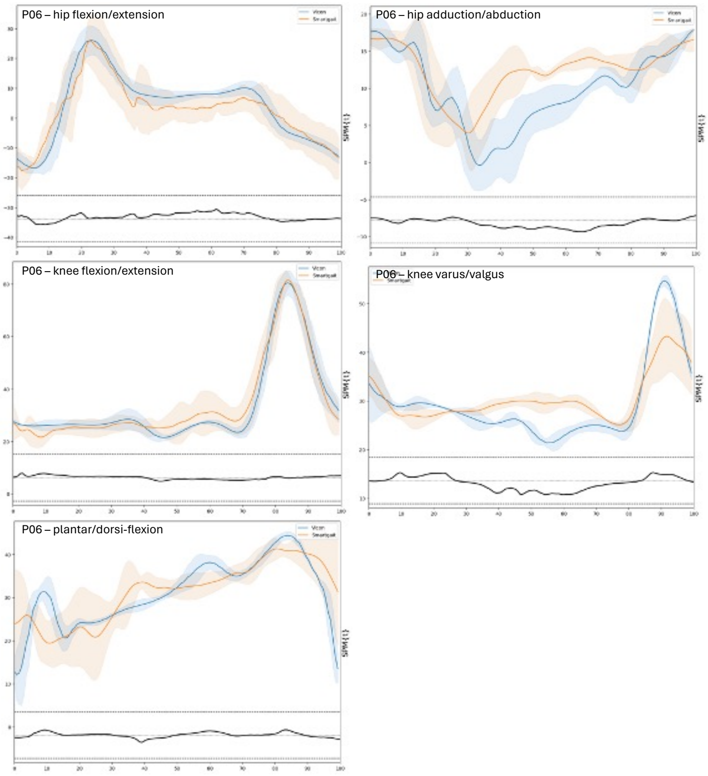
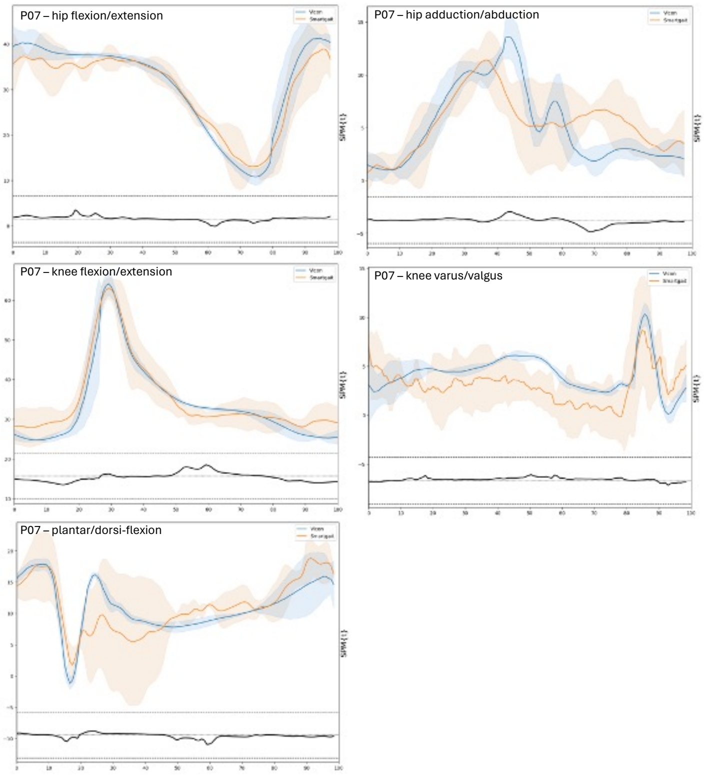


Figure Appendix




P06 – hip flexion/extension
P06 – hip adduction/abduction
P06 – knee flexion/extension
P06 – knee varus/valgus
P06 – plantar/dorsi-flexion
SPM{t}


P07 – hip flexion/extension
P07 – hip adduction/abduction
P07 – knee flexion/extension
P07 – knee varus/valgus
P07 – plantar/dorsi-flexion
SPM{t}

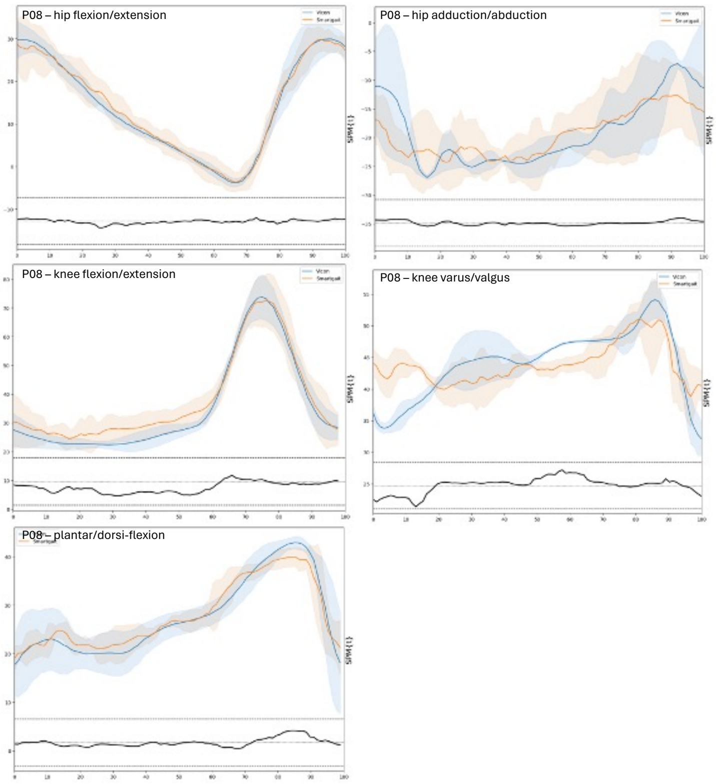

P08 – hip flexion/extension
P08 – hip adduction/abduction
P08 – knee flexion/extension
P08 – knee varus/valgus
P08 – plantar/dorsi-flexion
SPM{t}

Table1

Participant	*Age [years]*	*Sex*	*Weight [kg]*	*Height [mm]*	*Time since stroke [months]*	*Paretic bodyside*	*Type of stroke*	*Fugl-Meyer-Lower extremities [FMA-LE]*	*Functional Ambulation Categories [FAC]*	*10-meter walk test [10MWT, s]*	*Walking aid*
P01	79	m	71	171	51	right	Ischemic	21	5	n.r.	No
P02	44	m	78	170	1	left	Hemorrhagic	26	4	15.6	No
P03	36	m	76	171	4	right	Hemorrhagic	31	5	7.15	No
P04	62	m	79	170	130	left	Ischemic	20	5	n.r.	No
P05	60	m	80	163	4	right	Hemorrhagic	13	2	41.2	Walking stick and foot lift orthosis
P06	62	f	60	166	4	left	Ischemic	18	3	35.7	Quad stick and foot lift orthosis
P07	61	f	65	160	4	left	Hemorrhagic	19	3	28.55	Quad stick and foot lift orthosis
P08	71	m	93	174	3	left	Hemorrhagic	17	3	20.85	Walking stick and foot lift orthosis

Table2

Plane	*Movement*	*Pearson's r*	*RMSE [°]*	*MAE [°]*	*Max_ err [°]*	*Min_ err [°]*	*SPM [p-value]*
Sagittal	Hip flex./ext.	0.95	3.5	2.7	2.6	2.5	0.011
	Knee flex./ext.	0.94	3.7	2.8	2.4	2.9	0.009
	Plantar/Dorsi flex.	0.79	4.6	3.2	2.1	4.5	0.012
Frontal	Hip abd./add.	0.75	4.2	3.0	2.3	2.2	0.009
	Knee var./val.	0.71	3.9	2.9	3.7	2.8	0.008

Parameters	*ICC Point Estimate*	*Lower 95% CI*	*Upper 95% CI*
Cadence (steps/min)	0.987	0.971	0.994
Stride time (s)	0.982	0.960	0.992
Step time (s)	0.963	0.918	0.984
Speed (m/s)	0.997	0.994	0.999
Stride length (m)	0.985	0.967	0.994
Step length (m)	0.781	0.562	0.899

Walking Aid	*Patient*	*Correlation [r]*	*RMSE [°]*	*MAE [°]*	*SPM [p]*	*Correlation [r]*	*RMSE [°]*	*MAE [°]*	*SPM [p]*
			Hip flex./ext.				*Knee flex./ext.*		
Without walking aid	P01	0.93	3.2	2.5	0.007	0.98	3.2	2.6	0.006
	P02	0.99	2.9	2.2	0.026	0.99	2.6	1.9	0.010
	P03	0.99	3.0	2.4	0.020	0.98	3.0	2.3	0.015
	P04	0.99	2.9	2.1	0.017	0.99	3.2	2.4	0.011
With walking aid	P05	0.88	4.0	3.2	0.006	0.73	4.2	3.2	0.006
	P06	0.92	5.6	4.5	0.007	0.95	5.7	4.0	0.004
	P07	0.96	3.5	2.3	0.004	0.95	3.6	2.7	0.008
	P08	0.97	2.8	2.1	0.004	0.99	3.8	2.8	0.014
			Plantar/Dorsi flex.				*Hip abd./add.*		
Without walking aid	P01	0.76	3.9	2.9	0.012	0.85	5.2	3.8	0.005
	P02	0.90	4.7	3.3	0.014	0.76	3.0	2.2	0.025
	P03	0.77	4.5	3.5	0.022	0.85	2.7	2.2	0.009
	P04	0.89	3.8	2.5	0.016	0.97	3.7	2.4	0.005
With walking aid	P05	0.60	5.5	3.5	0.016	0.36	6.1	4.8	0.010
	P06	0.69	6.6	4.7	0.004	0.65	4.7	3.2	0.009
	P07	0.71	4.2	2.4	0.004	0.69	3.0	1.8	0.005
	P08	0.95	3.4	2.5	0.007	0.86	5.0	3.6	0.004
			Knee var./val.						
Without walking aid	P01	0.70	3.1	2.2	0.009				
	P02	0.68	3.6	2.7	0.008				
	P03	0.78	3.1	2.5	0.014				
	P04	0.84	3.9	3.0	0.006				
With walking aid	P05	0.55	4.9	3.6	0.001				
	P06	0.82	5.3	3.4	0.012				
	P07	0.38	2.8	2.4	0.004				
	P08	0.89	4.3	3.2	0.013				

Walking Aid	*Patient*	*Cadence [steps/min]*		*Stride time [s]*		*Step time [s]*		*Speed [m/s]*		*Stride length [m]*		*Step length [m]*	
		SMARTGAIT	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*	*SMARTGAIT*	*Vicon*
Without walking aid	P01	91.5	90.5	1.3	1.3	0.6	0.7	0.7	0.6	0.9	0.9	0.4	0.4
	P02	78.4	79.8	1.5	1.5	0.8	0.8	0.5	0.5	0.7	0.7	0.4	0.4
	P03	112.7	112.4	1.1	1.1	0.5	0.5	1.2	1.2	1.3	1.2	0.6	0.6
	P04	100.1	98.4	1.2	1.2	0.6	0.6	1.0	1.0	1.2	1.2	0.5	0.6
With walking aid	P05	36.2	35.9	3.3	3.4	1.7	1.9	0.2	0.2	0.7	0.7	0.4	0.4
	P06	49.5	50.5	2.4	2.4	1.2	1.4	0.2	0.2	0.5	0.5	0.3	0.3
	P07	42.6	54.0	2.8	2.4	1.4	1.3	0.2	0.2	0.5	0.4	0.3	0.4
	P08	81.4	85.4	1.5	1.4	0.7	0.7	0.5	0.6	0.8	0.8	0.4	0.4
	MAE + SD	1.80	4.27	-0.06	0.15	0.05	0.12	0.01	0.03	-0.02	0.04	0.03	0.07

Conflict of Interest

Manuel Stein, Daniel Seebacher and Philip Zimmermann are part of Subsequent GmbH which provided the AI-based skeleton reconstruction and analysis tool and were involved in the measurements.