Journal of Biomechanics 193 (2025) 113008

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech

Validation of markerless motion capture for spatiotemporal gait measures in people with Parkinson's disease

Jana Seuthe [a], Fabio Augusto Barbieri [b], Jule Grotherr [c], Björn Hauptmann [a,c], Christian Schlenstedt [a,*]

[a] Institute for Interdisciplinary Exercise Science and Sports Medicine, MSH Medical School Hamburg, Hamburg, Germany
[b] Human Movement Research Laboratory (MOVI-LAB), School of Sciences, Department of Physical Education, São Paulo State University (UNESP), Bauru, SP, Brazil
[c] Parkinson's Disease and Movement Disorders Unit, Department of Neurology, Segeberger Kliniken, Bad Segeberg, Germany

ARTICLE INFO

Keywords:
Gait analysis
Motion capture
Parkinson's disease
Markerbased

ABSTRACT

Spatiotemporal gait measures are increasingly important for the characterization of gait impairments in people with Parkinson's disease (PD). Hence new assessment methods, like markerless motion capture using Theia3D, are of rising interest. This study aims to validate markerless motion capture in people with PD to retrieve spatiotemporal gait measures during overground and treadmill walking. Overground- and treadmill walking at comfortable speed were assessed in 30 individuals with PD. Markerbased and markerless motion capture were carried out in randomized order with the markerbased method using a model with markers at the heel, the lateral ankle and the toe. The markerless data (Theia Markerless Inc., Kingston, ON, Canada) was analyzed 1) with the same model as the markerbased data and 2) within the automatic report pipeline. Agreement between the measurements was assessed via mean differences, Pearson correlation coefficients, intraclass correlation coefficients and Bland-Altman methods. The results show good to excellent agreement (ICC $>$ 0.75) between spatiotemporal gait measures of the two measurements for overground walking, except for double support time (ICC $<$ 0.5), when analyzed with our custom algorithm. For treadmill walking all outcomes had excellent agreement (ICC $>$ 0.9). Mean differences were below the minimal clinical differences for gait speed and step length. For the results of the automatic report during overground gait agreement between methods was poor except for gait speed and step length. Overall, the markerless motion capture system used in this study provides valid results for the assessment of spatial and temporal gait variables in people with PD, when using a gait detection algorithm that is suitable for this population.

1. Introduction

Parkinson's disease (PD), a degenerative disorder increasing in prevalence (Grotewold & Albin, 2024), is characterized by its motor symptoms. Besides the cardinal symptoms like bradykinesia, tremor, and rigidity, patients experience gait disturbances(Mirelman et al., 2019), which can be associated with falls (Lord et al., 2016). Therefore, spatiotemporal gait measures are important clinical end-points in the assessment of neurological populations (Bishnoi et al., 2023) like those with PD. They are assessed to objectively quantify gait impairment or investigate the effectiveness of rehabilitation or therapy interventions (Mehrholz et al., 2015). Furthermore, they can also be used to classify people with PD with and without falls (Delval et al., 2021). Three-dimensional motion capture using infra-red cameras and reflective markers for gait analysis is a widespread valid and reliable method. In recent years the development of artificial intelligence has introduced new methods of markerless motion capture using 2D videos. Complex algorithms can retrieve a 3D pose of the participant with virtually generated markers similar to markerbased motion capture.

The main advantage of markerless versus markerbased motion capture is that the markerless assessment can be done quicker, as no markers need to be attached to the participants' skin. This can save a lot of time and work, especially as reflective markers can fall off or be visually blocked during the assessment. Furthermore, typical clothing has minimal impact (Keller et al., 2022), which makes it more accessible for different populations. Therefore, this method might be more useful in clinical settings where time is a limiting factor. Other advantages are that the system can potentially be used outside a laboratory in the future and that less experience is required by operators of the system.

The markerless motion capture using Theia3D (Theia Markerless

* Corresponding author.

https://doi.org/10.1016/j.jbiomech.2025.113008
Accepted 2 October 2025
Available online 3 October 2025

Inc., Kingston, ON, Canada) has been validated for healthy individuals (Kanko et al., 2021a; Kanko et al., 2021b; Riazati et al., 2022) and the system was deemed to have high inter-session repeatability (Kanko et al., 2020). As people with PD present with gait impairment such as short, shuffling steps or increased gait variability (Mirelman et al., 2019), it is crucial to know whether the markless data provide valid spatiotemporal measures in this population.

The aim of this study is to investigate the validity of markerless motion capture for assessing spatial and temporal gait parameters during overground and treadmill walking in people with PD.

2. Methods

2.1. Participants

Participants were included if they were diagnosed with Parkinson's disease by a neurologist. Exclusion criteria were other neurological disorders and orthopedic or other conditions that influence gait and balance and cognitive impairment (Mini Mental State Examination $\leq$ 24). People with PD were assessed in the laboratory of the MSH Medical School Hamburg. Written informed consent was obtained by the participants prior to participation. The study protocol was approved by the ethical committee of the MSH Medical School Hamburg and the study was conducted in accordance with the Declaration of Helsinki. The assessments were carried out ON-medication, which was checked by enquiring the time of the last dose of medication and via a subjective visual analogue scale asking about perceived ON– and OFF–status. To characterize PD participants the Movement Disorder Society-Unified Parkinson's Diseas Rating Scale part III (MDS-UPDRS-III) and the Montreal Cognitive Assessment (MoCA) were administered.

2.2. Gait analysis

Participants were instructed to walk along a 12-meter walkway 10 times at their comfortable walking speed. This procedure was repeated twice, with a short break in between. Following a two-minute rest, treadmill gait was assessed. Participants walked on the treadmill at their self-selected overground walking speed for two trials, each lasting one minute, with a brief rest period between them. For both overground- and treadmill walking, gait was recorded via markerbased motion capture and via markerless motion capture (Qualisys with Theia3D, 85 Hz) separately. The order of the two methods was stratified by blocked randomization according to the Hoehn&Yahr stage and Freezing of Gait (FOG) status (Freezer or Non-Freezer) based on the New Freezing of Gait Questionnaire item 1. No freezing episodes were observed in participants during the gait assessments.

The motion capture setup consisted of 10 Miqus Hybrid cameras (infrared and video) and 2 Miqus Video cameras (Qualisys, Sweden). For the markerbased gait analysis we placed three markers on each foot, lateral malleolus, heel and tip of the shoe and recorded gait with the Qualisys Track manager. For the markerless gait analysis we also recorded with Qualisys Track manager. The software enabling markerless motion capture is Theia3D (Theia Markerless Inc., Kingston, ON, Canada), which uses 2D videos for the estimation of human features and poses which are generated by a deep-learning algorithm. The software creates a skeletal model from which numerous kinematic outcomes can be retrieved. One static measurement in relaxed stance was recorded prior to the gait trial for the markerless tracking as a reference. Participants did not have to wear specific clothing for this, as the system has already shown good validity with different types of clothing (Keller et al., 2022).

2.3. Data processing

Marker position data from the markerbased motion capture was retrieved in c3d-format. The data from the markerless motion capture was processed by exporting the virtual markers of the generated model from Visual3D, which were equivalent to the markers used for the markerbased capture, also using c3d-format. Using a customized Matlab script the gait events (heelstrike and toe-off) were detected using heel and toe marker velocities (Pijnappels et al., 2001) and from that the following spatiotemporal gait measures were computed: gait speed (overground gait only), step length, stride time, stance time, swing time, double support time and step width (in the following referred to as "custom analysis report"). Computation of each gait parameter is described in the supplementary material. In a second instance the data from the markerless motion capture data was also analyzed by an internal algorithm provided within the Qualisys software which gave an automatic report with temporal and spatial gait parameters (in the following referred to as "automatic report"). In contrast to our own velocity-based gait event detection this algorithm used relations between pelvis and heel to detect gait events (Zeni et al., 2008). Note that the manufacturers state that the algorithm has not been tested on people with pathological gait.

2.4. Statistical analysis

To investigate the validity of the markerless motion capture and the automatic report, we compared the two approaches against the markerbased motion capture, which we considered as the gold-standard. Intraclass correlation coefficients (ICCs), with two-way random effects, absolute agreement, single measurement and its respective upper and lower limits were calculated. According to Koo and Li (2016) ICCs below 0.5 are interpreted as poor, between 0.5 and 0.75 as moderate, between 0.75 and 0.9 as good above 0.9 as excellent. Additionally, we calculated the Pearson correlation coefficient. Furthermore, we calculated the mean difference between the methods as well as the lower and upper limits of agreement and created Bland-Altmann plots.

Differences between the markerless- versus markerbased method can be caused by the algorithms providing the virtual markers within the markerless approach or by differences in calculating the spatio-temporal gait measures. To account for this, we conducted the above-mentioned statistical analysis for the following conditions: a) markerbased-custom analysis report versus markerless-custom analysis report, b) markerbased-custom analysis report versus markerless-automatic report and c) markerless-custom analysis report versus markerless-automatic report.

To investigate whether validity is impacted by motor symptom severity, the MDS-UPDRS-III was correlated (Pearson coefficient correlation) with the differences between markerless and markerbased for all gait outcomes for overground gait.

The statistical analysis was carried out using RStudio software (version 2024.04.2) (RStudio Team, 2018).

3. Results

Thirty-three individuals with PD were recruited for this study of which 30 completed the study protocol and could be included in the data analysis. Participants had a mean MDS-UPDRS-III score of 19.4, which means they were mildly affected (Skorvanek et al., 2017). Participants' characteristics are displayed in Table 1.

3.1. Overground walking

3.1.1. Markerless-custom analysis report versus markerbased-custom analysis report

We found varying ICCs for the different outcomes during overground walking. For gait speed ICC was excellent with a mean difference (MD) of −0.016 m/s (Fig. 1). We found similarly excellent ICCs for step length where the MD between the two measurements was about −8 mm (Fig. 2). Furthermore, step width also showed excellent agreement with a MD of 3 mm. While gait speed and step length were slightly

Table 1
Participants characteristics.

Measure	Mean (SD)
Sex (m/f)	20/10
Height (cm)	177.7 (9.5)
Weight (kg)	84.6 (15.7)
Age (years)	61.4 (9.2)
Hoehn & Yahr (1/2/3/4)	0/18/12/0
Disease duration (years)	5.3 (5.0)
MoCA (0–30)	26.6 (2.7)
MDS-UPDRS-III (0–132)	19.4 (7.8)

Abbreviations: m = male, f = female, MoCA = Montreal Cognitive Assessment, MDS-UPDRS-III = Movement Disorder Society –Unified Parkinson's Disease Rating Scale Part III, SD = standard deviation

overestimated by the markerless system, step width showed a slight tendency of being underestimated.

For temporal outcomes, excellent agreement was found for stride time with a corresponding MD of 0.001 s. For stance time and swing time our data showed good ICCs with absolute MDs of 0.02 s for both, with stance time being underestimated and swing time been overestimated by the markerless system. The only variable with poor ICC was double support time with a MD of 0.04 s, which was underestimated by the markerless system. More detailed results can be found in Table 2.

3.1.2. Markerless-automatic report versus markerbased-custom analysis report

We found excellent ICCs for gait speed (MD = −0.02 m/s) and step length (MD = −0.38 mm) for the comparison of markerless-automatic report versus markerbased-custom analysis report. All other outcomes showed poor ICCs with large MDs (see Supplementary material).

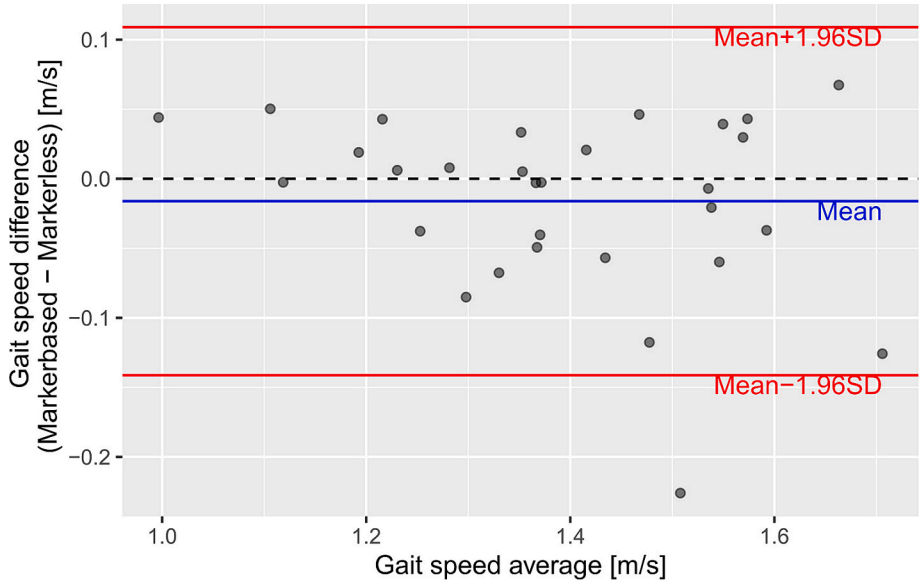

Fig. 1. Bland Altman Plot of gait speed (m/s) difference between markerbased and markerless motion capture. The blue line represents the mean difference and the red line the 95 % limits of agreement of the measurements.

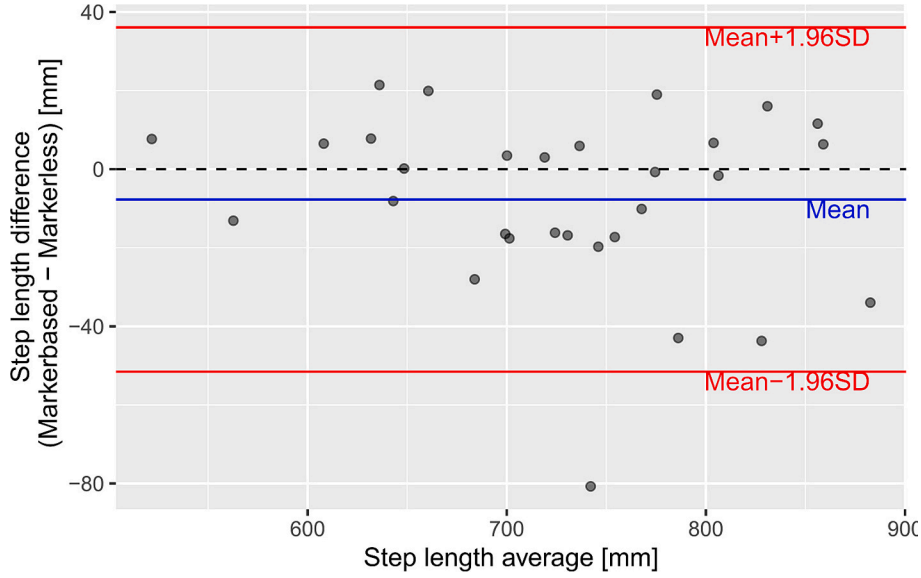

Fig. 2. Bland Altman Plot of step length (mm) difference between markerbased and markerless motion capture. The blue line represents the mean difference and the red line the 95 % limits of agreement of the measurements.

Table 2
Mean differences, agreement and correlation characteristics between spatial and temporal gait outcomes for markerless and markerbased motion capture for overground gait.

Overground Gait (Markebased − Markerless)	*Mean difference*	*Lower LOA*	*Upper LOA*	*Pearson r*	*ICC (2,1)*	*Lower ICC*	*Upper ICC*
Gait speed (m/s)	−0.016	−0.141	0.109	0.937	0.931	0.862	0.967
Step length (mm)	−7.729	−51.546	36.088	0.969	0.966	0.927	0.984
Stride time (s)	0.001	−0.035	0.037	0.973	0.973	0.945	0.987
Stance time (s)	0.021	−0.009	0.052	0.958	0.889	0.141	0.970
Swing time (s)	−0.020	−0.034	−0.006	0.970	0.767	−0.041	0.944
Step width (mm)	2.927	−22.678	28.533	0.939	0.929	0.857	0.965
Double support time (s)	0.040	0.010	0.071	0.884	0.495	−0.059	0.830

Abbreviations: LOA = limit of agreement, ICC = Intraclass correlation coefficient.

3.1.3. Markerless-automatic report versus markerless-custom analysis report

Similarly, we found excellent ICCs for gait speed (MD = −0.004 m/s) and step length (MD = 7.35 mm) for the comparison of markerless-automatic report versus markerless-custom analysis report. All other outcomes showed poor ICCs with large MDs (see Supplementary material).

3.2. Treadmill walking

3.2.1. Markerless-custom analysis report versus markerbased-custom analysis report

For treadmill walking we have found excellent ICC for all investigated variables. For step length mean difference between the measurements was 10.7 mm, which was slightly underestimated by the markerless system, and for step width 0.5 mm. Temporal outcomes had mean differences of 0.005 s for stride time, 0.003 s for stance time, 0.002 s for swing time and 0.001 s for double support time, all with a tendency to be overestimated by the markerless system. More detailed results can be found in Table 3.

3.2.2. Markerless-automatic report versus markerbased-custom analysis report

We found moderate ICCs for step length (MD = −72,76 mm). Stance time, on the other hand, showed an excellent ICC with a MD of −0.02 s. Moderate ICCS were also found for swing time (MD = 0.02 s) and double support time (MD = −0.02 s). Lastly, step width showed a poor ICC with MD of −44.67 mm (see Supplementary material for detailed results).

3.2.3. Markerless-automatic report versus markerless-custom analysis report

Similarly to the comparison of markerless-automatic report versus markerless-custom analysis report, we found a moderate ICC for step length (MD = −83.44 mm) and excellent ICC for stance time (MD = −0.02 s). Moderate ICCS were also found for swing time (MD = 0.02 s) and double support time (MD = −0.02 s), while step width showed a poor ICC with MD of −44.17 mm (see Supplementary material for detailed results).

3.3. Correlation analysis

For the overground gait data, we found significant correlations of the differences between gait speed between markerless and markerbased and the differences in the other variables between the two methods. The correlations were significant for step length ($p < 0.001$, $r = 0.961$), for stride time ($p < 0.001$,$r = -0.819$), for stance time ($p < 0.001$,$r = 0.785$), for swing time ($p = 0.025$, $r = 0.409$), for double support time ($p < 0.001$, $r = 0.573$) and not significant for step width ($p = 0.928$, $r = 0.017$).

No significant correlations were found for the MDS-UPDRS-III and the differences between markerless and markerbased methods for all gait outcomes.

4. Discussion

In this study we investigated the validity of a markerless motion capture system to assess spatial and temporal gait parameters in people with PD during overground and treadmill walking. We found good to excellent agreement for most spatial and temporal gait variables compared to the markerbased motion capture, when using our custom computation algorithm. Temporal gait parameters showed slightly less agreement compared to the spatial parameters during overground walking. During treadmill walking all spatial and temporal gait variables showed excellent agreement. This lesser agreement in temporal gait parameters compared to the spatial parameters during overground walking indicates that the markerless-system provides better results in a controlled setting. Conversely, comparing the results of markerbased and markerless measurement to the automatic report (based on markerless recording) showed surprisingly high mean differences and low agreement for some variables. These were similar when comparing the automatic report with markerless and markerbased measurements. From this, we conclude that the differences we found are mainly due to differences in the computation of the gait variables or determination of gait events, rather than the detection of the landmark points on the body. Furthermore, we could show that differences were not correlated with the MDS-UPDRS-III, indicating that severity of motor symptoms did not influence validity and proving the usefulness of the markerless system for this population which were individuals with PD with a H&Y

Table 3
Mean differences, agreement and correlation characteristics between spatial and temporal gait outcomes for markerless and markerbased motion capture for treadmill gait. LOA = limit of agreement, ICC = Intraclass correlation coefficient.

Treadmill Gait (Markerbased − Markerless)	*Mean difference*	*Lower LOA*	*Upper LOA*	*Pearson r*	*ICC (2,1)*	*Lower ICC*	*Upper ICC*
Step length (mm)	10.685	−12.062	33.433	0.990	0.979	0.863	0.993
Stride time (s)	−0.005	−0.034	0.024	0.985	0.982	0.961	0.991
Stance time (s)	−0.003	−0.024	0.018	0.985	0.984	0.966	0.992
Swing time (s)	−0.002	−0.016	0.013	0.951	0.942	0.883	0.972
Step width (mm)	−0.502	−20.798	19.794	0.963	0.964	0.927	0.983
Double support time (s)	−0.001	−0.011	0.010	0.971	0.972	0.942	0.986

Abbreviations: LOA = limit of agreement, ICC = Intraclass correlation coefficient.

stage of 2 and 3.

When comparing our markerless vs. markerbased results to previous evidence in healthy individuals during overground walking we can see similar ICCs for the computed outcomes (Kanko et al., 2021a). The variable with the least agreement in our study was double support time, which was equivalent to (Kanko et al., 2021b) and for swing time we found better agreement than was previously found in healthy individuals (Kanko et al., 2021a). There are some differences in the results of healthy individuals regarding the mean differences, which were very close to zero for gait speed and step length (Kanko et al., 2021b) whereas our results showed that markerless motion capture slightly overestimated gait speed and step length. Due to the limitation of not measuring with both systems simultaneously it is difficult to interpret the reasoning for this. Bland-Altman plots show a tendency that mean differences deviate further from zero when average step length is larger. This overestimation was however inconsistent when compared to the results of the treadmill gait, where step length was underestimated. This discrepancy could be caused by the different method of calculating step length for treadmill gait.

The measured differences between the markerless versus markerbased methods for overground walking and treadmill walking are far beyond the moderate clinically meaningful change of 0.08–0.14 m/s for gait speed (Baudendistel et al., 2024; Hass et al., 2014), and 3.6 cm for step length (Baudendistel et al., 2024) in people with PD. This is highly relevant as it enables the detection of clinically meaningful changes despite differences between the two methods. However, the inconsistencies of both measurements with the automatic report, especially during treadmill walking are much larger and come close to the clinically meaningful change for step length. This is a relevant finding as health professionals who are not movement analysis experts who might use the automatic report to assess their patient's gait, are getting results with less validity according to our analysis. Therefore, clinicians should seek an accurate markerless motion capture for measuring spatiotemporal gait parameters in people with Parkinson's disease, in order to improve measurement precision in clinical settings, avoid incorrect clinical decision-making, and benefit from the speed and reduced setup burden of this technique.

A possible reason for the difference between the markerless versus markerbased methods for overground walking and treadmill walking might be that algorithms were developed for healthy individuals and not for people with neurological disease (Zeni et al., 2008), whereas our computation algorithms, especially regarding gait event detection, are suited for this population (Romijnders et al., 2022). This discrepancy could be addressed by establishing a different analysis pipeline for fully automated gait analysis for people with neurological disorders. Furthermore, Parkinsonian-specific motor symptoms, such as rigidity and bradykinesia, may influence algorithm performance and should be taken into account when interpreting our findings. Alternatively, these differences may be explained by the reduced gait variability during treadmill walking compared to overground walking. The treadmill provides consistent sensory inputs and demands greater attentional resources than walking overground (Ambrus et al., 2019; Bello and Fernandez-Del-Olmo, 2012; Warlop et al., 2018) . It may stimulate spinal locomotor circuitry, thereby triggering intact circuits and bypassing the impaired pallidocortical circuit associated with Parkinson's disease (Bello and Fernandez-Del-Olmo, 2012). In addition, treadmill walking may shift gait control away from the basal ganglia-supplementary motor area network toward the relatively preserved cerebellum-premotor area circuit (Warlop et al., 2018). It could imply that the markerless system performs best in controlled settings and may be less reliable for free-living gait assessment.

4.1. Limitations

Due to the limited number of cameras available, we could not measure with markerless and markerbased methods simultaneously. This poses the limitation that we could not compare the same gait trials of both methods to each other. However, by testing on the treadmill as well, we could make sure that participants were walking at the exact same speed for both trials, hence eliminating some of the limitations of the overground walking trials. Furthermore, the markerbased system previously has been shown to be reliable (McGinley et al., 2009), reducing the risk of any test–retest differences. Finally, although our custom gait analysis algorithm is an established algorithm which has previously been shown to be valid and robust to neurological conditions (Zeni et al. 2008; Wren et al., 2023), it may also have limitations in its' validity compared to the automated algorithm.

5. Conclusions

Overall, the results of this study show that markerless motion capture appears to be valid for the assessment of most spatio-temporal gait features during overground- and especially treadmill walking in people with Parkinson's disease. However, the automatic report should be used cautiously in people with Parkinson's disease, as the results were less valid. Markerless motion capture is promising to be used in clinical settings where time is a limiting factor, but future work should focus on how gait features are calculated to provide the most valid results. Additionally, future studies should investigate the validity of markerless motion capture for other gait characteristics, such as asymmetry, and across different Parkinson's disease subtypes and disease stages.

CRediT authorship contribution statement

Jana Seuthe: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Fabio Augusto Barbieri:** Writing – review & editing, Writing – original draft. **Jule Grotherr:** Writing – review & editing, Resources. **Björn Hauptmann:** Writing – review & editing, Resources. **Christian Schlenstedt:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

No funding was received for this work.

We want to thank Anna Kauter (B.Sc.) for the contributions to this work during data acquisition.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2025.113008.

References

Ambrus, M., Sanchez, J.A., Fernandez-Del-Olmo, M., 2019. Walking on a treadmill improves the stride length-cadence relationship in individuals with Parkinson's disease. Gait Posture 68, 136–140. https://doi.org/10.1016/j.gaitpost.2018.11.025.

Baudendistel, S.T., Haussler, A.M., Rawson, K.S., Earhart, G.M., 2024. Minimal clinically important differences of spatiotemporal gait variables in Parkinson disease. Gait Posture 108, 257–263.

Bello, O., Fernandez-Del-Olmo, M., 2012. How does the treadmill affect gait in Parkinson's disease? Curr Aging Sci 5 (1), 28–34. https://doi.org/10.2174/1874609811205010028.

Bishnoi, A., Shankar, M., Lee, R., Hu, Y., Hernandez, M.E., 2023. Effects of therapeutic intervention on spatiotemporal gait parameters in adults with neurologic disorder: Systematic review and meta-analysis. Arch. Phys. Med. Rehabil. 104 (3), 451–474.

Delval, A., Betrouni, N., Tard, C., Devos, D., Dujardin, K., Defebvre, L., Moreau, C., 2021. Do kinematic gait parameters help to discriminate between fallers and non-fallers with Parkinson's disease? Clin. Neurophysiol. 132 (2), 536–541.
Grotewold, N., Albin, R.L., 2024. Update: Descriptive epidemiology of Parkinson disease. Parkinsonism Relat. Disord. 120, 106000.
Hass, C.J., Bishop, M., Moscovich, M., Stegemöller, E.L., Skinner, J., Malaty, I.A., Okun, M.S., 2014. Defining the clinically meaningful difference in gait speed in persons with Parkinson disease. J. Neurol. Phys. Ther. 38 (4), 233–238.
Kanko, R., Laende, E., Selbie, S., & Deluzio, K. (2020). Inter-session repeatability of Theia3D markerless motion capture gait kinematics. *bioRxiv*, 2020.2006. 2023.155358.
Kanko, R.M., Laende, E.K., Davis, E.M., Selbie, W.S., Deluzio, K.J., 2021a. Concurrent assessment of gait kinematics using marker-based and markerless motion capture. J. Biomech. 127, 110665.
Kanko, R.M., Laende, E.K., Strutzenberger, G., Brown, M., Selbie, W.S., DePaul, V., Deluzio, K.J., 2021b. Assessment of spatiotemporal gait parameters using a deep learning algorithm-based markerless motion capture system. J. Biomech. 122, 110414.
Keller, V.T., Outerleys, J.B., Kanko, R.M., Laende, E.K., Deluzio, K.J., 2022. Clothing condition does not affect meaningful clinical interpretation in markerless motion capture. J. Biomech. 141, 111182.
Koo, T.K., Li, M.Y., 2016. A guideline of selecting and reporting intraclass correlation coefficients for reliability research. J. Chiropr. Med. 15 (2), 155–163.
Lord, S., Galna, B., Yarnall, A.J., Coleman, S., Burn, D., Rochester, L., 2016. Predicting first fall in newly diagnosed P arkinson's disease: I nsights from a fall-naïve cohort. Mov. Disord. 31 (12), 1829–1836.
McGinley, J.L., Baker, R., Wolfe, R., Morris, M.E., 2009. The reliability of three-dimensional kinematic gait measurements: a systematic review. Gait Posture 29 (3), 360–369.
Mehrholz, J., Kugler, J., Storch, A., Pohl, M., Elsner, B., & Hirsch, K. (2015). Treadmill training for patients with Parkinson's disease. *Cochrane Database of Systematic Reviews*(8).
Mirelman, A., Bonato, P., Camicioli, R., Ellis, T.D., Giladi, N., Hamilton, J.L., Almeida, Q. J., 2019. Gait impairments in Parkinson's disease. The Lancet Neurology 18 (7), 697–708.
Pijnappels, M., Bobbert, M.F., van Dieën, J.H., 2001. Changes in walking pattern caused by the possibility of a tripping reaction. Gait Posture 14 (1), 11–18.
Riazati, S., McGuirk, T.E., Perry, E.S., Sihanath, W.B., Patten, C., 2022. Absolute reliability of gait parameters acquired with markerless motion capture in living domains. Front. Hum. Neurosci. 16, 867474.
Romijnders, R., Warmerdam, E., Hansen, C., Schmidt, G., Maetzler, W., 2022. A deep learning approach for gait event detection from a single Shank-worn IMU: validation in healthy and neurological cohorts. Sensors 22 (10), 3859.
RStudio Team. (2018). *RStudio: Integrated Development for R*. http://www.rstudio.com/.
Skorvanek, M., Martinez-Martin, P., Kovacs, N., Rodriguez-Violante, M., Corvol, J.C., Taba, P., Foltynie, T., 2017. Differences in MDS-UPDRS scores based on Hoehn and Yahr stage and disease duration. Movement Disorders Clinical Practice 4 (4), 536–544.
Warlop, T., Detrembleur, C., Stoquart, G., Lejeune, T., Jeanjean, A., 2018. Gait Complexity and Regularity Are Differently Modulated by Treadmill Walking in Parkinson's Disease and Healthy Population. Front Physiol 9, 68. https://doi.org/10.3389/fphys.2018.00068.
Wren, T.A.L., Isakov, P., Rethlefsen, S.A., 2023. Comparison of kinematics between Theia markerless and conventional marker-based gait analysis in clinical patients. Gait Posture 104, 9–14.
Zeni Jr, J., Richards, J., Higginson, J., 2008. Two simple methods for determining gait events during treadmill and overground walking using kinematic data. Gait Posture 27 (4), 710–714.