

Article

Smartphone Accelerometer for Gait Assessment: Validity and Reliability in Healthy Adults

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Abstract: Smartphone-based accelerometers offer a cost-effective and portable alternative to traditional gait analysis systems, with high reliability in measuring key parameters such as walking speed, cadence, and distance. This study assessed their validity compared to the GAITRite system, a widely recognized gold-standard tool, using data from 30 healthy adults walking at 3 self-selected speeds: preferred, slow, and fast. The results demonstrated a high degree of agreement between the two systems, with intraclass correlation coefficients (ICCs) ranging from 0.778 to 0.999. Although the findings emphasize the potential of smartphone accelerometers for clinical and real-world applications, certain limitations were noted, including participant homogeneity and minor discrepancies at extreme walking speeds. To address these limitations, incorporating data from additional sensors, such as gyroscopes and magnetometers, may enhance the accuracy and reliability of spatial parameter estimation. Overall, the findings support the use of smartphone accelerometers as a promising tool for advancing gait monitoring technologies, particularly in the contexts of telerehabilitation and mobility assessments.

Keywords: gait analysis; smartphone accelerometer; wearable technology; intraclass correlation; applied ergonomics



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1. Introduction

Human gait analysis plays a crucial role in healthcare, biometrics, and neurophysiology, enabling clinicians and researchers to monitor health, track disease progression, and aid in rehabilitation for conditions such as Parkinson's disease, stroke, and orthopedic surgeries [1]. Advanced technologies, such as machine learning, have further enhanced gait analysis by identifying unique walking patterns, making it a powerful tool for biometric recognition and security [2]. The application of statistical physics to gait analysis also offers insights into how gait reflects both physical and neurological disorders, contributing to a deeper understanding of human motor control [3].

Recent studies underscore the growing importance of gait analysis across various fields. One study demonstrated the application of Ultra-Wide Band (UWB) radar for gender classification, achieving high accuracy through machine learning models such as Multilayer Perceptron and Support Vector Machine, which are particularly useful in biometrics and surveillance [4]. Another review highlighted long-term gait impairments in patients following total knee arthroplasty, emphasizing the need for better rehabilitation methods [5]. Future trends in gait analysis will involve the integration of multiple sensing modalities with AI, which is expected to enhance accuracy and expand its applications in both clinical and wearable technology contexts [6].

Wearable devices are transforming gait analysis by enabling continuous, real-time monitoring in clinical, rehabilitation, and community settings. Inertial measurement units (IMUs) embedded in wearables provide precise data on joint kinematics, facilitating gait analysis outside traditional laboratory environments. Advances in sensor miniaturization and the development of flexible pressure sensors have made gait analysis more accessible in daily life, while 5G-enabled flexible antennas further enhance real-time data transmission [7–9]. These technologies are making gait analysis more convenient, less intrusive, and increasingly accurate for clinical use, providing reassurance to both clinicians and patients.

In clinical applications, wearable devices play a significant role in the diagnosis and management of neurodegenerative diseases and movement disorders. For example, in Parkinson's disease, wearable systems equipped with force-sensitive insoles and IMUs continuously monitor abnormal gait patterns, providing real-time feedback to clinicians and assisting in early diagnosis [10]. These devices also significantly improve rehabilitation outcomes by enabling real-world gait assessments during post-surgical recovery, offering hope for better recovery experiences, and helping to detect subtle gait changes in conditions like Alzheimer's disease [8,11]. Overall, wearables provide real-time data that optimize treatment strategies, making gait analysis more accessible in both clinical and home settings.

Smartphone-based accelerometers provide a promising, cost-effective alternative to traditional gait analysis methods, such as optical motion capture and pressure-sensitive walkways. These systems have demonstrated accuracy and reliability in capturing kinematic gait parameters, making them viable for use in clinical and non-clinical environments [12]. Studies have confirmed their validity in measuring parameters such as step time, walking speed, and step length under various conditions, including treadmill walking and different head-turning scenarios [13,14]. Advanced algorithms, such as feed-forward neural networks and signal segmentation techniques, enhance data quality by adapting to gait speed and individual variations [15]. Despite these advancements, challenges persist in measuring complex metrics, such as step asymmetry and nonlinear dynamics. Moreover, factors such as demographic attributes (e.g., sex and height) influence the outcomes, emphasizing the need for algorithmic customization. Future research should focus on refining algorithms, expanding demographic validations, and integrating waveform analysis to improve reliability further and expand applicability to diverse clinical conditions [13–15].

Portable and cost-effective solutions are needed to enable telerehabilitation and patient monitoring. Therefore, this study aims to address these gaps by evaluating the reliability and validity of smartphone-based accelerometers compared to the GAITRite system across different walking speeds. Unlike prior research, which often focused on static or clinical settings, this study explores the potential of smartphone accelerometers for real-world gait monitoring. The primary research question is whether smartphone-based accelerometers can achieve comparable reliability and validity to GAITRite in assessing key gait parameters. We hypothesize that smartphone accelerometers will demonstrate high agreement with GAITRite, particularly for parameters such as walking speed and cadence, while highlighting areas for improvement in spatial parameter estimation.

2. Materials and Methods

2.1. Participants

This study recruited male and female adults in their 20s and 30s. Prior to the experiment, all participants were provided with a detailed explanation of the study procedures and subsequently signed informed consent forms. A total of 30 participants who met the following inclusion criteria were selected for the study: (1) individuals without visual impairments affecting posture, (2) individuals with no history of neurological or cardiopulmonary disorders, and (3) individuals capable of understanding and performing the tasks required for the study. Exclusion criteria were as follows: (1) individuals experiencing walking difficulties due to dizziness or balance disorders, and (2) individuals who had sustained musculoskeletal injuries within the past six months.

This study was conducted in compliance with the ethical principles outlined in the Declaration of Helsinki and received prior approval from the Institutional Review Board of Gachon University (1044396-202211-HR-181-01).

2.2. Procedure

The experimental procedure was based on a previous study [16]. The subjects wore comfortable clothes and socks and were instructed to walk on the GAITRite mat under the following three conditions while firmly attaching a smartphone with an accelerometer to the second sacral vertebra, which is the center of gravity of the body, with an elastic band: (1) preferred walking speed, (2) slow walking speed of their choice, and (3) fast walking speed of their choice (Figure 1).

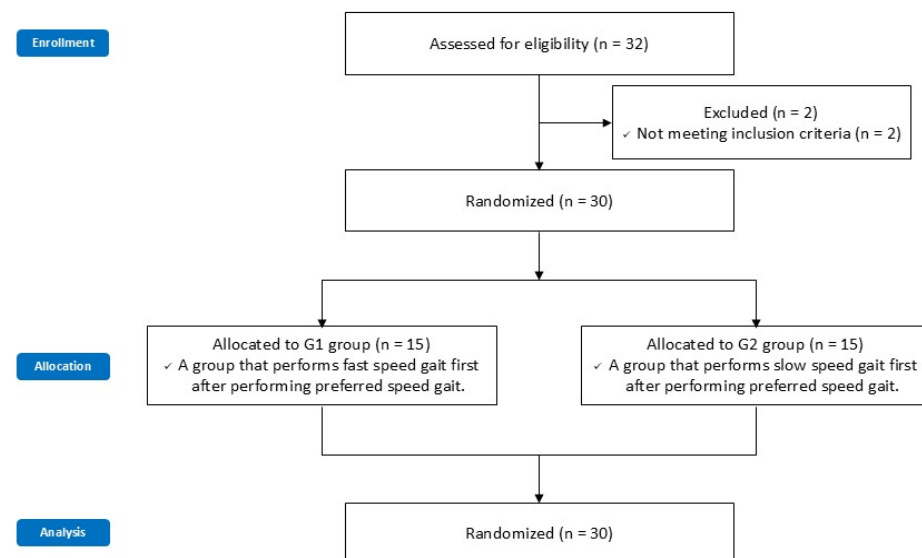


Figure 1. Flowchart.

For the familiarization process before the walking task, the participants naturally walked on the GAITRite mat twice with the smartphone attached to their waist. No measurements were taken during this process. After the familiarization process, the sequence of speed conditions was randomized for each participant using a computer-generated randomization algorithm to minimize potential order effects. For example, some participants performed the preferred walking speed condition first, followed by the slow and fast walking speed conditions, while others followed different sequences. This randomization ensured that potential fatigue or learning effects did not systematically influence the results. All conditions were measured four times, and the average value was calculated.

The measurer instructed the subjects, “Walk at your usual walking pace (Preferred), slower than your usual walking pace (Slow), and faster than your usual walking pace (Fast)”. Five minutes were given between each condition to avoid potential fatigue effects or overlap, and a 1-min rest period was given between repeat measurements. To exclude accelerators and decelerators during the gait cycle from the measurements, the subjects stood at a line marked 2 m before the start of the GAITRite mat, started walking when they heard the start signal, and stopped when they reached a line marked 2 m after the end of the mat. If the subject stepped into the inactive areas at either end of the mat where no pressure sensors were distributed or stepped off the mat during walking, the measurement was retaken.

This study consisted of a single-group, repeated-measures design. To exclude the order effect that repeated measures may cause, the order of repeated measures for each subject was randomized. Research personnel responsible for data collection were blinded to the assigned speed condition to eliminate potential bias during measurement. All repeated

measures were performed within 1 h by the same physical therapist. The physical therapist involved in the measurements had over 3 years of clinical experience.

2.3. Measurements

This study collected acceleration data using an acceleration sensor embedded in a smartphone (Galaxy S20, Samsung, Yongin, Republic of Korea). The dimensions of the smartphone were 151.7 mm × 69.1 mm × 7.9 mm (length × width × height), and it weighed 163 g. Data acquisition was facilitated through a custom-developed gait analysis application (ver. 1.0, Multi-Modality Medical Imaging Lab, Incheon, Republic of Korea). The sampling rate for data collection was set at 250 Hz. This sampling rate was chosen based on its demonstrated accuracy in detecting spatiotemporal gait parameters, such as step length and cadence, in prior validation studies [16]. Upon the initiation of walking, the administrator launched the application and pressed the start/stop button to record the data, which were subsequently stored on the smartphone's SD card.

The recorded acceleration data were processed into gait variables using GaitAnalyzer_params (ver. 1.0, Multi Modality Medical Imaging Lab, Incheon, Republic of Korea), a software tool developed based on engineering algorithms within the Visual Studio 2017 (vc15) environment. The gait variables extracted at this stage included: walking distance (Distance, cm), walking time (Ambulation Time, s), walking velocity (Velocity, cm/s), mean normalized velocity (Leg Length/s), and cadence (Steps/Min).

To validate these findings, the GAITRite walkway system (CIR Systems Inc., Franklin, NJ, USA), a floor-mounted, mobile gait analysis device, was employed to measure official spatiotemporal gait variables. The mat used in this study measured 180 × 35.5 × 0.25 inches, with an active area of 144 × 24 inches containing pressure sensors. The sampling rate for the GAITRite system was set at 240 Hz. Data collected during walking were transmitted via a serial port to a connected PC, where they were stored and processed using GAITRite Plus software (ver. 4.7, CIR Systems Inc., Franklin, NJ, USA). The gait variables obtained from this system included walking distance (Distance, cm), walking time (Ambulation Time, s), walking speed (Velocity, cm/s), mean normalized velocity (Mean Normalized Velocity, Leg Length/s), and cadence (Steps/Min).

2.3.1. Application of Using Smartphone Accelerometers

Acceleration Data Collection and Processing

The acceleration data of walking exhibits a distinct pattern, with the minimum value, denoted as A, occurring when the foot contacts the ground, and the maximum value, B, observed when the knee straightens. Acceleration, a physical quantity representing the rate of change in velocity over time, is recorded along the x , y , and z axes. By utilizing gravitational acceleration (9.81 m/s^2), which consistently acts in the vertical direction, the degree of inclination (roll and pitch) about the x and y axes can be determined. However, the rotation around the z -axis, which aligns with the direction of gravity, cannot be detected through acceleration alone and must instead be measured using an additional sensor embedded in the smartphone, namely the geomagnetic sensor.

The acceleration value along the x -axis, representing the forward direction during walking, tends to remain relatively constant, while the lateral acceleration along the y -axis, which varies when the body tilts, exhibits minimal change during steady walking. In contrast, the vertical acceleration (z -axis) undergoes pronounced fluctuations, resulting in a repetitive sine wave-like pattern. Consequently, the degree of tilt of the smartphone during walking is measured and compensated for, and the acceleration data across all three axes are condensed into a single representative value, corresponding solely to the vertical direction (z -axis). This representative z -axis acceleration data are utilized for all subsequent processing and analysis [17,18].

Analysis and Calculation

The vertical acceleration data were initially collected at 200 Hz using the smartphone's accelerometer and geomagnetic sensor and later resampled at 250 Hz (4 ms) for further processing. While the acceleration data provide high precision, analyzing the oscillatory motion of walking requires additional processing to improve clarity. To do this, we applied a smoothing filter with a cutoff frequency of approximately 30 Hz twice, effectively reducing high-frequency noise while preserving the essential oscillatory patterns of walking.

Step length was calculated by applying double integration to the processed acceleration data. Double integration, while useful for deriving displacement from acceleration, is prone to accumulating errors over time due to sensor noise and drift. This study mitigated these errors by resetting the velocity to zero at specific points in the gait cycle. These points, corresponding to the step initiation (minimum acceleration, A) and mid-stance phase (maximum acceleration, B), are moments where the velocity is theoretically zero. A low-pass filter was also applied to the acceleration data before integration to minimize the impact of high-frequency noise, reducing the potential for error amplification during the integration process (Figure 2) [17–19].

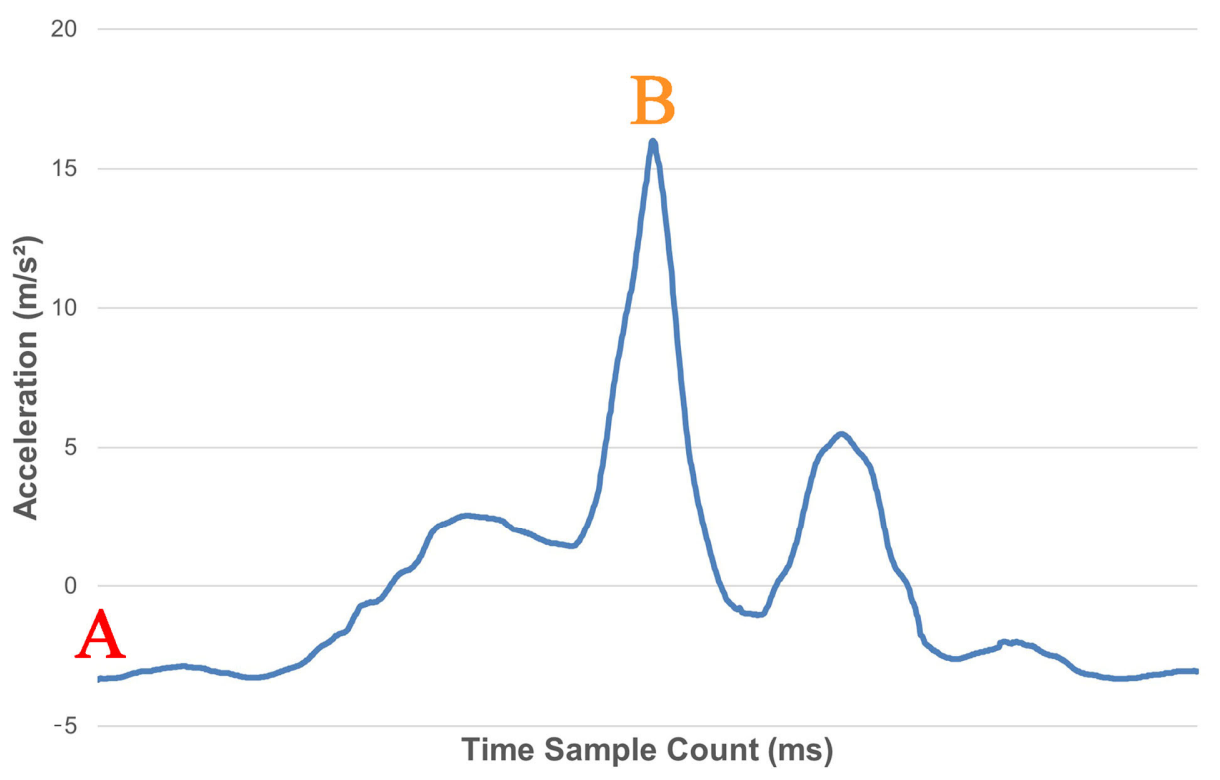


Figure 2. Acceleration during a single step. A, step initiation; B, mid-stance.

The vertical displacement of the center of gravity, derived from this integration, was combined with the leg length using the Pythagorean theorem to estimate step length. Cadence and velocity were calculated based on the total walking time and distance covered (Figure 3).

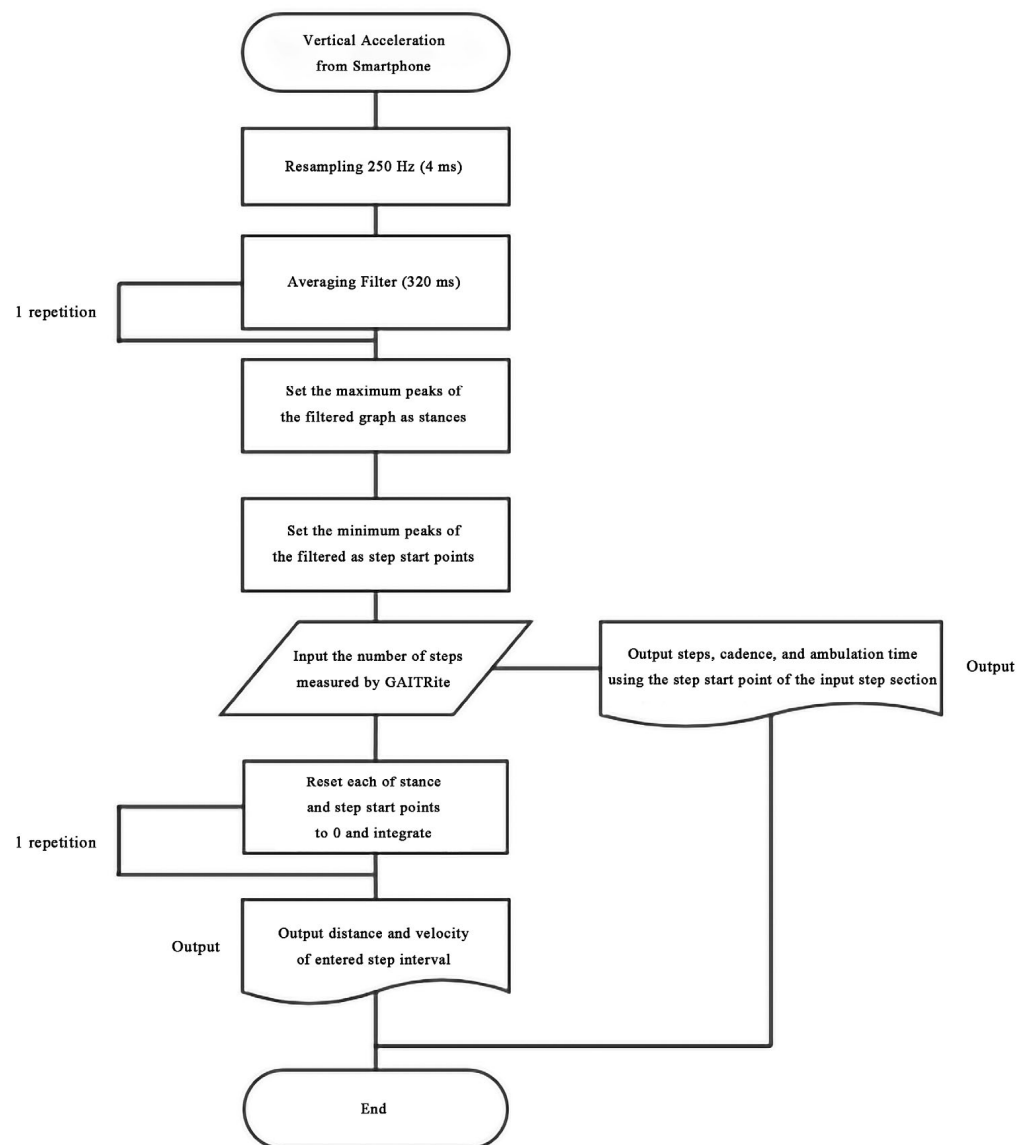


Figure 3. Calculation process.

2.4. Statistical Analysis

The statistical analysis of this study was performed using SPSS 25.0 software (IBM Corp., Armonk, NY, USA). All outcome variables were expressed as the mean and standard deviation of four repeated measurements for each condition, and the Shapiro-Wilk test was used to test the normality of the raw data. To determine whether there was a significant difference between the repeatedly measured data, all variables that followed normality were compared using the repeated measures analysis of variance (RM ANOVA). The degree of correlation between the data measured by the acceleration sensor built into the smartphone and the GAITRite data was expressed as the intraclass correlation coefficients (ICC), and the degree of agreement between the two systems was visualized using Bland-Altman plots. All statistical significance levels were set at $\alpha = 0.05$.

3. Results

3.1. General Characteristics of Participants

All participants in this study successfully completed the measurements without any dropouts. The characteristics of the 30 subjects are as follows (Table 1).

Table 1. General characteristics.

Variables	Value
Age (y) ^a	22.43 ± 3.25
Sex (M/F) ^b	14/16
Height (cm) ^a	166.60 ± 9.07
Weight (kg) ^a	61.96 ± 14.09
BMI (kg/m ²) ^a	22.09 ± 3.45
Leg Length (cm)—Left side	86.70 ± 4.60
—Right side	86.76 ± 4.61

^a Values are expressed as mean ± SD. ^b Values are expressed as numbers.

3.2. Correlation Between Gait Analysis Results Using Smartphone Acceleration System and GAITRite Gait Analysis Results

There was no significant difference in the average of the values measured four times for each condition among the gait variables measured by smartphone and GAITRite, respectively ($p > 0.05$).

The degree of correlation between the two systems is expressed in Table 2. When the intraclass correlation analysis was applied to the average data measured by the two systems, the ICC of Distance, Ambulation Time, Velocity, Mean Normalized Velocity, and Cadence at preferred walking speed was 0.877–0.999, at fast walking speed, it was 0.810–0.995, and at slow walking speed, it was 0.778–0.999, showing a high (Good) level ($p < 0.001$).

Table 2. Correlation of gait analysis using smartphone accelerometer system and GAITRite system.

Variables	Smartphone Accelerometer (Mean ± SD)	GAITRite (Mean ± SD)	ICC	95% CI	<i>p</i> -Value
Distance (cm)					
Preferred	267.75 ± 28.43	258.22 ± 24.71	0.877	0.659–0.948	<0.001
Fast	264.85 ± 23.40	256.93 ± 16.07	0.810	0.547–0.915	<0.001
Slow	273.55 ± 21.43	268.76 ± 18.79	0.778	0.540–0.894	<0.001
Ambulation Time (s)					
Preferred	2.10 ± 0.37	2.10 ± 0.37	0.999	0.998–0.999	<0.001
Fast	1.69 ± 0.29	1.67 ± 0.30	0.995	0.987–0.998	<0.001
Slow	2.77 ± 0.51	2.75 ± 0.52	0.999	0.997–0.999	<0.001
Velocity (cm/s)					
Preferred	129.62 ± 15.57	125.28 ± 14.57	0.921	0.772–0.967	<0.001
Fast	159.74 ± 20.29	158.07 ± 23.11	0.948	0.891–0.975	<0.001
Slow	101.25 ± 13.94	100.12 ± 13.13	0.938	0.870–0.970	<0.001
Mean Normalized Velocity (LL/s)					
Preferred	1.49 ± 0.14	1.44 ± 0.14	0.880	0.651–0.951	<0.001
Fast	1.81 ± 0.20	1.79 ± 0.23	0.939	0.874–0.971	<0.001
Slow	1.17 ± 0.13	1.15 ± 0.13	0.911	0.815–0.958	<0.001
Cadence (steps/min)					
Preferred	115.76 ± 7.27	115.93 ± 7.36	0.989	0.978–0.995	<0.001
Fast	130.03 ± 10.6	130.76 ± 10.66	0.993	0.984–0.997	<0.001
Slow	102.16 ± 8.31	102.79 ± 8.55	0.990	0.977–0.995	<0.001

ICC, Intraclass correlation coefficient; CI, Confidence Interval; cm, centimeters; s, seconds; LL, Leg length.

3.3. Consistency Between the Results of Gait Analysis Using the Smartphone Acceleration System and the Results of GAITRite Gait Analysis

The Bland-Altman analysis, which compared two measurement systems across various gait parameters at preferred, fast, and slow walking speeds, revealed differences between the systems (Table 3) (Figure 4). For walking distance, the mean differences ranged from 4.79 cm to 9.53 cm across the different speeds. Ambulation time differences were minimal, with mean differences of up to 0.02 s and limits of agreement (LOA) within 0.09 s.

For walking velocity, the mean differences ranged from 1.13 cm/s to 4.34 cm/s, while normalized velocity showed mean differences between 0.01 LL/s and 0.05 LL/s. Cadence differences were also minor, with mean differences ranging from -0.16 to -0.73 steps/min.

Table 3. Consistency of gait analysis using smartphone accelerometer system and GAITRite system.

Variables	Mean $\pm$ SD	Upper Limit of Agreement (95% CI)	Lower Limit of Agreement (95% CI)
Distance (cm)			
Preferred	9.53 $\pm$ 15.67	40.25 (30.533, 49.961)	-21.19 (-30.904 , -11.476)
Fast	7.92 $\pm$ 14.83	37.00 (27.802, 46.190)	-21.15 (-30.347 , -11.959)
Slow	4.79 $\pm$ 16.93	37.97 (27.480, 48.469)	-28.40 (-38.892 , -17.903)
Ambulation Time (s)			
Preferred	0.00 $\pm$ 0.02	0.05 (0.034, 0.064)	-0.05 (-0.060 , -0.030)
Fast	0.02 $\pm$ 0.04	0.09 (0.070, 0.117)	-0.05 (-0.077 , -0.031)
Slow	0.01 $\pm$ 0.04	0.09 (0.064, 0.110)	-0.06 (-0.083 , -0.036)
Velocity (cm/s)			
Preferred	4.34 $\pm$ 7.21	18.47 (14.000, 22.935)	-9.79 (-14.256 , -5.320)
Fast	1.67 $\pm$ 9.71	20.71 (14.688, 26.729)	-17.37 (-23.389 , -11.348)
Slow	1.13 $\pm$ 6.58	14.02 (9.943, 18.098)	-11.77 (-15.847 , -7.691)
Mean Normalized Velocity (LL/s)			
Preferred	0.05 $\pm$ 0.08	0.21 (0.156, 0.254)	-0.10 (-0.154 , -0.056)
Fast	0.03 $\pm$ 0.10	0.23 (0.163, 0.289)	-0.17 (-0.237 , -0.110)
Slow	0.01 $\pm$ 0.07	0.16 (0.115, 0.208)	-0.13 (-0.178 , -0.086)
Cadence (steps/min)			
Preferred	-0.16 ± 1.51	2.80 (1.864, 3.737)	-3.12 (-4.062 , -2.188)
Fast	-0.73 ± 1.58	2.37 (1.391, 3.354)	-3.83 (-4.814 , -2.852)
Slow	-0.62 ± 1.62	2.56 (1.555, 3.568)	-3.80 (-4.811 , -2.798)

CI, Confidence Interval; cm, centimeters; s, seconds; LL, Leg length.

In all graphs, the x -axis represents the mean values obtained from the smartphone application and the GAITRite system, while the y -axis depicts the differences between these values. The lightest-colored line indicates the mean of the differences, and the dotted lines above and below this line represent the limits of agreement (LOAs).

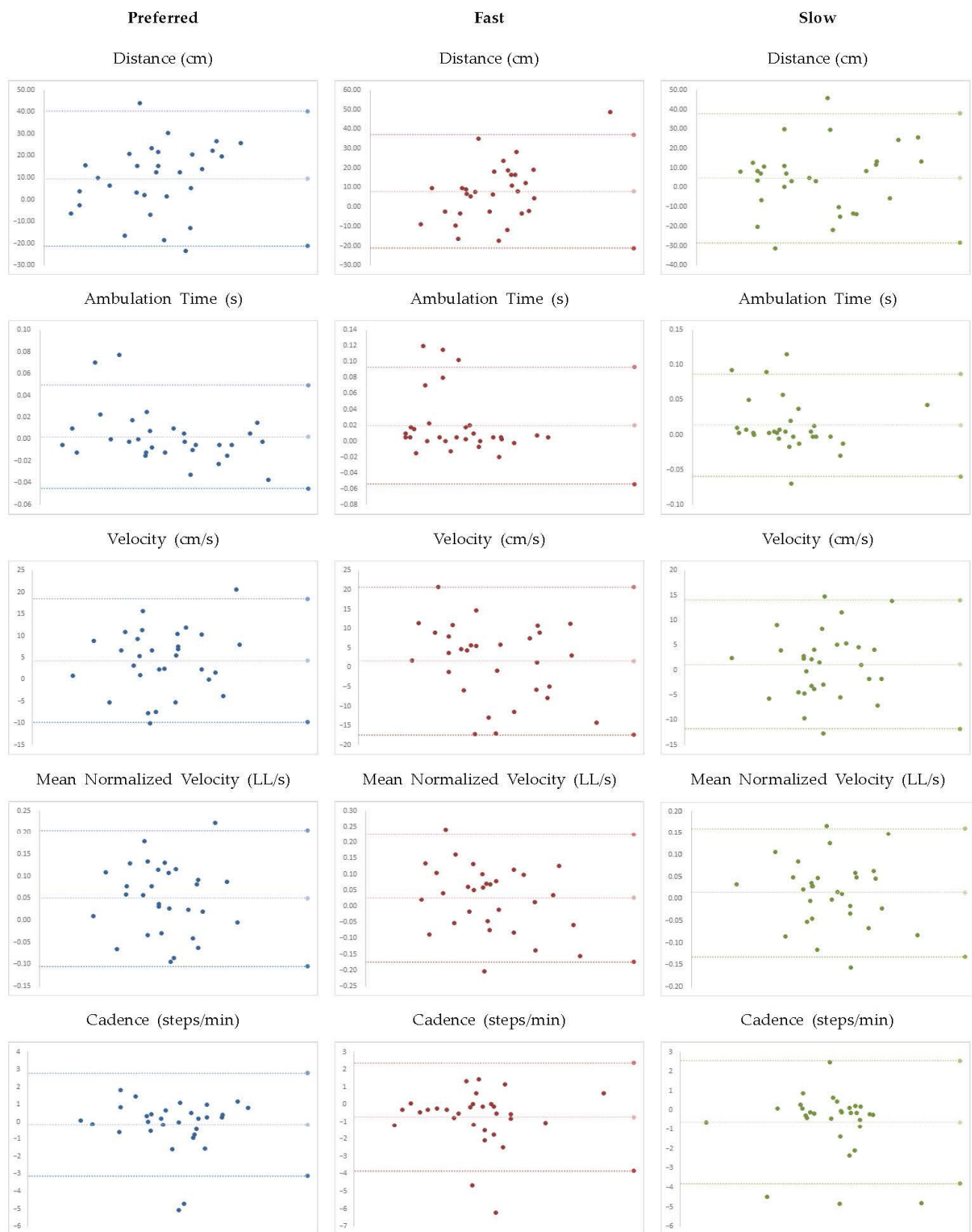


Figure 4. Bland-Altman plots.

4. Discussion

The results of this study demonstrate a high degree of agreement between the smartphone accelerometer system and the GAITRite system across various walking conditions. Intraclass correlation coefficients (ICCs) ranged from 0.778 to 0.999, highlighting that despite methodological differences, both systems can reliably assess key gait parameters such as walking distance, velocity, and cadence. These results suggest that smartphone accelerometer systems, despite their portability and ease of use, offer comparable accuracy to traditional systems such as GAITRite, thus broadening the applications of gait analysis across clinical, home, and community settings. This finding is consistent with prior research that has validated the effectiveness of smartphone-based systems for gait analysis in both controlled and real-world environments [13,20].

The GAITRite system is widely recognized as the gold standard in gait analysis, particularly for its precision in measuring spatiotemporal gait parameters. It has been effectively utilized in clinical settings, especially in the evaluation of gait abnormalities in patients with neurodegenerative conditions such as Parkinson's disease and Alzheimer's disease, as well as in post-surgical rehabilitation [5,8]. However, its use is constrained by the need for controlled environments and the relatively high costs associated with the system.

In contrast, the smartphone accelerometer system provides significant advantages in terms of portability and the potential for use in non-clinical environments. Recent technological advancements have equipped smartphones with improved accelerometers and gyroscopes, which can now accurately measure basic gait parameters such as walking speed, distance, and cadence in real time [21,22]. Studies have demonstrated that smartphone-based systems show high reliability, even when validated against gold-standard tools such as GAITRite [20], making them particularly useful for continuous real-world monitoring and for assessing patient progress over time, especially in orthopedic and stroke rehabilitation [23].

In this study, the Bland-Altman analysis revealed minimal differences between the two systems, with mean discrepancies in distance ranging from 4.79 cm to 9.53 cm and cadence differences ranging from -0.16 to -0.73 steps per minute across different walking speeds. Such minor variations have been reported in prior validation studies of smartphone-based gait analysis systems [24], further reinforcing the viability of smartphone systems in providing accurate and continuous gait assessments.

When comparing the two systems across different walking speeds, performance varied slightly. Both systems exhibited high reliability in moderate, stable walking conditions, as ICCs often exceeded 0.90 for parameters such as walking speed and cadence [23,24]. However, at faster walking speeds, the smartphone system displayed minor discrepancies, particularly in step length and gait variability, likely due to signal noise and minor integration drift during data collection [19]. At slower walking speeds, the smartphone system also struggled to capture certain joint-specific kinematic data, such as stride duration and stance time, which were better measured by GAITRite [21].

Cadence remained one of the most consistent variables across both systems, regardless of walking speed. Differences in cadence between the systems were found to be negligible, as supported by similar studies [20]. However, step length exhibited more pronounced discrepancies at both slow and fast walking speeds, with the smartphone system occasionally overestimating or underestimating distance due to increased body sway or instability during measurement [22].

Gait variability, particularly in measures such as stride length or time asymmetry, was better captured by the GAITRite system in controlled environments. Smartphone accelerometers, although reliable for basic gait parameters, tended to show more variation in these measures, particularly at faster walking speeds, where raw acceleration data may become noisy [13].

The results of this study reveal that the 95% confidence intervals (CIs) for certain variables, such as Distance and Mean Normalized Velocity (LL/s) under preferred walking speed conditions, were wider compared to other parameters. For instance, the CI for

distance ranged from 0.540 to 0.894, suggesting variability in measurement consistency. This variability may stem from the inherent limitations of calculating spatial parameters such as distance using double integration. While this method is effective for deriving displacement from acceleration data, it is susceptible to noise and drift, leading to cumulative errors during integration [16,17]. Velocity resetting and low-pass filtering were employed in this study to mitigate such errors, but residual inconsistencies likely contributed to the observed CI variability.

The sensitivity of spatial parameters to experimental conditions, such as walking speed, may also explain the broader CIs. Faster walking speeds are associated with increased signal noise due to more significant body sway, while slower speeds can amplify the effects of gravitational acceleration on the sensor. These factors can influence the consistency of distance measurements, as demonstrated in prior research on gait variability under different experimental conditions [22].

Despite these challenges, the ICC values (ranging from 0.778 to 0.999) indicate a generally strong agreement between the smartphone-based system and the gold-standard GAITRite system. However, the wider CIs underscore the need for further refinements in distance estimation methods. To improve the reliability of spatial parameters, future studies could explore the integration of advanced error correction techniques, such as Kalman filtering, which dynamically adjusts for drift and noise, and zero-velocity updates, which reset velocity at stationary phases [18]. Incorporating multi-sensor data fusion (e.g., gyroscopes and magnetometers) could also enhance spatial accuracy and consistency [20].

In conclusion, while both the GAITRite and smartphone accelerometer systems demonstrate a high degree of overall agreement, the smartphone system performs best at moderate walking speeds and for basic gait parameters, such as cadence and velocity. The GAITRite system maintains an advantage in capturing more detailed gait parameters, particularly at the extremes of walking speeds and for joint-specific kinematics and variability. Combining both systems can provide a more comprehensive approach to gait analysis, improving diagnostic accuracy, rehabilitation outcomes, and expanding access to gait monitoring across a range of environments. As advancements in wearable technology and machine learning continue [25], the performance gap between smartphone-based systems and traditional clinical tools is expected to narrow, potentially making high-quality gait analysis more accessible.

This study has several limitations that should be considered when interpreting the findings. First, the participant pool consisted exclusively of healthy adults within a narrow age range. While the homogeneity of this group minimized inter-individual variability, this limited diversity in age and health status restricts the generalizability of the results to broader populations, including older adults and individuals with gait abnormalities. Future studies should include participants from a wider age range and those with specific gait impairments to assess the applicability of smartphone-based accelerometers in diverse populations. Second, while smartphone-based accelerometers offer a convenient and portable solution for gait analysis, they lack the capability to capture detailed joint-specific kinematics and more complex gait variables, particularly at extreme walking speeds (either faster or slower). Although the system demonstrated high reliability under moderate conditions, minor discrepancies were observed due to signal noise and integration drift, especially at higher walking speeds. Despite being mitigated through velocity resetting and filtering techniques, these residual errors highlight the inherent limitations of the current approach. Future research could use advanced error correction methods, such as Kalman filtering, which dynamically compensates for drift by combining sensor data with predictive models to enhance the accuracy. Similarly, zero-velocity updates during stationary phases could further reduce drift, and integrating data from multiple sensors, such as gyroscopes and magnetometers, may improve the overall reliability of spatial parameter estimation. Third, although the required sample size was calculated using established statistical methods, the relatively small sample size of 30 participants may limit the generalizability of the findings to larger or more heterogeneous populations. While the

statistical power was sufficient to detect significant differences within the study design, caution should be exercised when extrapolating these results to other groups. Future studies with larger and more diverse participant pools are recommended to validate the robustness of the findings and ensure broader applicability.

5. Conclusions

This study concludes that smartphone-based accelerometers provide a portable and cost-effective alternative to traditional gait analysis systems, with high reliability across walking speeds. However, the results are limited by the homogeneity of participants and variability in spatial parameters under different conditions. Expanding the participant pool to include older adults or those with gait abnormalities, and addressing measurement errors through advanced signal processing techniques, will enhance the applicability of this technology. These findings lay the groundwork for broader use of smartphone-based accelerometers in real-world gait monitoring and telerehabilitation settings.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to ethical restrictions.

Conflicts of Interest: The authors declare no conflicts of interest.

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