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Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket

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ABSTRACT

The assessment of spatiotemporal gait parameters is a useful clinical indicator of health status. Unfortunately, most assessment tools require controlled laboratory environments which can be expensive and time consuming. As smartphones with embedded sensors are becoming ubiquitous, this technology can provide a cost-effective, easily deployable method for assessing gait. Therefore, the purpose of this study was to assess the reliability and validity of a smartphone-based accelerometer in quantifying spatiotemporal gait parameters when attached to the body or in a bag, belt, hand, and pocket. Thirty-four healthy adults were asked to walk at self-selected comfortable, slow, and fast speeds over a 10-m walkway while carrying a smartphone. Step length, step time, gait velocity, and cadence were computed from smartphone-based accelerometers and validated with GAITRite. Across all walking speeds, smartphone data had excellent reliability ($ICC_{2,1} \geq 0.90$) for the body and belt locations, with bag, hand, and pocket locations having good to excellent reliability ($ICC_{2,1} \geq 0.69$). Correlations between the smartphone-based and GAITRite-based systems were very high for the body ($r = 0.89$, 0.98, 0.96, and 0.87 for step length, step time, gait velocity, and cadence, respectively). Similarly, Bland-Altman analysis demonstrated that the bias approached zero, particularly in the body, bag, and belt conditions under comfortable and fast speeds. Thus, smartphone-based assessments of gait are most valid when placed on the body, in a bag, or on a belt. The use of a smartphone to assess gait can provide relevant data to clinicians without encumbering the user and allow for data collection in the free-living environment.

1. Introduction

Assessment of gait spatiotemporal parameters can provide valuable insight regarding overall health [1], cognitive performance [2], quality of life [3], and mortality [4]. The majority of gait assessments utilize optoelectronic motion capture systems, force plates, and instrumented walkways such as the GAITRite [5,6]. Although these instruments are highly accurate, they require controlled laboratory environments, are bulky, expensive, and involve tremendous time investment for setup and analysis. Furthermore, these tools are not available in all clinical settings, and cannot measure gait across more than a few steps or in home-based environments. Nonetheless, due to their high reliability and validity, these devices are frequently used as a gold standard for gait assessment [7].

Recently, tri-axial accelerometers have been used in gait analysis as an alternative to laboratory assessments. Not only can accelerometers accurately quantify spatiotemporal gait parameters, but they also have a number of advantages including a lower cost, portability, and ease of use. Furthermore, accelerometer-based devices can collect data from many gait cycles and allow measurements in more challenging contexts [8]. Previous studies have demonstrated the validity of body-worn accelerometers to quantify activities [9], steps [10], and gait parameters [7]. Utilizing an accelerometer placed on the lower back, Hartmann and colleagues [11] demonstrated excellent concurrent validity for assessing walking speed, cadence, step duration, and step length among older adults. However, accelerometer-based systems have a number of disadvantages [12]. First, they usually attach directly onto the body (e.g. trunk, wrist, ankle) which can lead to discomfort. Second, problems with memory and recall can reduce compliance. Lastly, the cost of commercial software packages is relatively high.

As smartphones are becoming ubiquitous across age groups, utilizing embedded sensors to assess gait is cost-effective, convenient, and user-friendly. Instead of attaching directly onto the body, a smartphone device can be engaged in the user's hands, bag, belt, or pocket [13].

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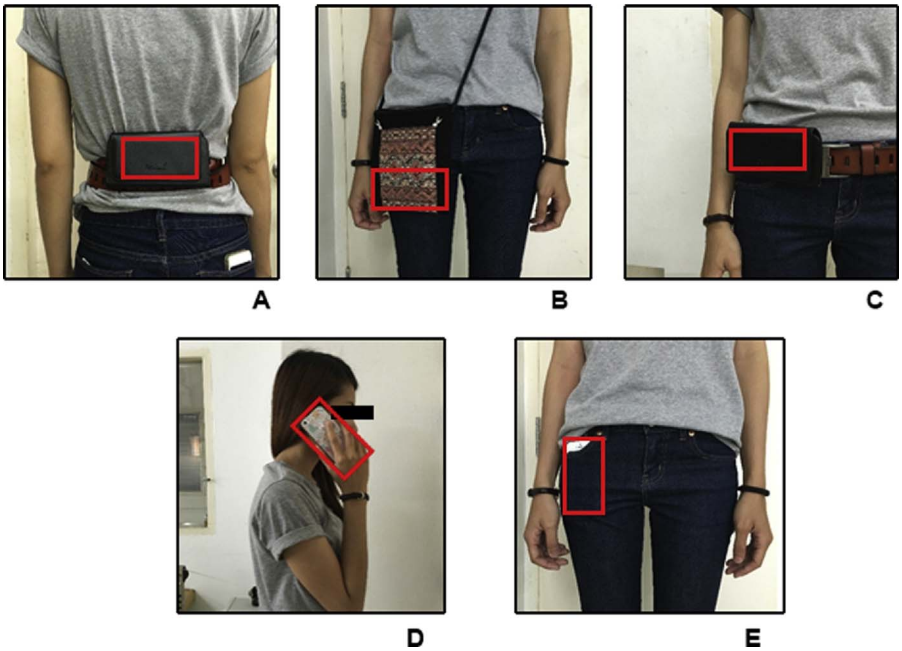

Fig. 1. Location of the smartphone during all walking trials: body (A), bag (B), belt (C), hand (D), and pocket (E). The rectangular border indicates the orientation and placement of the smartphone in each condition.

Furthermore, measuring gait from smartphones is a practical solution for lowering cost as well as improving accessibility, convenience, and portability. Furrer and colleagues [14] have examined the intra-session reliability and concurrent validity of the center of mass displacement derived from the smartphone accelerometer, attached to the third lumbar vertebrae, during level walking. Fair to excellent reliability (ICC: 0.49–0.86) with moderate to strong correlations (Pearson r: 0.61–0.92) between smartphone and motion capture measurements indicates that the use of a smartphone-based assessment can be valid and feasible. Additionally, varying the placement of a smartphone on the individual's attire (i.e. hands, pockets, belt, or bag) has been found to be valid for assessing the type of activity an individual is performing [13].

To our knowledge, however, the ability to assess spatiotemporal gait parameters based on a smartphone-based accelerometer is unknown. Since people carry phones differently in everyday life, the effects of varying placement of a smartphone on the body or attire while assessing spatiotemporal gait parameters also needs to be investigated. Hence, the aims of this study are: 1) to quantify the reliability and validity of a smartphone-based tri-axial accelerometer in determining gait characteristics (i.e. step length, step time, gait velocity, and cadence) when attached to the body and when placed in a bag, belt, hand, or pocket; and 2) to assess the validity of smartphone-based gait parameters during slow, comfortable, and fast walking speeds. We hypothesized that the use of a smartphone to evaluate gait spatiotemporal variables will be reliable and valid across all gait speeds when attached to the body and belt. We further hypothesized that smartphone placement in a bag, hand, or pocket would result in reduced reliability and validity. Reference values for gait parameters were obtained from a GAITRite instrumented walkway.

2. Methods

2.1. Participants

This investigation included 12 healthy young adults (1 male; mean ± SD age 22.7 ± 0.9 years; body mass index (BMI) 21.2 ± 4.1 kg/m^2) and 22 healthy older adults (7 males; age 73.9 ± 5.6 years; BMI 23.7 ± 3.6 kg/m^2) who were able to walk continuously for at least ten meters without the assistance of another person or a walking aid. Participants were excluded if they presented with an unstable medical condition such as uncontrolled hypertension or diabetes, reported severe neurological, musculoskeletal, or cardiopulmonary problems, had visual impairment uncorrectable with conventional lenses, or had a lower limb amputation or arthroplasty.

All adults were recruited into the study through flyers posted in the surrounding communities and by an announcement through community leaders and primary health care providers. The study was approved by the University's Research Ethics Committee (Number 271/2016). Written informed consent for the study protocol was obtained from each participant prior to enrollment into the study.

2.2. Experimental design

Participants were asked to walk barefoot along a 10-m walkway at their self-selected walking speeds. Two markers were placed on the ground to indicate the start and end of the 10-m path, with the GAITRite (CIR Systems Inc., Sparta, NJ, USA) walkway placed in the middle of this path. To measure steady-state gait, only the middle 4.27-m active sensor area of the GAITRite was used to examine gait parameters.

During all walking trials, participants carried a smartphone (Vivo X5; Android 4.4.4; 143.3 mm × 71.1 mm × 6.3 mm; 141grams) in one of five locations: 1) attached with a belt to the body above the third lumbar vertebrae in the horizontal orientation; 2) in a shoulder bag (15 cm × 18 cm) placed in a horizontal orientation, with the non-adjustable strap placed over the left shoulder and the pouch on the right hip; 3) on a belt attached above the front right pant pocket in a horizontal orientation; 4) in the right hand, held in a telephone speaking position; 5) in the front right pant pocket placed in a vertical orientation (Fig. 1). Participants were first asked to walk at their self-selected comfortable walking speed over the 10-m walkway. After completing all comfortable gait speed trials, participants were asked to walk at fast and slow speeds. The location of the smartphone and order of fast and slow trials were randomized. To assess reliability, two trials were performed for each condition, with a total of 30 trials completed per participant. To ensure only steps that were collected concurrently by the smartphone and GAITRite were analyzed, a digital video camera was used to record all walking trials, with both systems reset after each walking trial. To assess validity, all trials were utilized, with the average value taken across all steps during each trial.

Table 1a
Step length reliability and validity across smartphone location and walking speed.

Location	Speed	GAITRite		Smartphone		Validity			
		Mean ± SD (m)	ICC (2,1)	Mean ± SD (m)	ICC (2,1)	r	Bias	LOA Lower	LOA Upper
Body	Comfortable	0.58 ± 0.07	0.97	0.56 ± 0.08	0.91	0.833 *	−0.027	−0.113	0.060
	Slow	0.51 ± 0.09	0.95	0.46 ± 0.09	0.89	0.798 *	−0.063	−0.187	0.061
	Fast	0.69 ± 0.08	0.97	0.64 ± 0.09	0.91	0.820 *	−0.050	−0.156	0.057
	All Speeds	0.60 ± 0.11	0.98	0.56 ± 0.11	0.95	0.892 *	−0.046	−0.156	0.064
Bag	Comfortable	0.58 ± 0.08	0.97	0.57 ± 0.09	0.86	0.837 *	−0.006	−0.106	0.093
	Slow	0.52 ± 0.10	0.97	0.47 ± 0.11	0.92	0.896 *	−0.050	−0.153	0.054
	Fast	0.69 ± 0.08	0.96	0.65 ± 0.11	0.84	0.825 *	−0.033	−0.163	0.097
	All Speeds	0.60 ± 0.11	0.98	0.57 ± 0.13	0.92	0.901 *	−0.030	−0.147	0.087
Belt	Comfortable	0.58 ± 0.08	0.97	0.56 ± 0.08	0.87	0.728 *	−0.026	−0.137	0.085
	Slow	0.51 ± 0.09	0.98	0.49 ± 0.09	0.88	0.774 *	−0.021	−0.146	0.104
	Fast	0.69 ± 0.08	0.96	0.59 ± 0.09	0.90	0.671 *	−0.098	−0.239	0.044
	All Speeds	0.60 ± 0.11	0.98	0.55 ± 0.10	0.90	0.761 *	−0.049	−0.192	0.095
Hand	Comfortable	0.58 ± 0.07	0.98	0.45 ± 0.08	0.74	0.442 *	−0.134	−0.292	0.024
	Slow	0.51 ± 0.10	0.94	0.38 ± 0.11	0.79	0.749 *	−0.123	−0.267	0.021
	Fast	0.69 ± 0.08	0.96	0.50 ± 0.12	0.85	0.574 *	−0.188	−0.387	0.116
	All Speeds	0.60 ± 0.11	0.98	0.45 ± 0.11	0.84	0.696 *	−0.149	−0.326	0.029
Pocket	Comfortable	0.57 ± 0.08	0.95	0.58 ± 0.10	0.86	0.824 *	0.006	−0.109	0.121
	Slow	0.51 ± 0.09	0.93	0.48 ± 0.11	0.85	0.850 *	−0.012	−0.226	0.201
	Fast	0.68 ± 0.08	0.97	0.67 ± 0.14	0.77	0.627 *	−0.034	−0.152	0.085
	All Speeds	0.59 ± 0.11	0.97	0.58 ± 0.14	0.88	0.827 *	−0.013	−0.172	0.146

Abbreviations: r, Pearson's Correlation; Bias, Mean Difference (Smartphone – GAITRite); LOA, Limits of agreement.
*P < 0.001.

2.3. Data analysis

Gait data obtained from GAITRite were considered the gold standard. The GAITRite measured 5 m × 0.6m, with a spatial accuracy of 1.27 cm, and sampled data at a frequency of 80 Hz. Step length and step time were reported automatically through the GAITRite software as the anterior-posterior displacement and time separation of each consecutive footstep, respectively. Step velocity was computed as the quotient of the step length and step time [15], with gait velocity being the average step velocity across all steps. Cadence (steps/min) was calculated as the number of steps taken over the total trial time. The GAITRite walkway has previously been shown to be valid and reliable for the quantification of step parameters [5,6].

A custom-built Android application, Sensor Data [16], was developed to collect system time and tri-axial accelerometer data from the built-in hardware sensor (ST Microelectronics LSM330 accelerometer, ± 16 g range, $0.01 m/s^2$ resolution) at the smartphone's maximum sampling frequency (Android: SENSOR_DELAY_FASTEST; 95–105 Hz range). All data obtained was downloaded offline following the completion of the data collection and analyzed using custom written programs in MATLAB 2013b (Mathworks Inc., Natick, MA, USA). Evaluations of step length, step time, and gait velocity were calculated based on algorithms previously described [15,17–19]. Specifically, all accelerometer data were first resampled to a frequency of 100 Hz, as the sampling rate of smartphone-based sensors are not constant [19]. Data in all three-axes were then filtered using a Butterworth 4th order low-pass filter with a 20 Hz cutoff frequency [15]. Antero-posterior (AP) accelerations were further filtered using a Butterworth 4th order low-pass filter with a cutoff frequency of 2 Hz [15,20]. Positive peaks in the filtered AP direction were identified as heel strikes utilizing a built-in MATLAB function (findpeaks.m). From visual observation and video inspection, only steps taken on the GAITRite platform were analyzed further.

Smartphone-based step time was defined as the time difference between heel strikes [18]. Step length was calculated from the change in height of the vertical position across each step cycle and the participant's leg length. Vertical position was computed by double integrating the vertical acceleration data, and high pass filtering the result using a Butterworth 4th order filter with a 0.1 Hz cutoff frequency to remove integration drift [20]. Step length was then computed by using the relationship:

$$SL = 2*\sqrt{2*h*l - h^2} \tag{1}$$

where SL is the step length, h is the change in vertical position, and l is the leg length. Cadence, and gait velocity were computed identically to the methods used for GAITRite.

2.4. Reliability

Reliability was assessed across trials for all derived gait parameters from both GAITRite and the smartphone using the intraclass correlation coefficient ($ICC_{2,1}$) [21]. For ICC values, the following guidelines were used to interpret results: values greater than 0.75 represented excellent reliability, 0.60-0.75 good reliability, 0.40–0.60 fair reliability, and less than 0.40 poor reliability [22]. All reliability data were analyzed in SPSS 20.0 (IBM Inc., Armonk, NY, USA).

2.5. Validity

To evaluate concurrent validity, gait parameters quantified by the two measurement devices across all gait speeds and locations were evaluated using the Pearson correlation coefficient (r). Using Mukaka's Rule of Thumb for correlations [23], we specify r-values of 0.90–1.00 as very high, 0.70–0.90 as high, 0.50–0.70 as moderate, 0.30–0.50 as low, and less than 0.30 as negligible. Furthermore, Bland-Altman results demonstrate the bias as the mean difference between systems, and 95% limits of agreement when comparing smartphone-derived gait parameters from GAITRite [24].

3. Results

All 34 participants completed the protocol as prescribed, though ten trials (1 body, 4 bag, 0 belt, 2 pocket, and 3 hand) could not be analyzed due to technical issues with the smartphone, leaving 1010 trials for further evaluation. As the focus of this study pertains to the reliability and validity of a smartphone-based assessment across all adult

Table 1b
Step time reliability and validity across smartphone location and walking speed.

Location	Speed	GAITRite		Smartphone		Validity			
		Mean ± SD (sec)	ICC (2,1)	Mean ± SD (sec)	ICC (2,1)	r	Bias	LOA Lower	LOA Upper
Body	Comfortable	0.53 ± 0.06	0.96	0.53 ± 0.08	0.96	0.972 *	0.001	−0.025	0.027
	Slow	0.64 ± 0.09	0.93	0.63 ± 0.08	0.89	0.905 *	−0.015	−0.092	0.062
	Fast	0.44 ± 0.05	0.96	0.44 ± 0.04	0.95	0.985 *	0.003	−0.013	0.018
	All Speeds	0.53 ± 0.11	0.97	0.53 ± 0.10	0.96	0.975 *	−0.003	−0.051	0.045
Bag	Comfortable	0.54 ± 0.06	0.96	0.54 ± 0.05	0.79	0.887 *	−0.002	−0.054	0.049
	Slow	0.65 ± 0.11	0.94	0.58 ± 0.07	0.50	0.175	−0.072	−0.307	0.164
	Fast	0.44 ± 0.05	0.97	0.44 ± 0.05	0.82	0.919 *	−0.001	−0.039	0.037
	All Speeds	0.54 ± 0.11	0.97	0.52 ± 0.08	0.80	0.728 *	−0.023	−0.172	0.126
Belt	Comfortable	0.54 ± 0.06	0.97	0.52 ± 0.06	0.80	0.603 *	−0.013	−0.113	0.087
	Slow	0.64 ± 0.10	0.97	0.58 ± 0.07	0.81	0.427 *	−0.058	−0.247	0.131
	Fast	0.44 ± 0.05	0.95	0.44 ± 0.05	0.88	0.952 *	0.001	−0.028	0.031
	All Speeds	0.54 ± 0.11	0.99	0.52 ± 0.09	0.91	0.789 *	−0.022	−0.153	0.109
Hand	Comfortable	0.53 ± 0.06	0.97	0.53 ± 0.06	0.89	0.840 *	−0.006	−0.069	0.057
	Slow	0.65 ± 0.10	0.96	0.58 ± 0.08	0.57	−0.059	−0.081	−0.342	0.181
	Fast	0.44 ± 0.05	0.95	0.46 ± 0.06	0.21	0.543 *	0.022	−0.084	0.128
	All Speeds	0.54 ± 0.11	0.98	0.52 ± 0.08	0.70	0.603 *	−0.018	−0.198	0.161
Pocket	Comfortable	0.55 ± 0.06	0.92	0.53 ± 0.06	0.53	0.584 *	−0.017	−0.126	0.092
	Slow	0.65 ± 0.09	0.93	0.55 ± 0.09	0.62	0.020	−0.104	−0.355	0.146
	Fast	0.44 ± 0.05	0.96	0.46 ± 0.07	0.62	0.402 *	0.017	−0.125	0.158
	All Speeds	0.54 ± 0.11	0.97	0.51 ± 0.08	0.69	0.468 *	−0.032	−0.231	0.167

Abbreviations: r, Pearson's Correlation; Bias, Mean Difference (Smartphone − GAITRite); LOA, Limits of agreement.
*P < 0.001.

populations versus a gold standard, no statistical comparisons were made between the young and older adult groups.

3.1. Reliability

All GAITRite spatial and temporal measures demonstrated excellent reliability (Tables 1a–1d). Among the smartphone-derived measures, ICCs were good to excellent (0.74–0.97) for all step length (Table 1a) and gait velocity measures (Table 1c). Similarly, good to excellent reliability was demonstrated for the body and belt conditions at all speeds for step time (Table 1b) and cadence (Table 1d). For these temporal variables, the bag and pocket conditions showed fair to excellent reliability (0.50–0.85). The hand condition demonstrated a large range of reliability scores across speeds for step time and cadence, with fast walking demonstrating poor reliability (0.21 and 0.30, respectively), slow walking showing fair reliability (0.57 and 0.51, respectively), and comfortable walking having excellent reliability (0.89 and 0.88, respectively).

3.2. Validity

Step length and step time correlations between the smartphone-

Table 1c
Gait velocity reliability and validity across smartphone location and walking speed.

Location	Speed	GAITRite		Smartphone		Validity			
		Mean ± SD (m/s)	ICC (2,1)	Mean ± SD (m/s)	ICC (2,1)	r	Bias	LOA Lower	LOA Upper
Body	Comfortable	1.11 ± 0.21	0.97	1.06 ± 0.21	0.93	0.903 *	−0.052	−0.234	0.129
	Slow	0.83 ± 0.22	0.95	0.76 ± 0.20	0.89	0.904 *	−0.042	−0.260	0.177
	Fast	1.60 ± 0.29	0.96	1.47 ± 0.25	0.94	0.863 *	−0.133	−0.421	0.155
	All Speeds	1.20 ± 0.40	0.99	1.11 ± 0.36	0.97	0.958 *	−0.076	−0.323	0.170
Bag	Comfortable	1.10 ± 0.21	0.97	1.08 ± 0.24	0.94	0.915 *	−0.008	−0.195	0.178
	Slow	0.83 ± 0.24	0.96	0.83 ± 0.19	0.86	0.914 *	0.020	−0.207	0.246
	Fast	1.58 ± 0.29	0.97	1.50 ± 0.30	0.92	0.881 *	−0.079	−0.370	0.212
	All Speeds	1.19 ± 0.40	0.99	1.15 ± 0.37	0.96	0.953 *	−0.023	−0.274	0.229
Belt	Comfortable	1.10 ± 0.22	0.97	1.07 ± 0.18	0.91	0.873 *	−0.327	−0.247	0.182
	Slow	0.83 ± 0.24	0.98	0.86 ± 0.18	0.92	0.889 *	0.039	−0.206	0.284
	Fast	1.57 ± 0.29	0.94	1.34 ± 0.23	0.86	0.756 *	−0.236	−0.617	0.145
	All Speeds	1.18 ± 0.40	0.99	1.09 ± 0.28	0.94	0.914 *	−0.078	−0.447	0.291
Hand	Comfortable	1.11 ± 0.22	0.98	0.86 ± 0.17	0.78	0.663 *	−0.255	−0.578	0.068
	Slow	0.81 ± 0.24	0.93	0.67 ± 0.19	0.82	0.803 *	−0.097	−0.406	0.212
	Fast	1.60 ± 0.29	0.96	1.10 ± 0.29	0.87	0.453 *	−0.495	−1.095	0.106
	All Speeds	1.19 ± 0.51	0.98	0.89 ± 0.28	0.91	0.785 *	−0.284	−0.822	0.254
Pocket	Comfortable	1.07 ± 0.22	0.93	1.11 ± 0.22	0.90	0.838 *	0.044	−0.204	0.291
	Slow	0.82 ± 0.22	0.92	0.91 ± 0.21	0.87	0.783 *	0.101	−0.197	0.400
	Fast	1.57 ± 0.31	0.95	1.47 ± 0.26	0.86	0.748 *	−0.101	−0.517	0.315
	All Speeds	1.16 ± 0.40	0.98	1.17 ± 0.33	0.94	0.897 *	0.013	−0.355	0.381

Abbreviations: r, Pearson's Correlation; Bias, Mean Difference (Smartphone – GAITRite); LOA, Limits of agreement.
*P < 0.001.

Table 1d
Cadence reliability and validity across smartphone location and walking speed.

Location	Speed	GAITRite		Smartphone		Validity			
		Mean ± SD (steps/min)	ICC (2,1)	Mean ± SD (steps/min)	ICC (2,1)	r	Bias	LOA Lower	LOA Upper
Body	Comfortable	113.5 ± 11.5	0.97	113.4 ± 11.5	0.97	0.966 *	−0.11	−5.99	5.78
	Slow	95.3 ± 13.5	0.94	96.8 ± 12.2	0.88	0.244 †	9.39	−29.55	48.34
	Fast	138.3 ± 14.7	0.96	137.3 ± 13.9	0.96	0.985 *	−0.97	−6.14	4.19
	All Speeds	116.7 ± 21.9	0.98	116.8 ± 20.7	0.97	0.868 *	2.69	−21.66	27.03
Bag	Comfortable	112.5 ± 11.5	0.96	112.6 ± 11.1	0.81	0.896 *	0.46	−9.65	10.56
	Slow	95.2 ± 14.8	0.95	105.7 ± 13.2	0.56	−0.088	16.35	−29.85	62.56
	Fast	137.4 ± 15.0	0.97	137.2 ± 14.9	0.80	0.912 *	0.14	−12.37	12.64
	All Speeds	115.8 ± 22.1	0.98	118.9 ± 18.9	0.85	0.739 *	5.67	−26.19	37.54
Belt	Comfortable	113.0 ± 11.9	0.97	115.9 ± 12.8	0.78	0.571 *	2.95	−19.52	25.43
	Slow	95.8 ± 14.2	0.98	104.0 ± 12.3	0.82	0.391 †	10.68	−21.47	42.82
	Fast	137.1 ± 15.2	0.95	136.7 ± 15.0	0.85	0.941 *	−0.47	−10.76	9.83
	All Speeds	115.8 ± 21.8	0.99	119.2 ± 19.0	0.91	0.837 *	4.33	−20.60	29.27
Hand	Comfortable	113.5 ± 11.8	0.98	114.9 ± 12.2	0.88	0.807 *	1.29	−13.37	15.95
	Slow	93.8 ± 14.0	0.94	106.2 ± 16.1	0.51	−0.026	17.56	−30.64	65.76
	Fast	139.1 ± 15.4	0.96	133.3 ± 16.1	0.30	0.621 *	−6.08	−33.21	21.05
	All Speeds	116.5 ± 23.0	0.98	118.7 ± 18.6	0.69	0.663 *	4.14	−33.92	42.19
Pocket	Comfortable	111.1 ± 12.0	0.91	114.7 ± 13.0	0.50	0.516 *	3.59	−20.64	27.83
	Slow	94.4 ± 12.6	0.92	112.8 ± 18.8	0.61	0.046	21.28	−25.63	68.20
	Fast	137.4 ± 17.6	0.96	133.3 ± 19.5	0.63	0.405 *	−4.06	−44.19	36.07
	All Speeds	114.9 ± 22.7	0.97	120.5 ± 19.6	0.70	0.514 *	6.76	−36.63	50.15

Abbreviations: r, Pearson's Correlation; Bias, Mean Difference (Smartphone – GAITRite); LOA, Limits of agreement.
*$P < 0.001$.
†$P < 0.05$.

based and GAITRite-based systems were high to very high for the body across all speeds (Tables 1a-1b; r: 0.798-0.985). While the bag and belt conditions demonstrated moderate to very high correlations for step length and step time across comfortable and fast walking (r: 0.603–0.952), negligible to low step time correlations were demonstrated for slow walking (r = 0.175 and 0.427, respectively). The hand and pocket locations similarly demonstrated negligible step time correlations at slow walking (r = −0.059 and 0.020, respectively), with low to high correlations across all other speeds for step length and step time. Step length bias was within 2.7 cm for comfortable speeds, 6.3 cm for slow speeds, and 9.8 cm for fast speeds, when the smartphone was placed on either the body, bag, belt, or pocket. The hand condition demonstrated larger biases ranging from 12.3 cm to 18.8 cm. Step time bias was within 22 ms for all locations across comfortable and fast speeds, with each location having a larger bias in step time at slow speeds (bias: 15–104 ms).

Gait velocity correlations were high to very high (Table 1c; r: 0.748–0.958) for all locations across all speeds except for the hand location at comfortable (r = 0.663) and fast speeds (r = 0.453). While cadence correlations were moderate to high for all locations except the pocket during comfortable or fast walking (Table 1c), slow walking demonstrated negligible to low correlations (r: −0.026–0.391) in all smartphone locations.

Bland-Altman analysis revealed that biases approached zero, particularly in the body, bag, and belt conditions (Fig. 2). Across gait measures, smaller limits of agreement were demonstrated in the body, bag, and belt conditions, with larger differences and outliers found mostly during slow walking conditions and in the hand and pocket conditions. The body condition showed the smallest bias, demonstrating consistent 0.04 m, 0.0 s, 0.08 m/s^2, and 2steps/min differences for step length, step time, gait velocity, and cadence, respectively, at walking speeds between 0.75 and 1.75 m/s^2.

4. Discussion

In this study, a comprehensive smartphone-based assessment of gait spatiotemporal variables among healthy adults across a range of gait velocities and body locations has been conducted. The main findings of this study are the excellent reliability and high validity of a smartphone-based gait assessment, particularly at comfortable and fast speeds. Results for spatiotemporal measures were encouraging when a smartphone was placed in various locations, though placement in the body, bag, or belt positions provided the greatest validity.

In support of our hypothesis, the body and belt conditions demonstrated excellent reliability and high to very high validity for most gait variables. Results of step length, step time, and gait velocity at varying gait speeds were comparable to those reported previously for a smartphone camera-based assessment [25]. Results from a validity study comparing accelerometer-based sensors placed on the lumbar vertebrae versus GAITRite were also similar to the current study for step length (r: 0.833–0.880), step time (r: 0.994–0.997), and step velocity (r: 0.882–0.900) [18]. Contrary to this hypothesis, reduced validity was seen for cadence results at slow speeds for both locations and step time at slow and comfortable speeds for the belt condition. At slow speeds, Bland-Altman plots also demonstrated an increased bias. While a majority of the trials demonstrated small differences between the smartphone and GAITRite (Fig. 2P–T), a few trials had outliers when walking at low speeds or cadence. Such outlier trials occurred due to peak AP accelerations being detected as steps in the smartphone-based algorithm earlier than GAITRite, leading to reduced step time and increased cadence values. The ability to assess slow velocities is of high importance, as improving gait speed is a strong predictor of mortality [4]. Further investigation is needed to identify and modify algorithms for slow walking, including the use of other smartphone-embedded sensors such as gyroscopes and magnetometers.

Contrary to our hypothesis, the bag condition revealed high reliability and validity across speeds. While the bag chosen in this study is not representative of all bags, it is possible that a single-shoulder bag in which the phone is held in a fixed position might yield good results. Of note is the size of the bag (15 cm width) in relation to our phone (14.33 cm length), and having no other objects in the bag, allowing for an undisturbed snug fit without extraneous movement applied to the smartphone. The hand and pocket conditions, however, did reveal relatively worse results. The selection of these five locations was based on

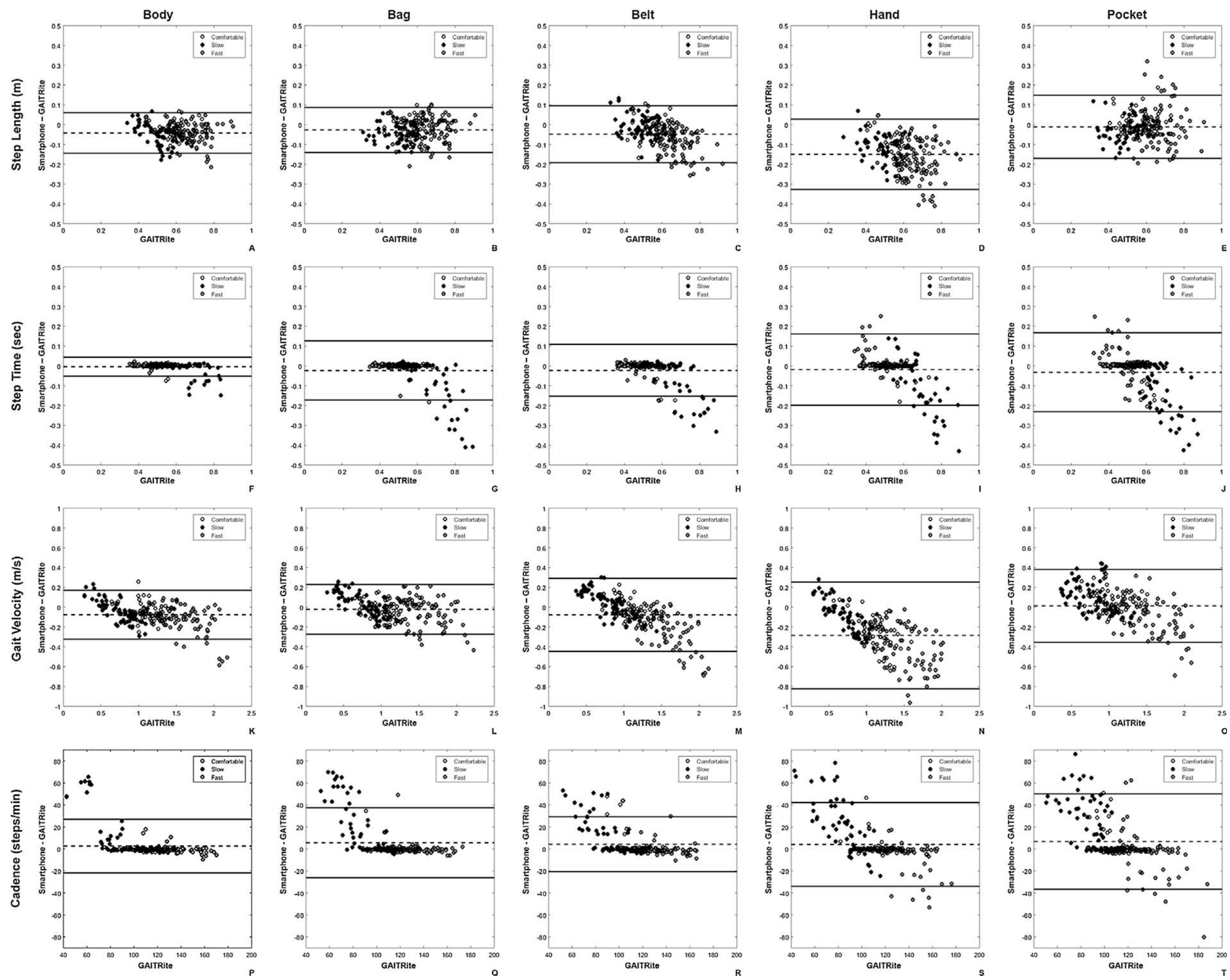

Fig. 2. Bland Altman plots for step length, step time, gait velocity, and cadence when using the smartphone-based accelerometer compared to GAITRite. The dashed line is the average difference, with the solid lines providing the repeatability coefficient (± 1.96 SD).

results from questionnaires [26] provided to over 1500 persons from nine countries, where phones were carried upwards of 60% of the time in bags or pant pockets for women and men, respectively. The following most common locations included the belt-clip (women 0.8%, men 13.8%), on the upper body (women 2.2%, men 8.3%), and in the hands (women 9.1%, men 3.5%). The hand location is of importance, as adults often perform dual-task walking with a smartphone, either talking or texting, leading to increased cognitive distraction, decreased gait velocity, and increased lateral deviation [27]. On average, when placed in the hand, the smartphone-based assessment in the current study underestimated (negative bias) gait parameters, with moderate to high correlations found. In order to properly evaluate the dual-task cost in home-based environments, future studies should investigate the use of unique algorithms for each phone location.

The current study has several limitations. First, knowledge of the phone location is known a priori. While methods for detecting the location of an accelerometer have been investigated [28], implementing these algorithms was beyond the scope of this study. Additionally, we utilized identical algorithms for each trial, therefore knowledge of location would not affect the presented results. Second, only five to nine steps were investigated per trial, with participants asked to walk in a straight line over a level surface. Although trials were short, Orendurff and colleagues [29] demonstrated that 40% of walking bouts last for fewer than 12 steps, with possibly greater validity in longer duration trials [9]. Furthermore, as it is recommended that a greater number of steps be used to assess variability [30], due to space constraints of G-AITRite, evaluation of gait variability from longer duration trials was not feasible. Further investigation into the effect of free-living conditions such as turning, walking on uneven or sloped surfaces, as well as maneuvering around environmental hazards and crowds is needed. Additionally, future work should investigate the generalizability of smartphone-based assessments for persons of varying weight or gait pathology. Assessment of compliance and validity across populations can allow for robust community-based monitoring and clinical intervention.

In conclusion, results of this study reveal that smartphone-based assessments of gait are reliable and valid when placed on the body, bag, or belt, particularly in comfortable and fast walking conditions. Smartphone sensors can provide relevant home-based walking data without the need for expensive instrumentation. Due to the ubiquity of smartphones, cost and complexity of distribution and analysis is minimized allowing for greater access to robust evaluations for clinicians and patients alike.

Conflict of interest statement

All authors state that there were no conflicts of interest in the preparation of this manuscript. Control One LLC had no role in any aspect of this study and confirms that there was no conflict of interest.

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