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The validity of smartphone-based spatiotemporal gait measurements during walking with and without head turns: Comparison with the GAITRite® system

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ABSTRACT

Smartphone accelerometry has potential to provide clinicians with specialized gait analysis not available in most clinical settings. The Gait&Balance Application (G&B App) uses smartphone accelerometry to assess spatiotemporal gait parameters under two conditions: walking looking straight ahead and walking with horizontal head turns. This study investigated the validity of G&B App gait parameters compared with the GAITRite® pressure-sensitive walkway. Healthy young and older adults (age range 21–85 years) attended a single session where a smartphone was secured over the lumbosacral junction. Data were collected concurrently with the app and GAITRite® systems as participants completed the two walking conditions. Spatiotemporal gait parameters for 54 participants were determined from both systems and agreement evaluated with partial Pearson's correlation coefficients and limits of agreement. The results demonstrated moderate to excellent validity for G&B App measures of step time (r_p 0.97, 95 % CI [0.96, 0.98]), walking speed (r_p 0.83 [0.78, 0.87]), and step length (r_p 0.74, [0.66, 0.80]) when walking looking straight ahead, and results were comparable with head turns. The validity of walking speed and step length measures was influenced by sex and height. G&B App measures of step length variability, step time variability, step length asymmetry, and step time asymmetry had poor validity. The G&B App has potential to provide valid measures of unilateral and bilateral step time, unilateral and bilateral step length, and walking speed, under two walking conditions in healthy young and older adults. Further research should validate this tool in clinical conditions and optimise the algorithm for demographic characteristics.

1. Introduction

Gait analysis is a fundamental part of clinical practice. Its applications include diagnosis of gait abnormalities, assessment of falls risk, monitoring of degenerative conditions, and evaluation of the effectiveness of orthoses, rehabilitation, or surgery (Chen et al., 2016). In clinical settings, there are a range of options for gait analysis. The GAITRite® pressure-sensitive walkway is considered a portable gold-standard for spatiotemporal gait analysis and has been used extensively to validate more novel gait-analysis systems (Kobsar et al., 2020; Sacco et al., 2023). While the portability of the GAITRite® (GAITRite®, 2023) enables its use in a range of environments, its outlay cost exceeds $30 k USD (EMS Physio Ltd, 2023) and therefore it is generally seen only in specialised clinics. Other portable options for clinical gait analysis include wearable sensors that use inertial measurement units (IMUs) and/or pressure sensors. These devices can be attached to the trunk, thigh, lower leg, or insole of the shoe (Prasanth et al., 2021) and thus offer potential for use outside the laboratory setting. However, wearable sensors are still out of reach for most clinics due to set up costs and requirements for specialised knowledge when interpreting data (Chen et al., 2016).

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Given these barriers to using specialised gait analysis systems, most clinicians rely on simple quantitative gait measures such as the 10-metre walk test, which measures gait speed and requires a simple timer to record the time taken to walk a set distance (Peters et al., 2013; Steffen et al., 2002). Such tests do not record parameters within individual gait cycles, such as step length or step time. To analyse gait in more depth, clinicians use subjective approaches such as observation-based scales (Wrisley et al., 2004); however, such scales are prone to ceiling effects and lack sensitivity to small changes in those with mild impairments (Pardasaney et al., 2012). Non-instrumented video analysis is also used by clinicians; however, these assessments are subjective, influenced by the experience of the observer (Viehweger et al., 2010) and demonstrate poor inter-rater reliability (Brunnekreef et al., 2005; Eastlack, 1991; Williams et al., 2009). Thus, current methods for clinical gait analysis are either expensive, or lack sensitivity and reliability.

A less expensive, more accessible option for spatiotemporal gait analysis is the use of technology built into standard smartphones. Given the ubiquitous nature of smartphones, this approach offers advantages over more expensive systems. One smartphone-based technology is digital 2D video capture which can be combined with pose tracking algorithms to quantify gait parameters (Mehdizadeh et al., 2021; Stenum et al., 2021). However, the accuracy of this approach can be influenced by the camera perspective, clothing, and lighting (Stenum et al., 2021; Viswakumar et al., 2021). An alternative approach involves securing a smartphone to an individual's body and utilising the accelerometers embedded within the smartphone to calculate gait parameters. The Gait&Balance Application (G&B App) is one such system that assesses gait and balance during four postural stability tasks and two walking tasks (Rashid et al., 2021). The two G&B App walking tasks are the focus of this paper and include: 1) walking while looking straight ahead, and 2) walking while turning the head from side to side. While the standard walking condition is common to smartphone accelerometry gait analysis systems, other systems do not assess walking while turning the head, which destabilises the visual field and increases reliance on the accurate integration of vestibular and proprioceptive information to maintain balance (Cullen, 2012; Singh et al., 2017). This head-turning task is included in several clinical balance scales (Franchignoni et al., 2010; Wrisley et al., 2004; Wrisley et al., 2003) and is known to be impaired in individuals with balance or vestibular disorders (Marchetti et al., 2008; Singh et al., 2017). Instead of walking with head turns, other smartphone accelerometry app's (Christensen et al., 2022; Manor et al., 2018; Zhong and Rau, 2020) assess dual-task walking while verbalising serial subtractions; whilst this task will assess the ability to divide attention while walking, it may not be difficult enough to destabilise balance (Porciuncula et al., 2016). Thus, the G&B App offers a protocol that aligns closely with clinical assessment and has potential to detect impairments in sensory input or sensory integration.

Prior to using the G&B App as a gait analysis tool, clinicians need to know how it compares with the widely-used gold-standard, which in this case is the portable GAITRite® system. Therefore, this study investigated the validity of spatiotemporal gait parameters assessed with the G&B App compared with the GAITRite® pressure-sensitive walkway. In addition, given the potential to use the G&B App across a range of individuals and evidence indicating gait biomechanics differ with various demographic characteristics (Chehab et al., 2017; Meng et al., 2017; Senden et al., 2012a; Suner-KeklİK et al., 2023), a post-hoc exploratory analysis was performed to evaluate whether age, sex, height, or body mass index (BMI) influenced the validity of the G&B App.

2. Method

2.1. Study design

This single-session, cross-sectional study compared gait parameters measured with the G&B App against those measured with the gold-standard GAITRite® pressure-sensitive walkway.

2.2. Participants

The participants (n = 64) were healthy community-dwelling adults over 20 years of age who could walk without walking aids and did not report any of the following: limited mobility within the home, falling in the previous 12 months, experiencing unsteadiness when standing or walking, feeling worried about falling, diagnosed vestibular disorders, neurological disorders that affected movement, impaired cognition, or any significant lower limb orthopaedic surgery. Participants provided written informed consent and the study was approved by the institutional ethics committee (20/38 and 21/51).

2.3. Sample size

This study used a combined sample from two smaller studies (n = 30 and n = 34) and was powered beyond that required for establishing validity with Pearson's correlation coefficients. The sample size justification is provided in the supplementary material.

2.4. Procedures

The study flow is illustrated in Fig. 1. Following consent, participants completed the Six-item Activities-specific Balance Confidence Scale (ABC-6) (Schepens et al., 2010) which involved rating their balance confidence on a scale from 0 % (not confident) to 100 % (completely confident). A smartphone (iPhone 7 or iPhone SE, Apple Inc, Cupertino, CA, USA) was fastened to the lumbo-sacral area (approximately L5/S1) with an elasticated core stability belt (Whiteley Allcare, Auckland, New Zealand) that had been customized by securing a phone casing (Sports armband, Tech.Inc, Auckland, New Zealand). Four retro-reflective 18 mm markers were attached on the participants bare feet at the left and right posterior calcanei and the left and right fifth metatarsal heads. The set up can be seen in Fig. 2.

Participants completed the G&B App test conditions (Rashid et al., 2021). The two walking tasks involved: 1) walking at a self-selected pace while looking straight ahead, and 2) walking at a self-selected pace while turning the head from side to side. Participants started on the hardwood floor, just behind the start of the GAITRite® 7-meter pressure-sensitive walkway (CIR Systems Inc, New York, USA). For each walking task, they completed four trials of 6 s duration, thus, each participant walked a slightly different distance. For each trial, the smartphone app provided auditory instructions to get "ready, set, go" and then after 6 s to "rest" and "turn around". Participants walked over the GAITRite® walkway so that spatiotemporal measures could be collected concurrently with the app and GAITRite® systems. The two gait tasks were performed three times each, with a rest period of 5 min between each set. 3D motion capture was also collected for a separate analysis (Olsen et al., 2022). During all tasks, stand-by supervision was provided.

2.5. Data processing

The G&B App data from the two walking tasks were processed according to methods described previously (Rashid et al., 2021) and the following parameters were calculated: walking speed, mean step length, mean left step length, mean right step length, mean step time, mean left step time, mean right step time, step length variability, step time variability, step length asymmetry, and step time asymmetry. The same parameters were exported from the GAITRite® system into Microsoft Excel, and then imported into R software for analysis (R Core Team, 2022). See supplementary table for further description of data processing.

2.6. Statistical analyses

A full description of the statistical analyses is provided in supplementary material. The participant-level consistency between the two

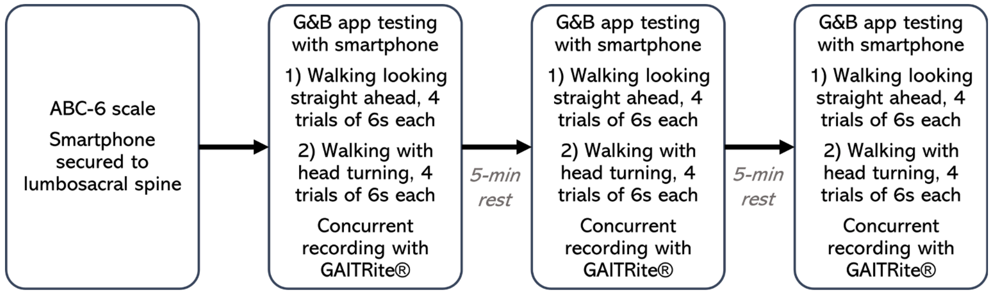

Fig. 1. Study flow.

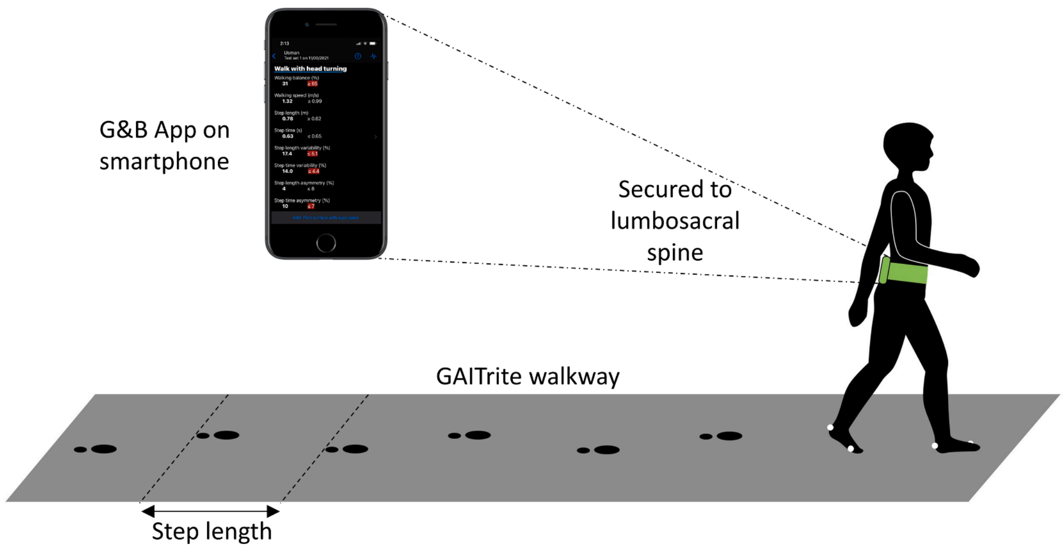

Fig. 2. Set up.

systems was evaluated with partial Pearson's correlation coefficients (r_p) (Kim, 2015). The absolute agreement between the two systems was evaluated with 95 % limits of agreement (95 % LoA = mean of differences between systems +/- 1.96 * their standard deviation) which accounts for both the systematic error (mean bias, or mean difference between the two systems) and the random error (95 % LoA, or differences around the mean for each participant). The 95 % LoA was expressed as the LoA% by dividing the 95 % LoA range by the mean of the gait parameter across the two systems. Consistency interpretation was based on the lower bound of the 95 % confidence interval (CI) of r_p and absolute agreement interpretation was based on the LoA% as follows: excellent (>0.90, 0.0–4.9 %), good (0.75–0.89, 5.0–9.9 %), moderate (0.50–0.74, 10.0–49.9 %) and poor (<0.50, >50.0 %) (Godfrey et al., 2015; Portney and Watkins, 2009). Only complete cases (participants with data from both systems) were included in the analysis.

Further post-hoc analyses were performed to evaluate the influence of demographic characteristics (age, sex, height, and BMI) on the validity results. Gait parameters were selected that had demonstrated at least moderate agreement between the two systems. For each gait parameter, the pair-wise differences between the two systems were regressed on demographic characteristics with a linear model using generalised least squares (Pinheiro and Bates, 2000). For each demographic characteristic, the sample was categorised into two subgroups; sex was separated by male/female, and other characteristics were bifurcated using the median value (age 66 years, height 168 cm, and BMI 25). To determine whether age, sex, height, and BMI influenced the systematic errors measured by the G&B App, the statistical significance ($p < 0.05$) of the regression model coefficients was evaluated. The model was refitted to compute separate standard error of the measures (SEM) and their 95 % CIs for each of the two subgroups; these represent the random errors in the app. To determine whether demographic characteristics influenced the random app errors, the 95 % CIs of the SEM for each subgroup were compared and non-overlapping CIs were considered statistically significant.

3. Results

3.1. Participants

Ten cases were incomplete due to the nature of the protocol. For example, some participants stopped walking on the GAITRite® mat which resulted in loss of data for that trial. In addition, there was some mislabelling of gait conditions which resulted in data loss. Therefore, 54 participants (20 males) with full datasets from both systems were included in the analysis. The included participants represented a range of ages from 21 to 85 years (mean = 61.6 years) and balance confidence ranged from 40 to 100 % on the ABC-6 scale (mean = 83 %). See Table 1 for participant demographics.

3.2. Validity of Gait&Balance App against GAITRite® system

The data from the validity evaluation of the G&B App is shown in Table 2. The highest correlations were seen for step time, walking speed, and step length; these are presented in Fig. 3 for the walking looking straight ahead condition. The findings demonstrated excellent agreement between the G&B App and the GAITRite system for step time when walking looking straight ahead (r_p 0.97, 95 % CI [0.96, 0.98], Fig. 3a) and walking with head turns (r_p 0.99, 95 % CI [0.98, 0.99]). Agreement

Table 1
Participant demographics and balance confidence assessed through ABC-6 scale by age band.

Age bands	*n*	Female: Male	ABC-6 (%) Median (range)
20–29	3	2:1	88 (85–100)
30–39	4	3:1	82 (55–100)
40–49	5	3:2	88 (81–96)
50–59	9	6:3	93 (77–100)
60–69	13	8:5	83 (73–97)
70–79	14	8:6	80 (60–97)
80–89	6	4:2	73 (40–94)

was slightly lower for left and right step time, more so when walking looking straight ahead, but still in the good to excellent range (see Table 2). For walking speed, there was good agreement between the two systems when walking looking straight ahead (r_p 0.83, 95 % CI [0.78, 0.87], Fig. 3b) and with head turns (r_p 0.87, 95 % CI [0.83, 0.90]). For step length, there was moderate agreement between the two systems when walking looking straight ahead (r_p 0.74, 95 % CI [0.66, 0.8], Fig. 3c) and with head turns (r_p 0.77, 95 % CI [0.69, 0.83]), and there were similar results for unilateral step length (see Table 2). G&B App measures of step length variability, step time variability, step length asymmetry, and step time asymmetry had poor agreement with the GAITRite® system.

3.3. *Influence of age, sex, BMI, and height on validity of Gait&Balance App*

Walking speed, mean step length, and mean step time demonstrated moderate agreement or better with the GAITRite system and were included in the evaluation of demographic characteristics. Demographic characteristics significantly influenced systematic and random app errors in a number of gait parameters (see Table 3 and supplementary material for further data). For age and BMI subgroups, most error differences were less than 3.5 %. However, systematic errors for walking speed and step length differed according to sex by 6–10 % (see Fig. 4, significant systematic errors can be visualised as the difference in means of female/male subgroups). Random errors in step length when walking looking straight ahead were also influenced by sex, with error differences between females and males of approximately 8 % (see Fig. 4, significant random errors can be visualised as the difference in distribution of data in female/male subgroups). Height influenced systematic error for walking speed and step length when walking with head turns, with error differences in the 3–4 % range.

4. Discussion

4.1. *Validity of mean step time, mean step length, and walking speed*

This study sought to validate gait measures collected with the G&B smartphone app against the gold-standard GAITRite® pressure sensitive walkway. The findings demonstrated excellent agreement for step time, good agreement for walking speed, and moderate agreement for step length, while walking forwards at a self-selected pace. These findings align with a previous study comparing the G&B App against gold-standard 3D motion capture in a Spanish cohort (Rashid et al., 2021). The findings also align with the wider literature that has compared smartphone accelerometry against gold-standard systems and shown excellent agreement for step time or stride time, moderate-to-good agreement for self-selected walking speed, and moderate-to-good agreement for step length (Christensen et al., 2022; Manor et al., 2018; Rentz et al., 2022; Silsupadol et al., 2017). In addition, our findings are comparable with an investigation of an accelerometer-based sensor placed on the lumbar spine which found moderate agreement with the GAITRite® for step length and walking speed, and excellent agreement for step time (Godfrey et al., 2015).

The G&B App also measured gait while walking with head turns. Under this more dynamic condition, mean step time, mean step length, and walking speed remained valid. Other smartphone apps have measured gait with a cognitive dual task (e.g., while verbalising serial subtractions); in agreement with our findings, these studies have demonstrated that mean step length, mean stride time, and walking speed, have similar validity when recorded under this cognitive dual-tasking condition (Christensen et al., 2022; Manor et al., 2018). The present study is the first to our knowledge to validate these mean gait

Table 2
Validity of Gait&Balance App compared with GAITRite® system.

	Gait parameter	G&B App Mean ± SD	GAITRite® Mean ± SD	r_p [95 % CI]	Consistency	LoA%	Agreement
Mean values							
i) Walking looking straight ahead	Walking speed (m/s)	1.20 ± 0.14	1.24 ± 0.17	0.83 [0.78, 0.87]	Good	17.9	Moderate
	Mean step length (m)	0.63 ± 0.06	0.65 ± 0.06	0.74 [0.66, 0.80]	Moderate	16.2	Moderate
	Left step length (m)	0.64 ± 0.06	0.65 ± 0.07	0.69 [0.59, 0.75]	Moderate	16.2	Moderate
	Right step length (m)	0.63 ± 0.07	0.65 ± 0.07	0.69 [0.60, 0.77]	Moderate	19.4	Moderate
	Mean step time (s)	0.530 ± 0.041	0.527 ± 0.043	0.97 [0.96, 0.98]	Excellent	4.4	Excellent
	Left step time (s)	0.54 ± 0.04	0.53 ± 0.05	0.88 [0.84, 0.91]	Good	9.2	Good
	Right step time (s)	0.52 ± 0.04	0.52 ± 0.05	0.84 [0.79, 0.88]	Good	9.6	Good
ii) Walking head turning	Walking speed (m/s)	1.14 ± 0.15	1.15 ± 0.17	0.87 [0.83, 0.90]	Good	15.3	Moderate
	Mean step length (m)	0.64 ± 0.07	0.64 ± 0.07	0.77 [0.69, 0.83]	Moderate	14.6	Moderate
	Left step length (m)	0.64 ± 0.07	0.63 ± 0.07	0.73 [0.64, 0.79]	Moderate	17.3	Moderate
	Right step length (m)	0.63 ± 0.07	0.64 ± 0.07	0.74 [0.66, 0.80]	Moderate	17.5	Moderate
	Mean step time (s)	0.560 ± 0.052	0.558 ± 0.054	0.99 [0.98, 0.99]	Excellent	3.7	Excellent
	Left step time (s)	0.57 ± 0.05	0.56 ± 0.06	0.95 [0.93, 0.96]	Excellent	7.3	Good
	Right step time (s)	0.55 ± 0.05	0.56 ± 0.06	0.96 [0.94, 0.97]	Excellent	6.3	Good
Variability							
i) Walking looking straight ahead	Step length variability (%)	5 ± 2	5 ± 4	0.26 [0.1, 0.4]	Poor	155.9	Poor
	Step time variability (%)	5 ± 2	9 ± 10	0.02 [-0.14, 0.18]	Poor	339.6	Poor
ii) Walking head turning	Step length variability (%)	6 ± 2	6 ± 4	0.29 [0.14, 0.43]	Poor	135.7	Poor
	Step time variability (%)	5 ± 2	9 ± 6	0.31 [0.16, 0.45]	Poor	208.1	Poor
Asymmetry							
i) Walking looking straight ahead	Step length asymmetry (%)	4 ± 3	3 ± 3	0.04 [-0.11, 0.2]	Poor	213.5	Poor
	Step time asymmetry (%)	4 ± 3	4 ± 5	0.03 [-0.13, 0.19]	Poor	302.7	Poor
ii) Walking head turning	Step length asymmetry (%)	4 ± 3	4 ± 3	0.1 [-0.06, 0.26]	Poor	212.3	Poor
	Step time asymmetry (%)	3 ± 3	3 ± 3	−0.04 [-0.19, 0.12]	Poor	262.1	Poor

For clarity, the number of decimal places for a measure was based on the corresponding standard error of that measure (Cole, 2015).

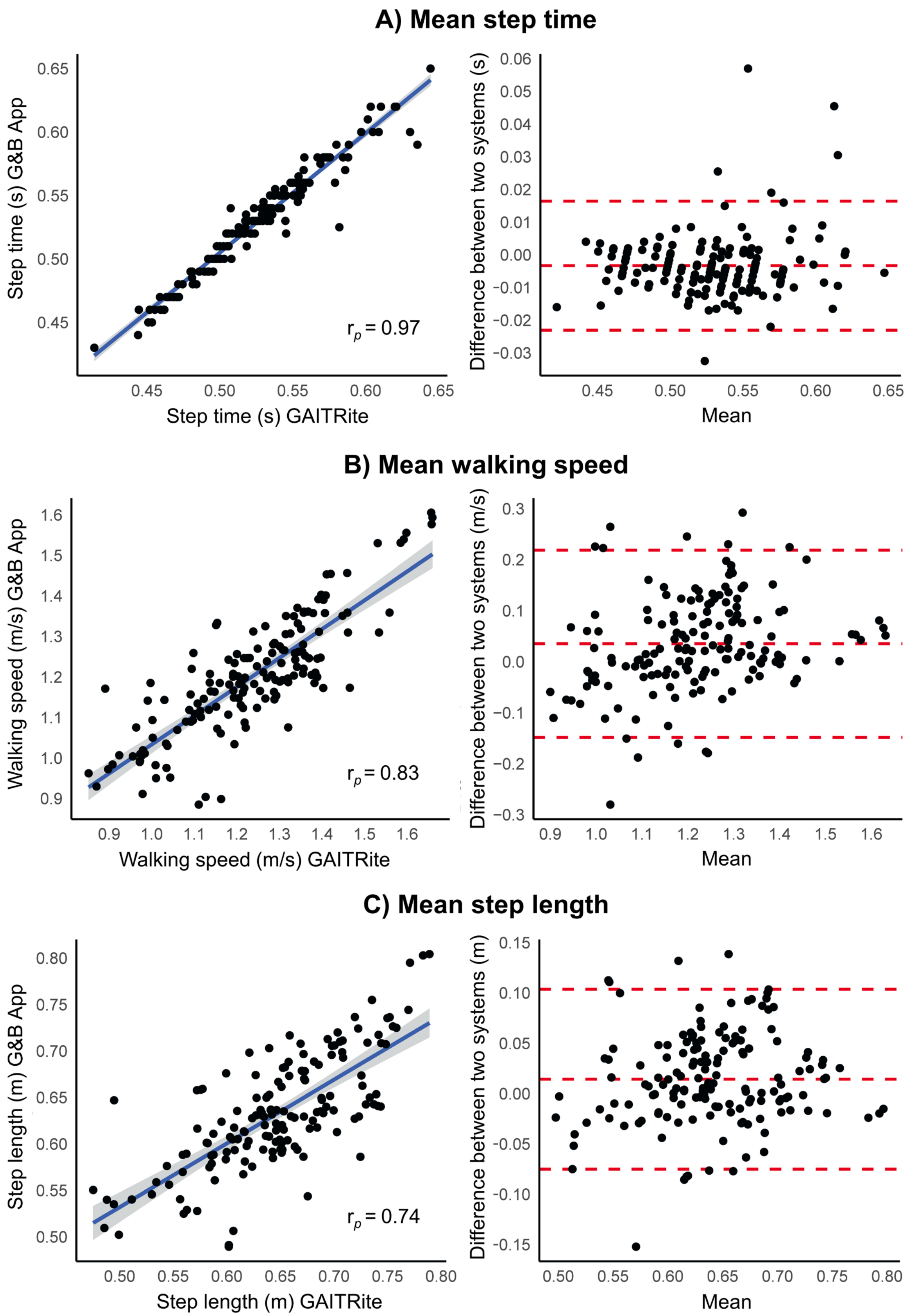

Fig. 3. Scatterplots and Bland-Altman plots demonstrating agreement between the G&B App and the GAITRite system for mean step time, mean walking speed, and mean step length, when walking looking straight ahead. Difference between two systems is calculated as GAITRite minus G&B App.

Table 3
Influence of age, sex, BMI, and height on validity of Gait&Balance App.

Demographic characteristic and subgroups	Walking condition	Gait parameter	Systematic error (% mean) * p < 0.05	Standard error of the measure, or random error (% mean) **(* Between subgroup difference p < 0.05)**
Age 1. Younger (<66 years) 2. Older (≥66 years)	i) Walking looking straight ahead	Walking speed (m/s)	**−0.04* (-3.59 %)**	<66 years: 0.078 (6.43 %), ≥66 years: 0.093 (7.61 %)
		Mean step length (m)	**−0.02* (-3.45 %)**	<66 years: 0.037 (5.77 %), ≥66 years: 0.046 (7.22 %)
		Mean step time (s)	0.001 (0.11 %)	**<66 years: 0.012 (2.30 %), ≥66 years: 0.008 (1.48 %)***
	ii) Walking head turning	Walking speed (m/s)	**−0.04* (-3.29 %)**	<66 years: 0.072 (6.28 %), ≥66 years: 0.078 (6.83 %)
		Mean step length (m)	**−0.02* (-3.10 %)**	<66 years: 0.036 (5.68 %), ≥66 years: 0.045 (7.01 %)
		Mean step time (s)	0.001 (0.19 %)	<66 years: 0.008 (1.51 %), ≥66 years: 0.01 (1.84 %)
Sex 1. Female 2. Male	i) Walking looking straight ahead	Walking speed (m/s)	**−0.08* (-6.69 %)**	Female: 0.075 (6.15 %), Male: 0.101 (8.30 %)
		Mean step length (m)	**−0.04 (-6.17 %)**	**Female: 0.035 (5.43 %), Male: 0.051 (8.02 %)***
		Mean step time (s)	−0.00 (-0.04 %)	**Female: 0.008 (1.46 %), Male: 0.013* (2.50 %)***
	ii) Walking head turning	Walking speed (m/s)	**−0.11* (-9.62 %)**	Female: 0.073 (6.40 %), Male: 0.078 (6.85 %)
		Mean step length (m)	**−0.06* (-8.97 %)**	Female: 0.038 *6.00 %), Male: 0.045 (7.00 %)
		Mean step time (s)	0.002 (0.43 %)	Female: 0.008 (1.52 %), Male: 0.011 (1.94 %)
BMI 1. Lower (<25) 2. Higher (≥25)	i) Walking looking straight ahead	Walking speed (m/s)	0.03 (2.22 %)	BMI<25: 0.084 (6.92 %), BMI≥25: 0.087 (7.17 %)
		Mean step length (m)	**0.014* (2.23 %)**	BMI<25: 0.043 (6.66 %), BMI≥25: 0.041 (6.40 %)
		Mean step time (s)	−0.00 (-0.03 %)	BMI<25: 0.008 (1.58 %), BMI≥25: 0.012 (2.22 %)
	ii) Walking head turning	Walking speed (m/s)	**0.03* (2.24 %)**	BMI<25: 0.082 (7.17 %), BMI≥25: 0.068 (5.91 %)
		Mean step length (m)	**0.017 (2.65 %)**	BMI<25: 0.044 (6.86 %), BMI≥25: 0.037 (5.89 %)
		Mean step time (s)	**0.003 (0.55 %)**	**BMI<25: 0.007 (1.33 %), BMI≥25: 0.011 (1.99 %)***
Height 1. Shorter (<168 cm) 2. Taller (≥168 cm)	i) Walking looking straight ahead	Walking speed (m/s)	0.02 (1.30 %)	<168 cm: 0.076 (6.23 %), ≥168 cm: 0.095 (7.79 %)
		Mean step length (m)	0.01 (1.34 %)	<168 cm: 0.035 (5.42 %), ≥168 cm: 0.048 (7.51 %)
		Mean step time (s)	0.001 (0.19 %)	<168 cm: 0.008 (1.55 %), ≥168 cm: 0.012 (2.24 %)
	ii) Walking head turning	Walking speed (m/s)	**0.05 (4.27 %)**	<168 cm: 0.071 (6.20 %), ≥168 cm: 0.079 (6.92 %)
		Mean step length (m)	**0.02 (3.42 %)**	<168 cm: 0.037 (5.87 %), ≥168 cm: 0.044 (6.88 %)
		Mean step time (s)	−0.002 (-0.29 %)	<168 cm: 0.009 (1.63 %), ≥168 cm: 0.01 (1.75 %)

Statistically significant findings are in bold ($p < 0.05$). Figures are rounded to 3 decimals digits or first significant number. The cut-off scores for age, height, and BMI were obtained using the median value. Systematic error interpretation: Differences between subgroups are calculated subgroup 2 minus subgroup 1. A negative score means the app underestimates the gait parameter for subgroup 1 relative to subgroup 2. A positive score means the app overestimates the gait parameter for subgroup 1 relative to subgroup 2.

parameters from smartphone accelerometry while walking with horizontal head turns.

This is the first G&B App study to evaluate unilateral measures of step length and step time. The findings demonstrated that left and right step length had similar accuracy to mean step length, and both demonstrated moderate agreement with the GAITRite system. This level of agreement is in line with previous research comparing a smartphone app attached to the thigh with a gold-standard pressure-sensitive walkway in people with musculoskeletal conditions (Shema-Shiratzky et al., 2022). Our findings for unilateral step time showed slightly lower agreement with the GAITRite system than mean step time parameters, however agreement was still in the good-to-excellent range. These unilateral measures would be particularly useful in clinical conditions that affect one side, such as stroke or osteoarthritis, and therefore their validity should be explored in clinical populations.

The findings revealed that sex influenced the validity of walking speed and step length G&B App data. Specifically, walking speed and step length were underestimated in females and overestimated in males (see Fig. 4), resulting in error differences between females and males of 6–7 % during normal walking and 9–10 % when walking with head turns. Sex differences could be partially related to height differences between females and males, although our findings showed that walking speed and step length were underestimated for taller compared with shorter individuals by 3–4 % when walking with head turns (Table 3), which contrasts with the sex findings. Whilst the G&B App applies an algorithm that accounts for the individual's height (Rashid et al., 2021) as height is known to influence step length (Senden et al., 2012a), these results suggest the current algorithm may not fully account for height and that other factors may account for the sex differences in systematic and random errors. For example, male gait has less consistent centre of mass accelerations (Kobsar et al., 2022) which might influence the larger random error seen in males for step length (Table 3). Future research should investigate how sex and height could be better accounted for in smartphone accelerometry algorithms.

4.2. Validity of variability and asymmetry parameters

Smartphone measures of step length and step time variability (the difference from step to step) and step length and step time asymmetry (the difference between left and right) had poor validity against the GAITRite® system. These findings are in agreement with a *meta*-analysis of three studies that showed poor agreement between IMUs placed on the lumbar spine and gold-standard systems for step length variability, step time variability, step length asymmetry, and step time asymmetry (Kobsar et al., 2020). The poor validity of these measures is likely related to their poor reliability demonstrated in healthy middle-to-older aged adults (Olsen et al., 2022). Similar issues with poor validity of gait variability measures are seen with 2D video pose estimation systems in healthy older adults (Mehdizadeh et al., 2021). It should be noted that the present study and the previous *meta*-analysis of accelerometry

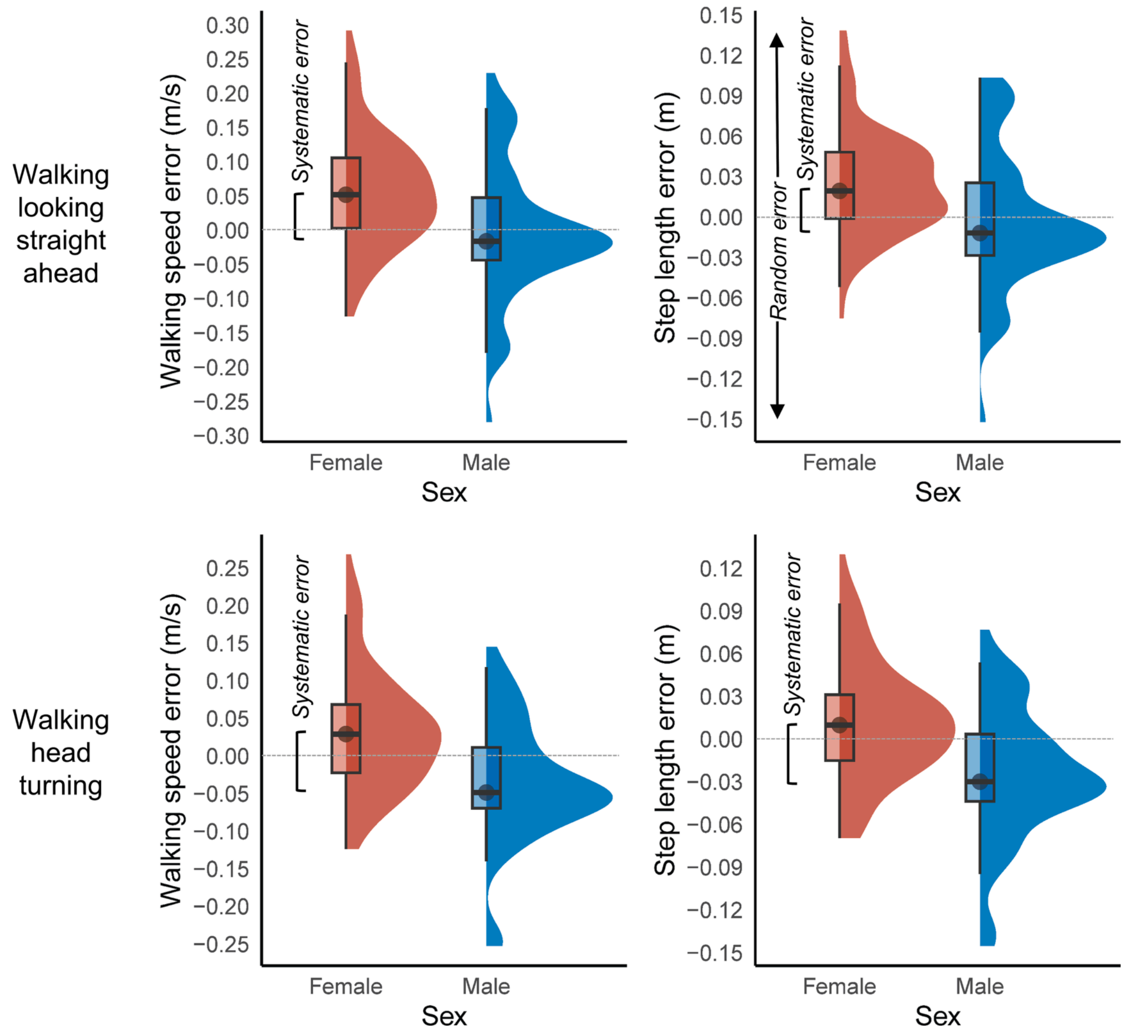

Fig. 4. Significant effects of sex on the validity of walking speed and step length recorded with the G&B App compared with the GAITRite system (n = 20 males, n = 34 females). Differences in systematic and random errors are presented. Error interpretation: Error is calculated GAITRite minus G&B App. Positive error means G&B App underestimates gait parameter. Negative error means G&B App overestimates gait parameter.

measures (Kobsar et al., 2020) investigated healthy populations which may have limited agreement for asymmetry measures between the two systems due to small differences between the left and right leg in healthy individuals. Given our healthy study demonstrated moderate-to-excellent validity for unilateral measures of step length and step time, this might suggest that it was the combination of the left and right parameters into the asymmetry measure that produced disagreement between the systems. In clinical populations such as stroke or osteoarthritis, where differences between the left and right are more apparent, these asymmetry measures may be more valid. This has been the case for 2D video pose estimation systems which demonstrated moderate-to-excellent agreement with gold-standard 3D motion capture for step length asymmetry and step time asymmetry measures in people with stroke (John et al., 2023). Further research should evaluate the validity of these variability and asymmetry parameters with smartphone accelerometry in clinical populations.

4.3. Clinical implications

The G&B App offers clinicians a valid method of measuring step time, step length, and walking speed in healthy young and older adults, reducing the need for more expensive equipment. The G&B App requires very little set up time and includes a structured and efficient protocol consisting of the two gait tasks investigated here and four quiet stance balance tasks that have been validated previously against laboratory gold-standard 3D motion capture (Olsen et al., 2022; Rashid et al., 2021). The head-turning gait task increases the balance demand of the walking task and is ecologically and clinically meaningful. The inclusion of quiet stance balance tasks distinguishes the G&B App from other accelerometry-based smartphone apps that measure gait only (Christensen et al., 2022; Manor et al., 2018; Rentz et al., 2022; Silsupadol et al., 2017; Zhong and Rau, 2020). The G&B App protocol requires a space of no more than 2 m wide by 10 m in length, making it a practical option within most rehabilitation environments. One potential inconvenience is the placement of the smartphone over the lumbar spine within an elasticated belt rather than in the pocket (Manor et al., 2018), however evidence suggests placement in the pocket provides less accurate results (Silsupadol et al., 2017).

An alternative to smartphone accelerometry is the use of pose estimation algorithms which estimate spatiotemporal gait parameters from 2D video recordings. Testing of the OpenPose algorithm applied to video camera footage showed high agreement with gold-standard 3D motion capture for step time, step length, and gait speed in healthy adults ($r > 0.95$) (Stenum et al., 2021), however the video camera was placed 3.3 m laterally to the walkway which requires additional clinic space. Camera placement at the end of the walkway provides less accurate results (Steinert et al., 2019; Stenum et al., 2023). This inaccuracy with frontal view recordings may pose a challenge for clinics without wide open spaces needed for lateral view recordings (Stenum et al., 2021). In such cases, smartphone methods such as the G&B App that place the phone on the individual's body may be preferred.

Clinicians routinely measure walking speed with a simple timer, but measures of step time and step length are not routinely available. With the G&B App, clinicians could collect walking speed parameters while concurrently measuring step time and step length which may provide a more comprehensive assessment and help inform rehabilitation planning. This could be particularly relevant in the rehabilitation of older adults who exhibit decreased step length and/or increased step time (Laufer, 2005) both of which have been associated with falls (Montesinos et al., 2018; Senden et al., 2012b). With improved access to smartphone accelerometry, clinicians could measure changes in step time and step length parameters following rehabilitation. However, the interpretation of these parameters would need to consider the many pathological and compensatory factors that can alter gait pattern (Baudendistel et al., 2021; Kwon et al., 2018; Wang et al., 2018). Notably, the present study involved healthy young and older adults, and therefore further research is needed to test the validity and responsiveness of the G&B App in older adults with gait and balance deficits.

The ability to measure gait parameters while walking with horizontal head turns has important clinical implications as this task is commonly tested in clinical practice (Horak et al., 2009; Wrisley et al., 2004) and requires continual integration of visual, vestibular and somatosensory information. This task is challenging for individuals with vestibular dysfunction, due to difficulty stabilising the visual field during head movements (Marchetti et al., 2008), and those with poor reactive balance (Singh et al., 2017) or difficulty attending to a secondary task while walking (Yogev-Seligmann et al., 2008). Thus, the G&B App has potential to be useful in several clinical scenarios. Further research should investigate the validity of the app during this head-turning task in a range of clinical conditions.

4.4. Strengths and limitations

This study used a combined sample from two separate studies collected by different research assistants. This implies robustness of the findings to protocol deviations. Moreover, it implies greater confidence in the reproducibility of these findings. To ensure the relevance of findings, this study focused on analysing gait parameters that are clinically relevant and have well understood implications. This study investigated the validity of the G&B App in a healthy cohort who were expected to have minimal gait asymmetry. Thus, the lack of validity for gait asymmetry measures should not be extrapolated to clinical populations.

5. Conclusion

This study demonstrated the validity of spatiotemporal gait parameters measured with the G&B App compared with the gold-standard GAITRite® system in a population of healthy young and older adults. There was excellent agreement between the two systems for mean step time, good agreement for walking speed, and moderate agreement for mean step length. Unilateral step length parameters had moderate agreement between the two systems and unilateral step time parameters had good to excellent agreement. The validity of walking speed and step length parameters was influenced by sex and height demographics, suggesting further refinement of the G&B App algorithms may be valuable. In addition, there was poor validity for G&B App measures of step length variability, step time variability, step length asymmetry, and step time asymmetry, compared with the GAITRite® system. The G&B App has potential to provide clinicians with access to valid measures of unilateral and bilateral step time, unilateral and bilateral step length, and walking speed. Future research should investigate the validity of the G&B App in people with gait impairments.

CRediT authorship contribution statement

Sharon Olsen: Conceptualization, Funding acquisition, Writing - original draft, Writing - review and editing, Visualization, Investigation, Methodology, Supervision, Project adminisation. **Usman Rashid:** Conceptualization, Funding acquisition, Data curation, Writing - review and editing, Visualization, Investigation, Validation, Formal analysis, Methodology, Supervision, Software, Resources. **David Barbado:** Writing – review & editing, Software, Methodology, Conceptualization. **Priyadharshini Suresh:** Writing – original draft, Validation, Investigation, Data curation. **Gemma Alder:** Writing – review & editing, Methodology, Conceptualization. **Imran Khan Niazi:** Conceptualization, Methodology, Resources, Software, Supervision, Writing - review and editing. **Denise Taylor:** Writing – review & editing, Supervision, Resources, Methodology, 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.

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Data statement

Ethical approval has not been obtained for data sharing.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2023.111899.

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