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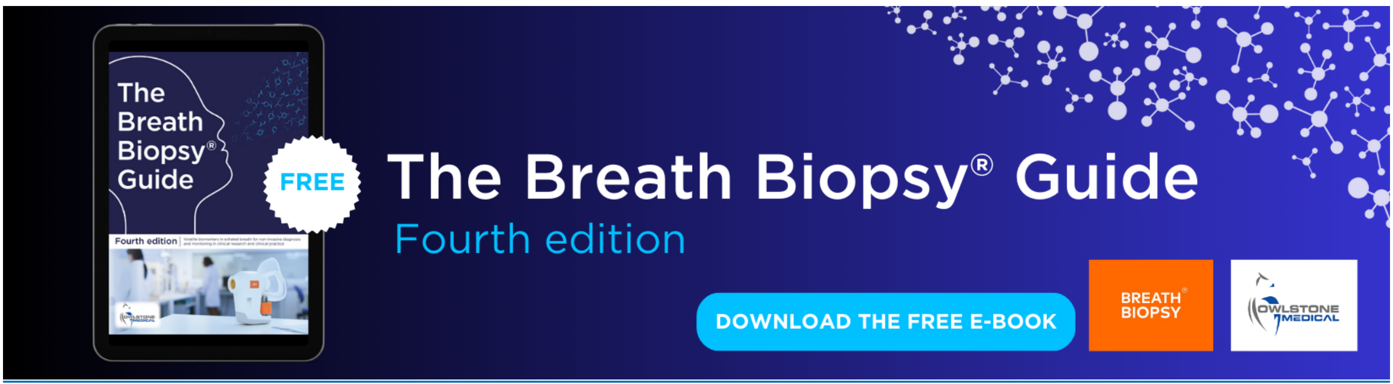

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PAPER

Validity and reliability of the DANU sports system for walking and running gait assessment

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Supplementary material for this article is available online

Abstract

Objective. Gait assessments have traditionally been analysed in laboratory settings, but this may not reflect natural gait. Wearable technology may offer an alternative due to its versatility. The purpose of the study was to establish the validity and reliability of temporal gait outcomes calculated by the DANU sports system, against a 3D motion capture reference system. *Approach.* Forty-one healthy adults (26 M, 15 F, age 36.4 ± 11.8 years) completed a series of overground walking and jogging trials and 60 s treadmill walking and running trials at various speeds (8–14 km hr^{-1}), participants returned for a second testing session to repeat the same testing. *Main results.* For validity, 1406 steps and 613 trials during overground and across all treadmill trials were analysed respectively. Temporal outcomes generated by the DANU sports system included ground contact time, swing time and stride time all demonstrated excellent agreement compared to the laboratory reference (intraclass correlation coefficient (ICC) > 0.900), aside from ground contact time during overground jogging which had good agreement (ICC = 0.778). For reliability, 666 overground and 511 treadmill trials across all speeds were examined. Test re-test agreement was excellent for all outcomes across treadmill trials (ICC > 0.900), except for swing time during treadmill walking which had good agreement (ICC = 0.886). Overground trials demonstrated moderate to good test re-test agreement (ICC = 0.672–0.750), which may be due to inherent variability of self-selected (rather than treadmill set) pacing between sessions. *Significance.* Overall, this study showed that temporal gait outcomes from the DANU Sports System had good to excellent validity and moderate to excellent reliability in healthy adults compared to an established laboratory reference.

1. Introduction

Gait analysis involves the systematic study of human walking or running, whereby quantitative information on walking or running performance and abnormalities arising from musculoskeletal (Bramah *et al* 2018), cardio-pulmonary (Zago *et al* 2018, Liu *et al* 2019) and neurological pathologies (Celik *et al* 2021) or injuries can be obtained (Dever *et al* 2022). As a result, gait analysis has been employed in sports performance and medicine, where information can be used to improve athlete performance (Boulgouris *et al* 2005, Shun-Ping *et al* 2014, Moore 2016, Burns *et al* 2019, Mason *et al* 2022) or diagnose and monitor injury or health conditions (Meardon *et al* 2011, Noehren *et al* 2012, Baker *et al* 2016). For example, gait has been found to be a useful biomarker for neurological concussion injuries (Celik *et al* 2021, Powell *et al* 2021, Dever *et al* 2022) or musculoskeletal injuries (Bramah *et al* 2018), which would otherwise be undetected.

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Traditional gait analysis has largely been performed in a laboratory setting using 2D video analysis (Pipkin et al 2016, Dingenen et al 2018), 3D motion-capture systems (Pfister et al 2014), force plates (Leitch et al 2011), instrumented walkway mats or treadmills (Donath et al 2016, Higginson 2009, Parati et al 2022). Although these methods have high accuracy in measuring gait outcomes (Dugan and Bhat 2005, Higginson 2009), there are inherent drawbacks, such as the expense of equipment, the need for trained practitioners to collect and analyze data and the requirement to attend a laboratory setting. Therefore, traditional 'gold-standard' techniques are not readily available within sport performance or clinical settings, and they lack generalizability and ecological validity (Dugan and Bhat 2005, Higginson 2009) (i.e. gait in a laboratory may not reflect gait in the real-world). Laboratory settings lead to the use of constrained protocols that may not represent typical real-world gait, such as assessing intermittent trials of single foot strikes on force plates, with unnatural force platform targeting (Challis 2001) and limited numbers of consecutive steps (Higginson 2009), whereas runners approximately take 1500 steps per mile (Hoeger et al 2008) and the clinical and general populations typically take 5000–10 000 steps per day in the real-world (Schuna et al 2013, Del Pozo Cruz et al 2022, Lempriere 2022). Gait analysis algorithms typically perform best under continuous walking bouts and with greater duration of recording, and due to potential changes in mechanics over long periods of walking or running, analyzing an abundance of steps may be beneficial (Storm et al 2018, Toth et al 2023, Veerubhotla et al 2021). Numerous studies have sought to overcome the issue of intermittent overground trials by using instrumented treadmills, however, further studies demonstrate the inconsistencies in gait between over-ground and treadmill locomotion (Chambon et al 2015), with the treadmill providing an external cue for gait (i.e. external rhythm of gait is set by the treadmill which influences gait metrics) (Thumm et al 2018). In order to enhance understanding of real-world gait, a range of intermittent and continuous gait tasks or conditions may be required within laboratory gait analysis assessment to represent the spectrum of gait (and gait outcomes) seen in the real-world (Mann et al 2016).

Wearable technology offers a low-cost (affordable) and lightweight alternative to overcome traditional gait assessment limitations (Stuart et al 2021), with such technology becoming increasingly accepted and adopted by users (sports professionals, patients etc) and clinicians (Willy 2018). The majority of commercial or research-grade wearables that have previously been used for gait analysis include accelerometers, gyroscopes, and magnetometers applied individually or in combination as an inertial measurement unit (IMU) (Tao et al 2012, Mason et al 2022). More recently, advances in textile technology have allowed for development of multi-modal devices through integration of pressure sensors and IMUs into flexible material that can be continuously worn in an unobstructive manner to provide comprehensive gait outcomes within any environment, such as instrumented socks. While wearable technologies for gait assessment are being increasingly used, fewer than 10% of commercially available wearable technologies for gait analysis are analytically validated against an accepted 'gold-standard' (reference tool) (Storm et al 2016), with even fewer establishing reliability of wearable sensor derived gait outcomes (Mason et al 2022). Establishing the analytical validity and reliability of such wearable technologies against reference tools is vital to ensure that underlying algorithms that provide gait outcomes are accurate and provide reliable outcomes within specific populations (i.e. healthy or clinical groups) that performance and clinical decisions could be definitively made (Goldsack et al 2020, Rochester et al 2020). Following initial analytical validation within cohorts of interest, wearable devices and outcomes can be examined for specific performance or clinical use with investigation of gait in various settings (i.e. lab or outdoor/real-world), thus developing greater understanding of gait in both clinical (i.e. neurological, musculoskeletal, or cardio-pulmonary conditions) (Hulleck et al 2022) and sporting contexts (i.e. performance, fatigue, and injury mechanisms) (Stuart et al 2021).

The DANU Sports System (DANU, Ltd, Dublin, Ireland) is a commercially available system that combines capacitive pressure sensors on the sole of the foot and tibia based IMUs (one on each leg) encompassed within a sock format, which wirelessly synchronizes and streams data to a mobile tablet. The DANU System offers a large quantity of capacitors and high sampling frequency (i.e. 15 capacitors and 250 Hz in DANU System) that is greater than other similar wearable systems (e.g. 13 capacitors and 50 Hz, Moticon insoles (Moticon GmbH, Munich, Germany)) (Stöggl and Martiner 2017), which will allow for more comprehensive and potentially more accurate gait outcomes (Tao et al 2019). The DANU system software allows for collection of gait data from the wearable socks within any environment and provides automatic analysis, without the requirement for gait research knowledge or expert data processing. The DANU software package allows the user to select various instrumented tests of walking or running (intermittent or continuous tasks) and automatically generates a report for each participant (or group of participants). At present, the DANU report provides temporal gait outcomes derived from initial contact (heel strike) and final contact (toe-off) of the feet, which include ground contact time (GCT), stride time and swing time. Monitoring temporal gait characteristics is important in clinical and sporting contexts. Regarding sport performance, GCT is the most reported outcome in running wearables and has been indicated as a critical factor to running economy (Santos-Concejero et al 2015, Mason et al 2022). Morin et al (Morin et al 2007) demonstrated that 90%–96% of the variance in leg stiffness can be explained by GCT, in turn less economical runners are shown to have a more slacken running style during ground contact as reflected by the low vertical stiffness (Heise and Martin 2001, Moore 2016). In clinical settings, temporal gait outcomes have been shown to be useful clinical measures that can detect gait deterioration due to aging (Hollman *et al* 2011, Chung *et al* 2022), or pathology (Lemke *et al* 2000) and improvements in gait due to rehabilitation or training (Patterson *et al* 2008, Smania *et al* 2011, Vitale *et al* 2012, Abd El-Kafy and El-Basatiny 2014). The simple and automatic gait output from the DANU system ensures that data collection is accessible and interpretable within performance or clinical settings, or within large trials. However, the DANU commercial multi-modal system has yet to be evaluated for analytical validity or reliability of gait outcomes, and such systems require validation against robust previously validated systems ('gold-standard reference tools') in controlled environments (i.e. laboratories) before being further validated and deployed within performance or clinical settings, or clinical trials (Goldsack *et al* 2020, Rochester *et al* 2020). Therefore, the purpose of this study was to determine the analytical validity, as well as test re-test reliability of gait outcomes obtained via the DANU Sport System during walking and running compared to a concurrently used 'gold-standard' 3D motion capture system in healthy adults.

2. Methods

2.1. Participants

Forty-one healthy participants were recruited from running clubs in the North-East of England. Inclusion criteria required participants to be aged >18 years, able to run unassisted for short periods. Prior to testing, all participants completed a questionnaire to provide information pertaining to their demographics, injury, and medical history, sporting pursuits and running personal bests. Injury was classified as 'any muscle, bone, tendon or ligament pain in the lower back/legs/knee/foot/ankle that caused a restriction or stoppage of running (distance, speed, duration or training) for at least 7 d or 3 consecutive scheduled training sessions, or that required the runner to consult a physician or other health professional' (Yamato *et al* 2015). Ethical approval was granted by the Northumbria University Research Ethics Committee (reference: 33358) and this study conformed to the Declaration of Helsinki. All participants were supplied with informed consent and gave verbal and written consent before performing testing in Northumbria University's Gait and Biomechanics Laboratory, City Campus.

2.2. Instrumentation

2.2.1. Wearable technology: DANU sports system

The DANU sports system (figure 1) consists of a pair of textile socks, that were worn on both feet. Each sock contains 15 silicone based capacitive pressure sensors, and an IMU module that attaches to the medial surface of the mid-shank of tibia. Each IMU module is Bluetooth enabled for data transmission and is comprised of two configurable tri-axial accelerometers (Accelerometer 1 ± 2 g, ± 4 g, ± 8 g or ± 16 g, Accelerometer 2 ± 100 g, ± 200 g and ± 400 g), gyroscope ($\pm 2000^\circ$ s^{-1}), magnetometer, and with variable sampling rates (60–250 Hz). The IMU module includes in-built memory for data collection. Here, the DANU sports system was configured to a default sampling rate of 250 Hz, ± 16 g, ± 200 g accelerometers and $\pm 2000^\circ$ s^{-1} gyroscope. A standing calibration trial was recorded prior to participant assessment. Data was collected via Bluetooth on Apple devices 2018 or later (iPad or iPhone devices are required to have at least Bluetooth 5.0 connectivity), and data processing was run through a custom-made Apple application for real-time feedback and visualization, as per the manufacturer's guidelines.

2.2.2. Reference systems

During the overground trials the reference system consisted of a 14-camera 3D motion capture system, distributed around a space of $9.8 \times 7.9 \times 3.2$ m^3, sampling at 250 Hz (VICON, Oxford, UK) and two staggered 0.5 m-long force plates (AMTI, Watertown, MA, USA), sampling at 1000 Hz, embedded in the middle of a walkway. For the treadmill running trials the reference system consisted solely of the 3D motion capture system. The calibration of the Vicon system was conducted before each participant. Sixteen reflective markers were placed on the participants lower limb before testing, and a static calibration trial was initially collected to form a musculoskeletal model (Kim *et al* 2021). Using a small amount of double-sided tape, the markers were attached bilaterally to the following landmarks: anterior superior iliac spine, posterior superior iliac spine, mid-lateral thigh, lateral knee joint line, lateral mid-shank, lateral malleoli, calcaneal tuberosity, and base of the second metatarsal.

Participant specific information of weight, height, ankle width, knee width, and leg length (from posterior iliac spine to medial malleolus) were measured and inputted in the lower body model (Sabharwal and Kumar 2008). The Plug-in-Gait (PiG) lower body model was used to analyse movement at the joints and evaluate all parameters (Leboeuf *et al* 2019). The lower body was modelled as seven segments (one pelvis, two thighs, two

Figure 1. DANU sports system. Reproduced with permission from Danu Sports Limited.

shanks, and two feet). A normal gait cycle was defined from the initial heel-to-heel contact with the same limb. Additional information of the PiG calculations can be found on Vicon's website.

Data processing was performed in Vicon Nexus. All markers were labelled, and marker trajectories were filtered using a fourth order low-pass Butterworth filter via dynamic plug-in gait model with 6 Hz cut-off frequency. For the overground trials, identification of gait events (initial contact and toe-off) was determined using the vertical ground reaction force from force plate data from Vicon Nexus. These events were detected by applying a threshold of 20 N in vertical ground reaction force (Smith *et al* 2015). For treadmill trials, gait identification was achieved through visual inspection of initial contact and toe off for consecutive strides over the trials. The trajectory of the heel and toe markers in the Z plane were examined, so that the minimum of the trajectory of one stride specified the timestamp of initial contact. The traced trajectory of the toe marker was used to specify the toe's movement, so that the minimum of the trajectory specified the timestamp of a toe-off event. The initial contact and toe-off events of left and right foot steps were combined in order to estimate for each step GCT, swing time and stride time (Falbriard *et al* 2018). Ground contact time and swing time were defined by the time between initial contact and toe-off events and between toe-off and initial contact events, respectively.

2.3. Procedures

A concurrent validation study was conducted to determine agreement between the DANU sports system and the 3D motion capture system (Mason *et al* 2023). Prior to commencing the protocol participants were provided the opportunity to run on the treadmill (Spirit fitness XT485) at a comfortable speed for a warm-up and to familiarise themselves. For the overground trials, participants were asked to walk at a self-selected speed across the walkway (10 m), three trials were collected. This process was repeated for the over-ground running trials. For the treadmill trials, participants completed 60 s of walking at a self-selected speed and then ran at four standardised speeds (i.e. 8, 10, 12 and 14 km hr^{-1}). If a participant could not reach a certain speed (i.e. 12 or 14 km hr^{-1}) or did not feel comfortable at that speed, then it was not completed (See table 1). To ensure participant safety, the order of speed was consistent across participants, starting at the slowest speed (i.e. 8 km hr^{-1}) and progressing to the fastest (i.e. 14 km hr^{-1}). Data was collected for 60 s at each speed. A period of 60 s was chosen as it generally aligns with other similar studies in the field with data capture periods ranging from 20 s (McGrath *et al* 2012) to 90 s (Bailey and Harle 2015, Tan *et al* 2020, Mason *et al* 2022). Participants could have breaks between trials or could abort the trial at any time. Participants were provided with a standardised, neutral cushioning running shoe (Saucony Guide Runner) to wear during testing to ensure consistency and remove bias from gait-affecting cushioning within e.g. support cushioning running shoes (Roca-Dols *et al* 2018). The reference and wearable technologies were recorded simultaneously to allow direct comparison of the gait outcomes. To assess test re-test reliability, participants completed the protocol in the same format in a repeated-measures design, approximately one week after the first session.

The outcome measures were the temporal gait characteristics as measured by the DANU sports system and reference system, GCT, swing time and stride time. Outcomes were derived from the proprietary DANU Sport System gait algorithms that processed data within the DANU software and mobile application/cloud. In brief

Table 1. Mean difference, ICC(2,1), limits of agreement (LOA%), and pearson correlation between the reference system and the DANU sports system.

Task	Outcome	Reference system Mean (SD)	DANU Mean (SD)	Validity							
				Mean difference	ICC	Lower bound	Upper bound	LoA (%)	LoA95%	*Pearson r*	*Pearson p*
					Overground						
Walk	GCT (ms)	691.04 (58.57)	690.45 (61.95)	0.62	0.914	0.901	0.925	7.1	49.26	0.915	<0.001
($n = 41$)	Swing Time (ms)	437.65 (47.62)	439.66 (47.66)	1.23	0.972	0.967	0.976	9.3	40.61	0.972	<0.001
	Stride Time (ms)	1121.07 (90.42)	1124.85 (90.39)	3.78	0.993	0.992	0.994	1.9	20.99	0.993	<0.001
Jog	GCT (ms)	294.69 (38.99)	294.07 (34.35)	0.55	0.778	0.758	0.814	15.6	46.34	0.792	<0.001
($n = 41$)	Swing Time (ms)	443.32 (49.56)	444.38 (50.85)	1.06	0.975	0.971	0.979	5.1	21.88	0.976	<0.001
	Stride Time (ms)	735.10 (53.17)	739.14 (53.74)	4.04	0.979	0.976	0.982	2.9	21.31	0.979	<0.001
					Treadmill						
Walk	GCT (ms)	663.55 (54.58)	659.22 (55.05)	4.33	0.981	0.976	0.986	3.1	20.81	0.981	<0.001
($n = 40$)	Swing Time (ms)	408.72 (41.01)	411.95 (39.80)	3.22	0.966	0.956	0.974	5.0	20.63	0.967	<0.001
	Stride Time (ms)	1072.19 (83.59)	1071.20 (84.60)	0.99	0.995	0.994	0.996	1.5	16.37	0.995	<0.001
8 km hr^{-1}	GCT (ms)	290.46 (27.17)	283.33 (26.84)	7.13	0.909	0.882	0.931	7.9	22.55	0.909	<0.001
($n = 30$)	Swing Time (ms)	454.12 (44.00)	462.48 (45.25)	8.37	0.979	0.972	0.984	3.9	18.01	0.979	<0.001
	Stride Time (ms)	745.36 (40.71)	745.81 (40.87)	0.45	0.998	0.998	0.999	0.6	4.70	0.998	<0.001
10 km hr^{-1}	GCT (ms)	281.74 (30.83)	273.48 (29.50)	8.26	0.936	0.920	0.949	25.3	69.56	0.937	<0.001
($n = 41$)	Swing Time (ms)	447.45 (45.11)	456.71 (43.71)	9.26	0.972	0.964	0.978	4.5	20.39	0.972	<0.001
	Stride Time (ms)	729.59 (40.98)	730.18 (39.19)	0.59	0.997	0.996	0.998	0.8	5.93	0.997	<0.001
12 km hr^{-1}	GCT (ms)	270.85 (33.43)	262.40 (30.78)	8.45	0.930	0.911	0.945	8.9	23.56	0.933	<0.001
($n = 40$)	Swing Time (ms)	438.76 (45.48)	446.75 (45.13)	7.99	0.970	0.961	0.976	4.9	21.93	0.970	<0.001
	Stride Time (ms)	707.70 (42.07)	709.15 (40.37)	1.46	0.996	0.995	0.997	0.9	6.69	0.996	<0.001
14 km hr^{-1}	GCT (ms)	258.77 (31.19)	249.06 (27.76)	9.71	0.909	0.884	0.928	9.8	24.74	0.915	<0.001
($n = 37$)	Swing Time (ms)	430.17 (43.37)	438.15 (41.51)	7.98	0.953	0.940	0.964	5.9	25.42	0.954	<0.001
	Stride Time (ms)	688.12 (39.62)	687.32 (39.81)	0.80	0.992	0.990	0.994	1.4	9.62	0.992	0.009

outcomes were defined as follows: GCT was measured as the time (in ms) elapsed between initial contact (where the foot first contacts the ground) and final/terminal contact (where the foot last leaves the ground). Swing time was defined as the time (in ms) the foot spends off the ground in the gait cycle, defined by the time from toe off to heel strike of the same foot. Stride time was measured as the time (in ms) between two consecutive heel strikes of the same foot time. These outcomes were obtained across overground and treadmill trials, during walking and running. Outcomes were averaged over the one-minute trials.

2.4. Statistical analyses

All gait outcomes calculated by DANU sports system were comparatively analysed with the same outcomes calculated within the 3D motion capture data. Gait outcomes were averaged over the 60 s trials. Data analysis was conducted in SPSS v27 (SPSS Inc., Chicago, IL, USA). Shapiro-Wilks tests indicated a normal distribution of all data ($p < 0.05$). Subsequently, intra-class correlation ($IC(2,1)$) models examined absolute agreement between the DANU sports system and the reference (Zago *et al* 2018)D motion capture system. A predefined ICC performance scale was deployed, defined as poor (<0.50), moderate (0.50–0.75), good (0.75–0.90) or excellent (>0.90) (Koo and Li 2016). Mean error were calculated between the DANU sports system and the reference (Zago *et al* 2018)D motion capture data for descriptive purposes and are observed as an accuracy metric in the outcomes. In order to demonstrate the bias within the limits of agreement (LoA) were calculate and Bland-Altman plots were used to visually assess the agreement between systems (Bland and Altman 1986). To determine the test re-test reliability of the DANU sports system, Pearson's correlation coefficients (r), ICCs and LoA between the two testing time-points were calculated (Shrout and Fleiss 1979). An acceptable statistically significant threshold was set at $p < 0.05$.

3. Results

3.1. Participants

A total of forty-one participants completed the study (26 Male, 15 Female; 36.4 ± 11.8 years; 173.3 ± 8.7 cm; 72.6 ± 12.2 kg). Participants exhibited a range of running abilities (5 km personal best; 23:31 ± 04:49). Of the 41 participants, some data loss or dropout during higher speeds was experienced (table 1). Upon preliminary observation of the quantified outcomes, no significant outliers were identified. For the validation aspect, a total of 1406 steps during overground walking and jogging trials were analysed. For treadmill testing, a total of 613 trials across all speeds were examined. For reliability analysis, 666 overground trials and 511 treadmill trials across all speeds were examined. Table 1 shows the descriptive gait data statistics from, along with the absolute agreement between the two systems for ICC, LoA (% and 95%) and r values. The agreement between the DANU sports system and 3D motion capture is visually displayed via Bland-Altman plots in figure 2.

3.2. Ground contact time

Agreement between the outcomes from the DANU Sport System and the reference system were weakest during the overground jogging, demonstrating good agreement (ICC(2,1) 0.778, LoA% 15.6). For overground walking and all treadmill trials excellent agreement was displayed (ICC(2,1) >0.900, LoA% 3.1 to 25.3) (table 1 and figures 2(a) and 3(a)). Minor variations in the validity of the DANU sports system with respect to sex can be seen (Supplementary tables 1(a) and 1(b)). Intraclass correlations show excellent agreement during overground walking and treadmill running at 8 km hr^{-1} for males (ICC(2,1) 0.936, LoA% 6.7 and ICC(2,1) 0.903, LoA% 6.2, respectively) and good agreement for females (ICC(2,1) 0.869, LoA% 8.0 and ICC(2,1) 0.782, LoA% 10.8, respectively). Ground contact time demonstrated low mean difference across all trials when compared to 3D motion capture. Conversely, mean difference rate increases as a function of speed during treadmill trials (4.33–9.71 ms), the DANU sports system tended to under-estimate GCT, table 1.

With respect to reliability, intraclass correlations show moderate reliability for GCT during overground walking and jogging (ICC(2,1) 0.741 and 0.677 respectively, LoA% 7.1 to 15.6), and excellent agreement (ICC (2,1) >0.900, LoA% 3.4 to 7.2) across all treadmill speeds, table 2. Differences in reliability of the DANU sports system based on sex were observed during overground trials. Females exhibited moderate and excellent reliability during overground walking and jogging, respectively (ICC(2,1) 0.647 and 0.978, LoA% 13.4 and 17.8). For males intraclass correlations show good and moderate reliability for GCT during overground walking and jogging, respectively (ICC(2,1) 0.787 and 0.516, LoA% 14.7 and 18.5) (supplementary tables 2(a) and 2(b)).

3.3. Swing time

Intraclass correlations demonstrate an excellent agreement between the DANU sports system and the reference system for swing time (ICC(2,1) >0.900, LoA% 3.9 to 9.3). Robustness at the full range of speeds is demonstrated, with low mean differences throughout (1.06–9.26 ms). The DANU sports system tends to over-

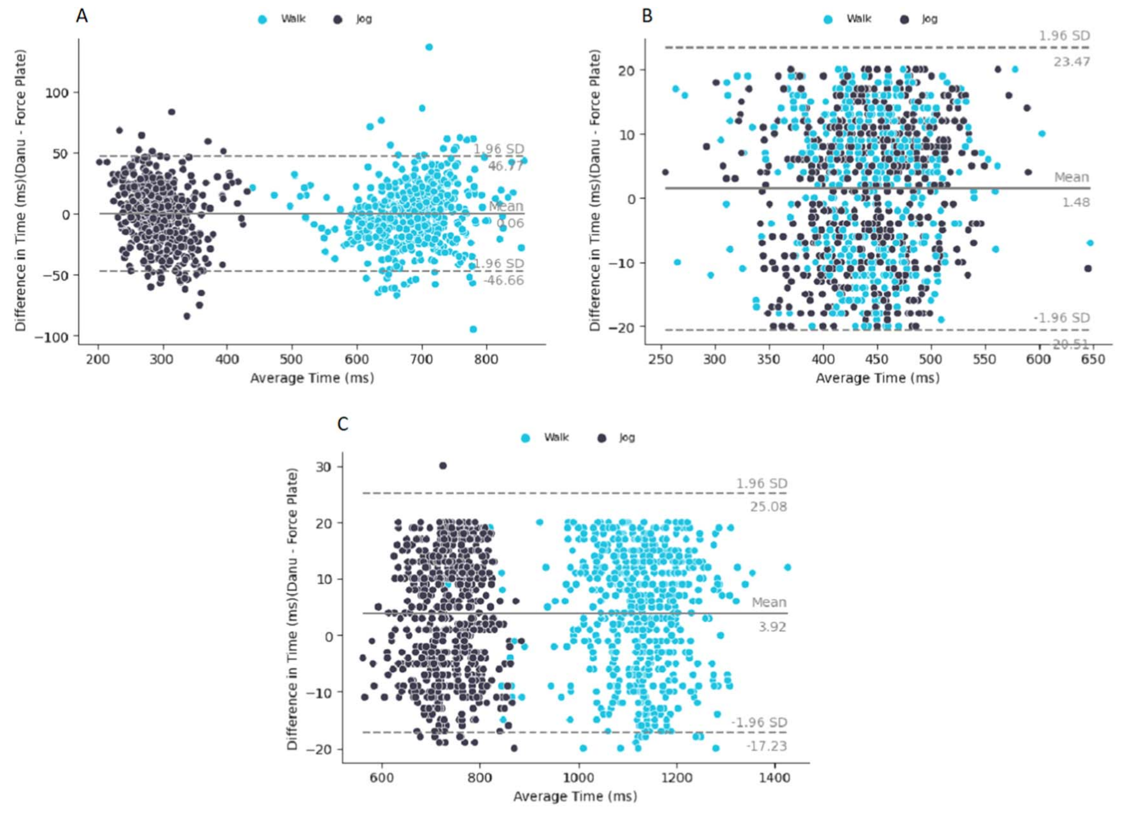

Figure 2. Bland-Altman plots illustrating the absolute agreement between the DANU sports system and 3D motion capture system during overground walking and running. (A) Ground contact time (ms), (B) Swing time (ms), (C) Stride Time (ms).

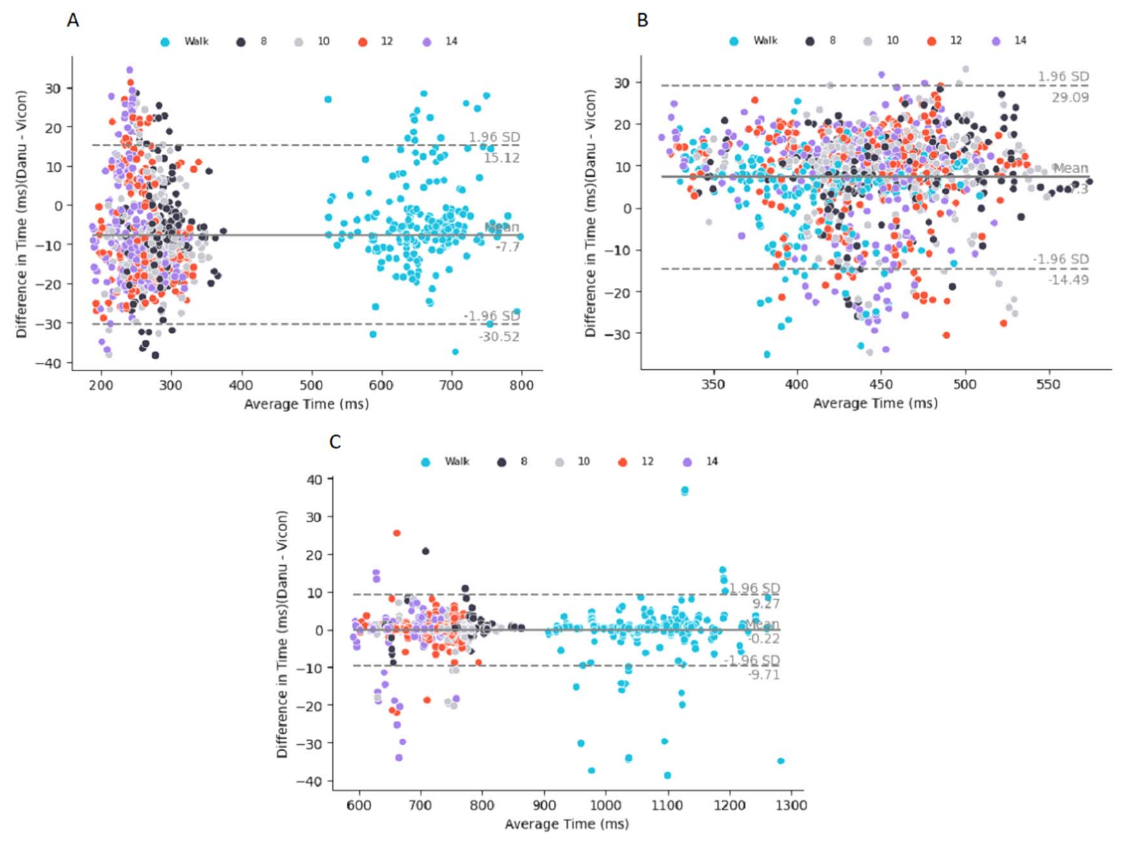

Figure 3. Bland-Altman plots illustrating the absolute agreement between the DANU sports system and 3D motion capture system during treadmill walking and running. (A) Ground contact time (ms), (B) Swing time (ms), (C) Stride time (ms).

Table 2. Mean difference, ICC(2,1), limits of agreement (LOA%), and pearson correlation between test-retest for the DANU Sports system.

Task	Outcome	Test	Retest	Reliability							
		Mean (SD)	Mean (SD)	Mean Difference	ICC (2,1)	Lower Bound	Upper Bound	LoA (%)	LoA95%	Pearson r	Pearson p
					Overground						
Walk	GCT (ms)	689.17 (64.17)	687.31 (60.07)	1.86	0.741	0.687	0.786	12.8	87.57	0.814	$<$0.001
($n=41$)	Swing Time (ms)	439.02 (48.13)	437.70 (45.59)	0.93	0.698	0.625	0.758	15.2	65.73	0.835	$<$0.001
	Stride Time (ms)	1116.25 (120.84)	1120.05 (87.33)	0.63	0.750	0.687	0.801	11.4	127.15	0.873	$<$0.001
Jog	GCT (ms)	295.23 (36.42)	292.91 (32.18)	2.31	0.677	0.616	0.730	17.9	53.81	0.687	$<$0.001
($n=41$)	Swing Time (ms)	444.05 (49.99)	444.70 (51.73)	0.65	0.672	0.533	0.775	16.6	74.17	0.712	$<$0.001
	Stride Time (ms)	740.01 (51.39)	738.30 (55.98)	1.71	0.685	0.619	0.742	11.0	82.16	0.694	$<$0.001
					Treadmill						
Walk	GCT (ms)	655.98 (54.43)	658.12 (54.19)	2.14	0.978	0.968	0.986	3.4	22.42	0.978	$<$0.001
($n=40$)	Swing Time (ms)	411.83 (40.21)	409.32 (40.31)	2.50	0.886	0.833	0.922	9.0	37.15	0.885	$<$0.001
	Stride Time (ms)	1067.61 (84.53)	1067.05 (83.32)	0.56	0.983	0.974	0.988	2.9	31.07	0.983	$<$0.001
8 km hr^{-1}	GCT (ms)	283.48 (27.78)	282.07 (28.09)	1.41	0.978	0.967	0.986	4.1	11.69	0.978	$<$0.001
($n=30$)	Swing Time (ms)	460.48 (45.88)	462.39 (45.75)	1.91	0.985	0.977	0.990	3.4	15.50	0.985	$<$0.001
	Stride Time (ms)	744.60 (40.26)	744.46 (40.44)	0.13	0.989	0.984	0.993	1.5	11.53	0.989	$<$0.001
10 km hr^{-1}	GCT (ms)	272.99 (29.36)	273.08 (30.94)	0.09	0.988	0.982	0.992	3.4	9.25	0.989	$<$0.001
($n=41$)	Swing Time (ms)	456.56 (42.99)	455.44 (44.80)	1.11	0.987	0.982	0.991	3.0	13.69	0.988	$<$0.001
	Stride Time (ms)	729.88 (37.97)	728.57 (38.89)	1.32	0.989	0.984	0.992	1.5	11.24	0.989	$<$0.001
12 km hr^{-1}	GCT (ms)	259.22 (31.35)	261.718 (31.26)	2.49	0.962	0.945	0.973	7.2	11.92	0.962	$<$0.001
($n=40$)	Swing Time (ms)	445.66 (46.20)	444.10 (46.05)	1.56	0.978	0.969	0.985	4.2	18.79	0.978	$<$0.001
	Stride Time (ms)	708.47 (40.48)	708.43 (40.80)	0.03	0.979	0.970	0.986	2.3	16.14	0.980	$<$0.001
14 km hr^{-1}	GCT (ms)	247.69 (27.29)	249.52 (28.14)	1.84	0.987	0.981	0.991	3.5	8.38	0.988	$<$0.001
($n=37$)	Swing Time (ms)	439.68 (43.32)	437.49 (42.93)	2.30	0.971	0.968	0.980	4.6	20.33	0.971	$<$0.001
	Stride Time (ms)	687.18 (41.21)	687.21 (39.85)	0.04	0.977	0.967	0.984	2.5	16.94	0.977	$<$0.001

estimate swing time, especially at higher speeds, table 1 and figures 2(b) and 3(b). With respect to sex and validity of the DANU sports system for measuring swing time, no significant differences were found (supplementary tables 1(a) and 1(b)).

Excellent reliability (ICC(2,1) >0.900, LoA% 3.0 to 4.6) across all treadmill running trials can be seen, with good reliability during treadmill walking (ICC(2,1) 0.886, LoA% 9.0). Overground walking and jogging demonstrated moderate reliability (ICC(2,1) 0.698 and 0.672, respectively, LoA% 9.3 and 5.1), table 2. Excellent reliability for swing time during overground jogging was observed for females (ICC(2,1) 0.941, LoA% 15.9), compared to moderate reliability in males (ICC(2,1) 0.677, LoA% 17.6). No additional significant differences were observed in the reliability of the DANU sports system for measuring swing time with respect to sex (supplementary tables 2(a) and 2(b)).

3.4. Stride time

Intraclass correlations demonstrate an excellent agreement between the DANU sports system and reference system for stride time across all trials (ICC(2,1) >0.900), with low mean differences throughout (0.45–4.04 ms), table 1 and figures 2(c) and 3(c). With respect to sex and validity of the DANU sports system for measuring stride time, no significant differences were found (supplementary tables 1(a) and 1(b)).

Overground walking demonstrated good reliability (ICC(2,1) 0.750, LoA% 11.4) and intraclass correlation performance slight degrades at higher speeds, demonstrating moderate reliability for overground jogging (ICC (2,1) 0.685, LoA% 11.0). Across all treadmill trials excellent reliability (ICC(2,1) >0.900, LoA% 1.5 to 2.9) was shown, table 2. Moderate reliability for stride time during overground walking was observed for females (ICC (2,1) 0.523, LoA% 11.7), compared to good reliability in males (ICC(2,1) 0.826, LoA% 10.8). No additional significant differences were observed in the reliability of the DANU sports system for measuring stride time with respect to sex (supplementary tables 2(a) and 2(b)).

4. Discussion

The present study conducted an examination of the analytical validity and test re-test reliability of gait outcomes (temporal outcomes of GCT, stride time and swing time) measured by the DANU sports system, demonstrating that walking and running gait outcomes had good to excellent agreement with a 'gold-standard' reference and moderate to excellent reproducibility in healthy adults in laboratory conditions. Across walking and running trials, the identified gait outcomes and differences between the chosen gait speeds fall within the expected ranges when compared to other validated and established gait analysis systems in healthy adults (Lee and Hidler 2008, Braun *et al* 2015, Mason *et al* 2022), and reliability values are consistent with those reported for other wearable technologies for gait analysis (Godfrey *et al* 2014).

4.1. Validity and reliability of gait outcomes during walking

Temporal gait outcomes of GCT, stride time and swing time that were derived during overground and treadmill walking in healthy adults, which generally had excellent validity (ICC(2,1) >0.900) (tables 1 and 2**,** figures 2 and 3). The test re-test reliability results indicated a moderate to good reliability (ICC(2, 1) 0.698–0.750) during overground walking trials and moderate to excellent reliability (ICC(2, 1) 0.886–0.9893) during treadmill walking trials. These analytical validation results are important, as temporal walking gait outcomes are clinically relevant/meaningful metrics. For example, temporal metrics are sensitive to classify fallers and non-fallers in neurological patients (Zhou *et al* 2020, Shema-Shiratzky *et al* 2022).

Our findings are comparable to others that have validated or examined repeatability of wearable technology for gait analysis. Other systems commonly detect gait by placing sensors, typically IMUs or accelerometers, at the lumbar (Bugané *et al* 2012, Morris *et al* 2019), tibia (Iosa *et al* 2016, Mancini and Horak 2016), or shoe (Donath *et al*) of the participant. Many other systems are shown to be reasonably valid and reliable (Henriksen *et al* 2004, Iosa *et al* 2016). Yet, this is the first study to use a gait analysis system that combined capacitive pressure sensors on the sole of the foot and tibia based IMUs encompassed within a sock form factor. In contrast to the current study, previous work has demonstrated better validity and reliability for basic spatiotemporal gait outcomes, such as GCT or stride time, rather than outcomes of relative phase, such as swing time that show poorer agreement (Aminian *et al* 2002, Sabatini *et al* 2005). Difficulties detecting relative phases of the gait cycle with other wearable systems have been suggested to be due to limitations in the accuracy of detecting toe off events (Washabaugh *et al* 2017), which may also underlie poorer agreement for the DANU systems GCT outcome. Typically, the outcomes of interest that are used for gait analyses are spatiotemporal gait outcomes which require the identification of initial contact (i.e. heel strike) and toe off events for each step (Sprager and Juric 2015, Benson *et al* 2019). However, the DANU systems gait event detection algorithm is proprietary, which limits detailed discussion or understanding of agreement results, which may require algorithms to become open-source to allow for future improvement.

The moderate reliability of temporal gait outcomes when walking may be due to the task being undertaken, as overground and treadmill walking have different underlying muscle activity (Lee and Hidler 2008). Additionally, self-selected paced overground trials may lead to unnatural force plate targeting (Challis 2001) and are influenced by landing patterns when compared with natural gait (Van Hooren *et al* 2020). The aforementioned could shed light on why variations in reliability emerged in the overground trials. Specifically, the DANU sports system exhibited lower reliability during walking and higher reliability during jogging for females in these scenarios. Interestingly, these outcomes did not align with the results obtained in treadmill trials. It's possible that participants needed to deliberately adjust their stride length during overground trials to interact with the force plates, for instance, with females potentially increasing their stride length during walking. This intentional alteration of stride length may have introduced greater variability into their gait patterns (Challis 2001). Similarly, the external prompt of the treadmill at set speeds of walking may reduce the variability of step timing and require less cognitive resources, therefore agreement between sessions would be better for treadmill rather than overground walking at a self-selected pace (Thumm *et al* 2018, Keller Xin Yu 2021). Therefore, the moderate to excellent test re-test reliability of the DANU system for walking outcomes may reflect task-dependent and intrinsic human variability.

4.2. Validity and reliability of gait outcomes during running

During running all reported gait outcomes showed excellent validity (ICC(2,1) >0.90) across overground and treadmill trials, as well as speeds, except for GCT during overground jogging that displayed good accuracy (ICC (2, 1) 0.78) (tables 1 and 2, figures 2 and 3). Validity results of the present study are comparable to previous research using pressure insole devices, where Pearson correlations of 0.84–0.96 (Stöggl and Martiner 2017) and 0.99 (Seiberl *et al* 2018) have been reported. However, within the current study GCT was shorter compared to these previous studies, but was similar to research examining running performance (de Ruiter *et al* 2014). Minor differences were demonstrated between the DANU and reference systems regarding GCT and swing time. Specifically, the DANU sports system slightly underestimated GCT and over-estimated swing time compared to a gold-standard reference, these differences became more apparent at faster speeds (i.e. 12 and 14 km hr^{-1}), especially for GCT. Previous research has shown similar degradation in accuracy of GCT measurement with respect to speed (Falbriard *et al* 2018, Young *et al* 2022), highlighting similar limitations in underlying algorithms used across wearable devices. Calculation of GCT is more challenging than other gait outcomes, as it requires more gait event information, such as timings of heel strike and toe off, as well as the orientation and trajectory of the foot (Schuna *et al* 2013). This is highlighted by the excellent accuracy (ICC(2, 1) >0.90) in stride time, which indicates subtle algorithm differences even between outcome measures of the same system (Donath *et al* 2016). The DANU sports system calculates temporal gait outcomes through the use of capacitive sensors embedded within a sock form factor, with event detection from a foot-shoe interaction, whereas the laboratory reference system examines a foot-floor interaction. The subtle difference in foot impact event detection between DANU and reference systems may impact event detection accuracy or timing comparison. Similarly, differences in agreement between the wearable and reference systems may be attributed to extraneous noise encountered at higher impact speeds that may be difficult to filter leading misidentification of gait events within underlying algorithms (Young *et al* 2022).

The test re-test reliability results indicated moderate to excellent agreement for running gait outcomes across the two sessions. Specifically, moderate reliability (ICC(2, 1) 0.67–0.69) was demonstrated for overground running trials, but there was excellent treadmill reliability during treadmill running trials (ICC(2, 1) 0.96–0.99), which was similar to our walking results and was likely affected by the same issues. The reliability results obtained here are comparable to previous research. For example, research examining the Myotest found test-retest reliability for GCT to be poor to moderate at different running speeds (Gouttebarge *et al* 2015). In contrast to the present study, GCT reliability decreased at slower speeds and lower GCTs were recorded which may relate to testing on an outdoor athletic track, using verbal feedback speeds (de Ruiter *et al* 2014, Gouttebarge *et al* 2015), rather than our indoor overground and treadmill laboratory assessment.

4.3. Limitations and future directions

Several limitations of the present research and future directions should be highlighted. Firstly, the sample consisted of healthy recreational runners, which may not adequately represent all cohorts of potential interest, such as professional athletes or clinical populations. It is necessary for future studies to evaluate the analytical and clinical validity of the DANU system within specific cohorts of interest to ensure accurate measurement of gait outcomes. Additionally, future studies should determine whether the DANU derived gait metrics are clinically meaningful outcomes through comparison to health metrics (e.g. quality of life, fatigue) or within different sub-populations (e.g. athlete performance level or disease) (Goldsack et al 2020). Furthermore, examination of the usability of the DANU sports system is required within specific populations to ensure generalizability.

Secondly, validity testing was conducted within a laboratory environment using force plates and a treadmill were used during walking and running, which may not entirely represent gait of prolonged overground walking and running in natural environments. Previous research has demonstrated that significant speed by surface interactions exist for the temporal outcomes (Hong et al 2012, Hollis et al 2021). Future work is needed to validate the DANU sports system in more ecologically valid settings (i.e. real-world, community, home environments), as an advantage of wearable devices is the portability and potential to use during real-world prolonged tasks (Benson et al 2018, Meyer et al 2021).

Lastly, data processing of the treadmill trials was conducted as an average over the 60 s trials, whereas the absolute difference of each individual step is reported for overground trials due to the nature of the intermittent overground protocol. Algorithms for gait analysis perform best when processing data from continuous trials, which may be more representative of real-world walking or running than intermittent trials (Ao et al 2018, Seiberl et al 2018, William et al 2021, Straczkiewicz et al 2023). However, future work is needed to compare continuous and intermittent gait outcomes collected in different populations in order to determine the impact on underlying DANU proprietary gait algorithms.

5. Conclusions

This study examined the analytical validity and test re-test reliability of a commercial wearable technology, the DANU sports system, for measurement of walking and running gait in healthy adults. The DANU system had good to excellent agreement with 3D motion capture in quantifying ground contact time, swing time and stride time during overground and treadmill walking and running at various speeds. Furthermore, the DANU system gait outcomes had moderate to excellent reproducibility across two different sessions in healthy adults. Future research is needed to establish the clinical validity and usability of the DANU Sport System wearable technology to measure gait in various specific populations before routine deployment within performance or clinical settings.

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Data availability statement

The data cannot be made publicly available upon publication because no suitable repository exists for hosting data in this field of study. The data that support the findings of this study are available upon reasonable request from the authors.

Conflict of interest

Rachel Mason is on a PhD programme co-funded by DANU Sports Ltd Hugh Robinson, Ben O'Callaghan and Oisin Lennon are employed by DANU Sports Ltd Other authors declare no conflicts of interest.

Author contributions

RM and GB conceptualized the question and hypothesis. RM, SS and GB designed the study from which the data originates. RM completed the data collection and analysis. RM wrote the first draft. RM, SS, AG, GB contributed to the interpretation, writing and editing of the manuscript.

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Ethical statement

Ethical approval was granted by the Northumbria University Research Ethics Committee (Reference: 33358) and this study conformed to the Declaration of Helsinki. All participants were supplied with informed consent and gave verbal and written consent before performing testing in Northumbria University's Gait and Biomechanics Laboratory, City Campus.

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References

Abd El-Kafy E M and El-Basatiny H M Y M 2014 Effect of postural balance training on gait parameters in children with cerebral palsy *Am. J. Phys. Med. Rehabil.* **93** 938–47

Aminian K *et al* 2002 Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes *J. Biomech.* **35** 689–99

Ao B *et al* 2018 Context impacts in accelerometer-based walk detection and step counting *Sensors* **18** 3604

Bailey G and Harle R 2015 Measuring temporal parameters of gait with foot mounted IMUs in steady state running *Proceedings of the 3rd International Congress on Sport Sciences Research and Technology Support* **1** 24–33

Baker R *et al* 2016 Gait analysis: clinical facts *Eur. J. Phys. Rehabil. Med.* **52** 560–74

Benson L *et al* 2019 Automated accelerometer-based gait event detection during multiple running conditions *Sensors* **19** 1483

Benson L C *et al* 2018 The use of wearable devices for walking and running gait analysis outside of the lab: a systematic review *Gait & Posture* **63** 124–138 1879-2219 (Electronic)

Bland Jm D G and Altman D G 1986 Statistical methods for assessing agreement between two methods of clinical measurement *Lancet (London, England)* **1** 307–310

Boulgouris N V, Hatzinakos D and Plataniotis K N 2005 Gait recognition: a challenging signal processing technology for biometric identification *IEEE Signal Process Mag.* **22** 78–90

Bramah C *et al* 2018 Is there a pathological gait associated with common soft tissue running injuries? *Am. J. sports Med.* **46** 3023–31

Braun B J *et al* 2015 Validation and reliability testing of a new, fully integrated gait analysis insole *J. Foot Ankle Res.* **8** 54

Bugané F *et al* 2012 Estimation of spatial-temporal gait parameters in level walking based on a single accelerometer: validation on normal subjects by standard gait analysis *Comput. Methods Programs Biomed.* **108** 129–37

Burns G T, Zendler J M and Zernicke R F 2019 Step frequency patterns of elite ultramarathon runners during a 100-km road race *J. Appl. Physiol.* **126** 462–8

Celik Y *et al* 2021 Gait analysis in neurological populations: progression in the use of wearables *Med. Eng. Phys.* **87** 9–29

Challis J H 2001 The variability in running gait caused by force plate targeting *J. Appl. Biomech.* **17** 77–83

Chambon N *et al* 2015 Shoe drop has opposite influence on running pattern when running overground or on a treadmill *Eur. J. Appl. Physiol.* **115** 911–8

Chung C M *et al* 2022 Determination of the predictors with the greatest influence on walking in the elderly *Medicina (Kaunas)* **58** 1640

Dever A *et al* 2022 Gait impairment in traumatic brain injury: a systematic review *Sensors* **22** (4) 1480

de Ruiter C J *et al* 2014 Stride frequency in relation to oxygen consumption in experienced and novice runners *Eur. J. Sport Sci.* **14** 251–8

Del Pozo Cruz B *et al* 2022 Prospective associations of daily step counts and intensity with cancer and cardiovascular disease incidence and mortality and all-cause mortality *JAMA Intern. Med.* **182** 1139–48

Dingenen B *et al* 2018 Test-retest reliability of two-dimensional video analysis during running *Phys. Ther. Sport.* **33** 40–7

Donath L *et al* 2016 Validity and reliability of a portable gait analysis system for measuring spatiotemporal gait characteristics: comparison to an instrumented treadmill *Journal of neuroengineering and rehabilitation* **13** 6

Dugan S A and Bhat K P 2005 Biomechanics and analysis of running gait *Phys. Med. Rehabil Clin. N. Am.* **16** 603–21

Falbriard M *et al* 2018 Accurate estimation of running temporal parameters using foot-worn inertial sensors *Front. Physiol.* **9** 610

Godfrey A *et al* 2014 Within trial validation and reliability of a single tri-axial accelerometer for gait assessment *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.* **2014** 5892–5

Goldsack J C *et al* 2020 Verification, analytical validation, and clinical validation (V3): the foundation of determining fit-for-purpose for Biometric Monitoring Technologies (BioMeTs) *npj Digital Med.* **3** 55

Gouttebarge V *et al* 2015 Reproducibility and validity of the myotest for measuring step frequency and ground contact time in recreational runners *J. Human Kinetics* **45** 19–26

Heise G D and Martin P E 2001 Are variations in running economy in humans associated with ground reaction force characteristics? *Eur. J. Appl. Physiol.* **84** 438–42

Henriksen M *et al* 2004 Test-retest reliability of trunk accelerometric gait analysis *Gait Posture* **19** 288–97

Higginson B K 2009 Methods of running gait analysis *Curr. Sports Med. Rep.* **8** 136–41

Hoeger W W K *et al* 2008 One-mile step count at walking and running speeds *ACSM's Health Fitness J.* **12** 14–19

Hollis C R *et al* 2021 Running biomechanics as measured by wearable sensors: effects of speed and surface *Sports Biomech.* **20** 521–31

Hollman J H, McDade E M and Petersen R C 2011 Normative spatiotemporal gait parameters in older adults *Gait Posture* **34** 111–8
Hong Y *et al* 2012 Comparison of plantar loads during treadmill and overground running *J. Sci. Med. Sport* **15** 554–60
Hulleck A A *et al* 2022 Present and future of gait assessment in clinical practice: towards the application of novel trends and technologies *Front. Med. Technol.* **4** 901331
Iosa M *et al* 2016 Wearable inertial sensors for human movement analysis *Expert Rev. Med. Devices* **13** 641–59
Keller Xin Yu C 2021 Neural correlates of gait during overground and treadmill walking *An FNIRS Study* **PP** – Nanyang Technological University
Kim B H *et al* 2021 Measurement of ankle joint movements using IMUs during running *Sensors (Basel)* **21** 4240
Koo T K and Li M Y 2016 A guideline of selecting and reporting intraclass correlation coefficients for reliability research *J. Chiropr. Med.* **15** 155–63
Leboeuf F *et al* 2019 The conventional gait model, an open-source implementation that reproduces the past but prepares for the future *Gait & posture* **69** 235–241
Lee S J and Hidler J 2008 Biomechanics of overground vs. treadmill walking in healthy individuals *J. Appl. Physiol.* **104** 747–55
Leitch J *et al* 2011 Identifying gait events without a force plate during running: a comparison of methods *Gait Posture* **33** 130–2
Lemke M R *et al* 2000 Spatiotemporal gait patterns during over ground locomotion in major depression compared with healthy controls *J. Psychiatric Res.* **34** 277–83
Lempriere S 2022 Daily step count linked to dementia risk *Nat. Rev. Neurol.* **18** 637637
Liu W Y *et al* 2019 Effects of pulmonary rehabilitation on gait characteristics in patients with COPD *J. Clin. Med..* **8** 459
Mancini M and Horak F B 2016 Potential of APDM mobility lab for the monitoring of the progression of Parkinson's disease. *Expert Rev. Med. Devices* **13** 455–62
Mann R *et al* 2016 Plantar pressure measurements and running-related injury: A systematic review of methods and possible associations *Gait Posture* **47** 1–9
Mason R *et al* 2022 Wearables for running gait analysis: a systematic review *Sports Med.* **53** 241–268
Mason R *et al* 2023 Wearables for running gait analysis: a study protocol *PLoS One* **18** e0291289
McGrath D *et al* 2012 Gyroscope-based assessment of temporal gait parameters during treadmill walking and running *Sports Eng.* **15** 207–13
Meardon S A, Hamill J and Derrick T R 2011 Running injury and stride time variability over a prolonged run *Gait Posture* **33** 36–40
Meyer F *et al* 2021 Continuous analysis of marathon running using inertial sensors: hitting two walls? *Int. J. Sports Med.* **42** 1182–90
Moore I S 2016 Is there an economical running technique? a review of modifiable biomechanical factors affecting running economy *Sports Med. (Auckland, N.Z.)* **46** 793–807
Morin J B *et al* 2007 Effects of altered stride frequency and contact time on leg-spring behavior in human running *J. Biomech.* **40** 3341–8
Morris R *et al* 2019 Validity of mobility lab (version 2) for gait assessment in young adults, older adults and Parkinson's disease. *Physiol. Meas.* **40** 095003
Noehren B *et al* 2012 Proximal and distal kinematics in female runners with patellofemoral pain *Clin. Biomech. (Bristol, Avon)* **27** 366–71
Parati M *et al* 2022 The reliability of gait parameters captured via instrumented walkways: a systematic review and meta-analysis *Eur. J. Phys. Rehabil. Med.* **58** 363–77
Patterson S L *et al* 2008 Effect of treadmill exercise training on spatial and temporal gait parameters in subjects with chronic stroke: a preliminary report *J. Rehabil. Res. Dev.* **45** 221–8
Pfister A *et al* 2014 Comparative abilities of microsoft kinect and vicon 3D motion capture for gait analysis *J. Med. Eng. Technol.* **38** 274–80
Pipkin A *et al* 2016 Reliability of a qualitative video analysis for running *J. Orthop. Sports Phys. Ther.* **46** 556–61
Powell D, Stuart S and Godfrey A 2021 Sports related concussion: an emerging era in digital sports technology *npj Digital Medicine.* **4** 164
Roca-Dols A *et al* 2018 Effect of the cushioning running shoes in ground contact time of phases of gait *Journal of the mechanical behavior of biomedical materials* **88** 196–200 (1878-0180 (Electronic))
Rochester L *et al* 2020 A roadmap to inform development, validation and approval of digital mobility outcomes: the mobilise-D approach (2504-110X (Electronic)) *Digital biomarkers* **4** (1) 13–27
Sabatini A M *et al* 2005 Assessment of walking features from foot inertial sensing *IEEE Trans. Biomed. Eng.* **52** 486–94
Sabharwal S and Kumar A 2008 Methods for assessing leg length discrepancy *Clin. Orthop. Relat. Res.* **466** 2910–22
Santos-Concejero J *et al* 2015 Gait-cycle characteristics and running economy in elite Eritrean and European runners *Int. J. Sports Physiol. Perform* **10** 381–7
Schuna J M, Johnson W D and Tudor-Locke C 2013 Adult self-reported and objectively monitored physical activity and sedentary behavior: NHANES 2005–2006 *Int. J. Behav. Nutrition Phys. Activity* **10** 126
Seiberl W *et al* 2018 Accuracy and precision of loadsol((R)) insole force-sensors for the quantification of ground reaction force-based biomechanical running parameters *Eur. J. Sport Sci.* **18** 1100–9
Shema-Shiratzky S *et al* 2022 Smartphone-based inertial sensors technology—validation of a new application to measure spatiotemporal gait metrics *Gait Posture* **93** 102–6
Shrout P E and Fleiss J L 1979 Intraclass correlations: uses in assessing rater reliability *Psychol. Bull.* **86** 420–8
Shun-Ping L *et al* 2014 Impact of center-of-mass acceleration on the performance of ultramarathon runners *J. Human Kinetics* **44** 41–52
Smania N *et al* 2011 Improved gait after repetitive locomotor training in children with cerebral palsy *Am. J. Phys. Med. Rehabil.* **90** 137–49
Smith L *et al* 2015 A comparison of kinematic algorithms to estimate gait events during overground running *Gait Posture* **41** 39–43
Sprager S and Juric M B 2015 Inertial sensor-based gait recognition: a review *Sensors (Basel)* **15** 22089–127
Stöggl T and Martiner A 2017 Validation of Moticon's OpenGo sensor insoles during gait, jumps, balance and cross-country skiing specific imitation movements. *J. Sports Sci.* **35** 196–206
Storm F A *et al* 2018 Free-living and laboratory gait characteristics in patients with multiple sclerosis *PLoS One* **13** e0196463
Storm F A, Buckley C J and Mazzà C 2016 Gait event detection in laboratory and real life settings: Accuracy of ankle and waist sensor based methods *Gait Posture* **50** 42–6
Straczkiewicz M, Huang E J and Onnela J-P 2023 A 'one-size-fits-most' walking recognition method for smartphones, smartwatches, and wearable accelerometers *npj Digital Med.* **6** 29
Stuart S *et al* 2021 chapter 15 - Sports medicine: bespoke player management *Digital Health* ed A Godfrey and S Stuart (UK: Academic) pp 231–51
Tan T, Strout Z A and Shull P B 2020 Accurate impact loading rate estimation during running via a subject-independent convolutional neural network model and optimal IMU placement *IEEE Journal of Biomedical and Health Informatics* **25** 1215–22 (2168-2208 (Electronic))
Tao H *et al* 2019 Spatiotemporal comparison of overground and treadmill running with pressure sensor insoles in division i collegiate runners *Int. J. Sports Phys. Ther.* **14** 731–9

Tao W *et al* 2012 Gait analysis using wearable sensors *Sensors (Basel)* **12** 2255–83
Thumm P C *et al* 2018 Treadmill walking reduces pre-frontal activation in patients with Parkinson's disease *Gait Posture* **62** 384–7
Toth L P *et al* 2023 Effects of brief intermittent walking bouts on step count accuracy of wearable devices *J. Meas. Phys. Behav.* **2** 13–21
Van Hooren B *et al* 2020 Is motorized treadmill running biomechanically comparable to overground running? a systematic review and meta-analysis of cross-over studies *Sports Med.* **50** 785–813
Veerubhotla A *et al* 2021 Comparing accuracy of step count detection algorithm at different activity monitor wear locations *Arch. Phys. Med. Rehabil.* **102** e79
Vitale C *et al* 2012 Effect of global postural rehabilitation program on spatiotemporal gait parameters of parkinsonian patients: a three-dimensional motion analysis study *Neurological Sci.* **33** 1337–43
Washabaugh E P *et al* 2017 Validity and repeatability of inertial measurement units for measuring gait parameters *Gait. Posture* **55** 87–93
Johnston W *et al* 2021 Recommendations for determining the validity of consumer wearable and smartphone step count: expert statement and checklist of the INTERLIVE network *Br. J. Sports Med.* **55** 780
Willy R W 2018 Innovations and pitfalls in the use of wearable devices in the prevention and rehabilitation of running related injuries *Phys. Therapy Sport* **29** 26–33
Yamato T P, Saragiotto Bt Fau - Lopes A D and Lopes A D 2015 A consensus definition of running-related injury in recreational runners: a modified Delphi approach *American journal of physical medicine & rehabilitation* **45** 375–80
Young F *et al* 2022 Examination of a foot mounted IMU-based methodology for a running gait assessment *Front. Sports Active Living* **4**
Zago M *et al* 2018 Gait analysis in patients with chronic obstructive pulmonary disease: a systematic review *Gait Posture* **61** 408–15
Zhou Y *et al* 2020 Classification of neurological patients to identify fallers based on spatial-temporal gait characteristics measured by a wearable device *Sensors* **20** 15