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Short communication

Evaluation of a smartphone accelerometer system for measuring nonlinear dynamics during treadmill walking: Concurrent validity and test-retest reliability

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ABSTRACT

The accelerometers embedded within smartphones may be a promising tool to capture gait patterns outside the laboratory and for extended periods of time. The current study evaluated the agreement and reliability of gait measures derived from a smartphone accelerometer system, compared to reference motion capture and footswitch systems during treadmill walking. Seventeen healthy young adults visited the laboratory on three separate days and completed three 8-minute treadmill walking trials, during each visit, at their preferred walking speed. The inter-stride interval series was calculated as the time difference between consecutive right heel contacts, located within the signals of the smartphone accelerometer, motion capture, and footswitch systems. The inter-stride interval series was used to estimate common linear gait measures and nonlinear measures, including fractal scaling index, approximate entropy, and sample entropy. Bland Altman plots with 95% limits of agreement and intraclass correlation coefficients assessed agreement and reliability, respectively. The smartphone system was found to be within the acceptable limits of agreement when compared to either reference system. The intraclass correlation coefficients values revealed moderate-to-excellent reliability for the smartphone system, with greater reliability found for linear compared to nonlinear measures and were similar to both reference systems, except for the fractal scaling index. These findings suggest the smartphone accelerometer system is a valid and reliable method for estimating linear and nonlinear gait measures during treadmill walking.

1. Introduction

Gait analysis is traditionally performed using linear measures such as the mean or standard deviation (SD) of the measure of interest (e.g., SD of stride time). However, evidence suggests that use of nonlinear approaches to analysis of gait dynamics (i.e., changes in stride-to-stride fluctuations) can provide greater sensitivity for detecting age-related changes associated with fall-risk and pathological gait patterns (Hausdorff et al., 1997). Nonlinear analysis provides a group of measures that are used to quantify the structure of gait patterns over time. For example, the detrended fluctuation analysis (DFA), which provides the fractal scaling index (FSI) as a measure of statistical persistence, estimates the degree to which a stride interval is correlated with previous and later stride intervals over different time scales (Hausdorff et al., 1996). Other common nonlinear measures include approximate entropy (ApEn) and sample entropy (SaEn), which quantify the statistical regularity of a time series; with higher values suggesting greater gait adaptability (Arif et al., 2004) defined as altering the typical stepping pattern to accommodate imposed constraints (Balasubramanian et al., 2014).

Nonlinear gait analysis requires hundreds (>200) of continuous strides, thereby restricting data collection to a controlled setting, while walking on a motorized treadmill, and recording with a research-grade reference system (Rhea et al., 2014; Kiriella et al., 2020). However, research-grade reference systems are expensive, limited to the laboratory, and require trained personnel for operation. With advancements in smartphones, researchers can access the built-in inertial sensors to monitor gait outside the laboratory for extended periods of time (Lugade et al., 2021). Although previous studies have validated smartphone accelerometer (SPAcc) systems for measuring traditional, spatial–temporal gait measures during overground walking (Silsupadol et al., 2017; Yang et al., 2012), only one study has assessed the use of

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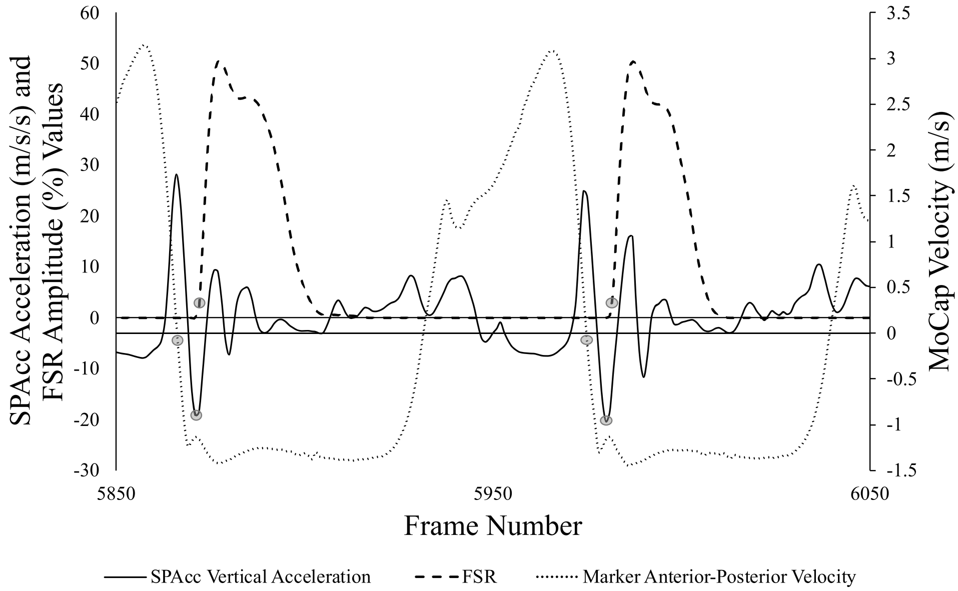

Fig. 1. Representative plot of right heel contact locations in the signals recorded from the motion capture (MoCap), force-sensing resistor (FSR), and smartphone accelerometer (SPAcc) systems. The gray circles represent heel contact event locations.

nonlinear analysis; Hammoud et al. (2015) reported statistical persistence derived using a SPAcc. The aim of this study is to evaluate the agreement and reliability of linear and nonlinear gait measures collected with a SPAcc during treadmill walking.

2. Methods

2.1. Participants

Seventeen adults (*8F/9M;* mean ± SD; age:24.7 ± 3.7 years, height:1.73 ± 0.1 m, weight:73.1 ± 14.2 kg, belt speed:1.26 ± 0.2 m/s) participated. Sample size was calculated *a priori* using an $\alpha = 0.05$, $\beta = 0.8$, and an expected intraclass correlation coefficient (ICC) between 0.4 and 0.5 (Raffalt et al., 2018) providing $n = 11$–17 (Bujang and Baharum, 2017). Participants provided written informed consent prior to participation. The university research ethics board granted approval for the study (certificate#2019–091). Inclusion criteria included: adults between 18 and 35 years old, ability to perform repeated 10-minute walking bouts, and no neurological or musculoskeletal conditions or injuries within the past six months that might affect gait.

2.2. Equipment and set-up

Participants wore comfortable walking shoes, full length pants with front pockets, and a t-shirt. A seven-camera motion capture system (Vicon, CO, USA), considered the reference motion capture system (MoCap), recorded movement of a single reflective marker affixed to the right heel of the shoe, using double-sided adhesive tape; sampling at 100 Hz. A wireless force sensitive resistor (FSR) footswitch sensor (12.7 mm round) (Delsys, MA, USA), affixed directly to the bottom of the right heel inside the shoe, with tape, considered the reference FSR system recorded the time of heel contact; sampling at 296 Hz. The FSR system had preset sampling rates, and the rate closest to that of the MoCap was selected. A Google Smartphone (Pixel 2, ROC), with a custom-built application accessing the embedded tri-axial accelerometer, was placed pointing downwards in the front right pants pocket and used as the SPAcc; sampling at 100 Hz. Participants walked on a motorized treadmill (Bodyguard Fitness, QC, Canada). The treadmill walking surface was ~ 6 in. above the ground and was level with the floor.

2.3. Protocol

Participants visited the laboratory three times, each separated by at least 24 h and wore the same attire for each visit. The preferred walking speed (PWS) was determined for each participant using the protocol from Dingwell and Marin (2006). Participants performed a five-minute treadmill familiarization walking period, at their PWS, prior to data collection trials (Zeni and Higginson, 2010). Participants completed three 8-minute treadmill walking trials at their PWS (Pierrynowski et al., 2005). During visits two and three, participants repeated the collection protocol while walking at their previously identified PWS. Each participant completed nine trials.

2.4. Data processing

Data were processed using Matlab (R2021b, Mathworks Inc, MA, USA). Temporal alignment of the three independent systems is described in supplementary material A. The vertical axis acceleration data were used to determine SPAcc. SPAcc and FSR data were sample interpolated to 100 Hz to match the MoCap sampling rate. Afterwards, the gravity bias was removed from the SPAcc data, and signals were multiplied by −1 to correct for the upside-down orientation. Two data streams were created for each system. One stream was kept in raw form for nonlinear measures calculations. To construct the second stream, used for linear measures calculations, the raw data were filtered using a fourth order low-pass Butterworth filter with cutoff frequencies selected based on a residual analysis approach (Fazlali et al., 2020). The MoCap, FSR, and SPAcc data were filtered with 6 Hz, 13 Hz, and 18 Hz cutoff frequencies, respectively. Each trial was truncated to 325 strides and the first 25 were discarded (Lindemann et al., 2008). The location of right heel contact (RHC) events within the signals of each system (Fig. 1) is described in supplementary material B.

2.5. Dependent measures

The inter-stride interval (ISI) was calculated for each system's signal as the time difference between each RHC event and used as the ISI series for all measures: average ISI (xISI; ms), stride time SD, (STv; ms), stride time coefficient of variation (COV; %), FSI using DFA (Terrier and Dèriaz, 2012), ApEn, and SaEn. The entropy algorithms used the following parameter values: similarity criterion, r = 0.2, window length,

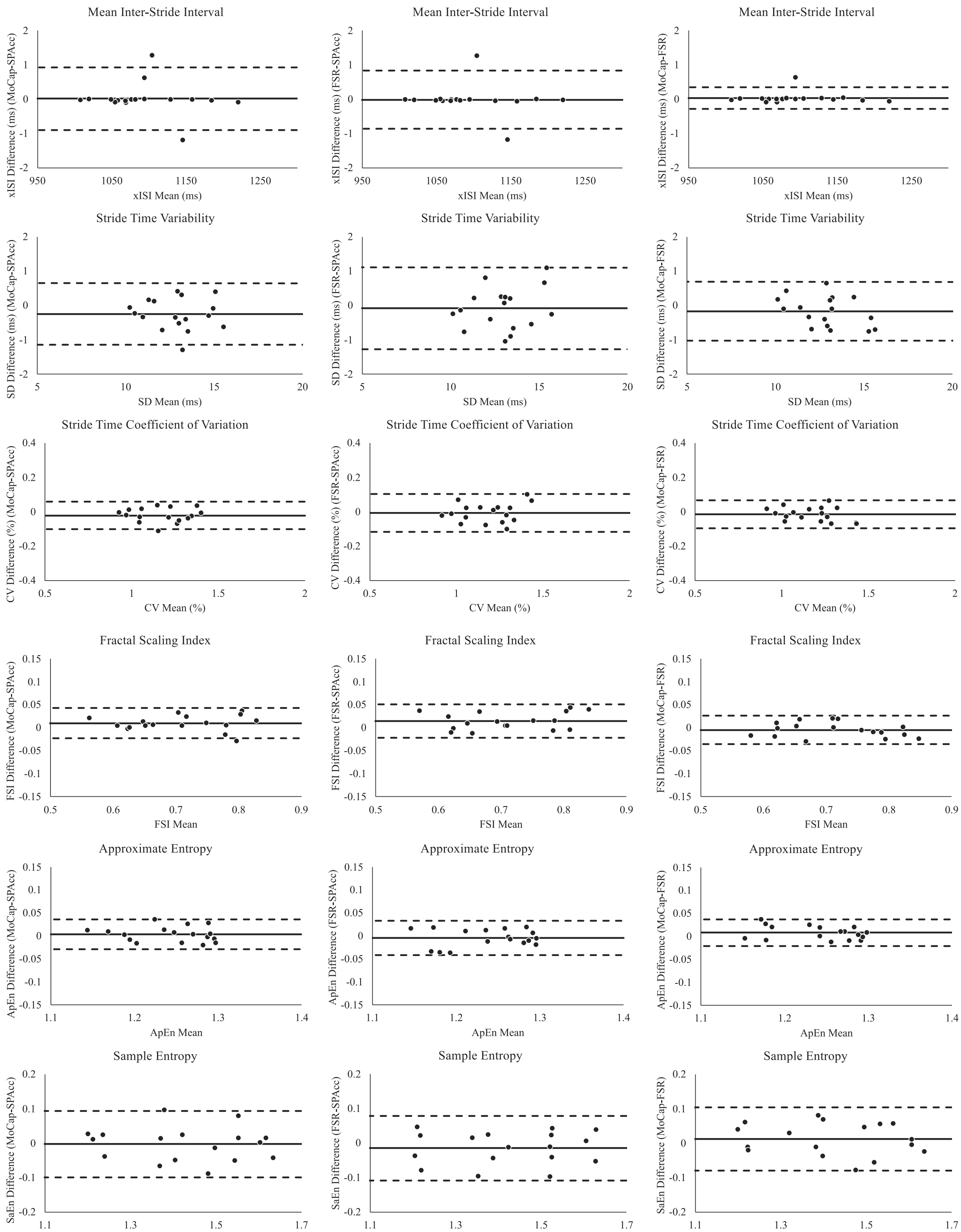

Fig. 2. Bland Altman plots with 95% limits of agreement (LOA) for each dependent measure between each measurement system. The dashed black lines represent the 95% LOA, the solid black line represents the bias, the black circles represent the average of all trials from each participant ($n = 17$). Compared to the motion capture (MoCap) system, the smartphone accelerometer (SPAcc) system revealed a slight negative bias for stride time variability, stride time coefficient of variation (CV), and sample entropy (SaEn) representing an overestimation of the SPAcc; a slight positive bias was found for mean inter-stride interval (xISI), fractal scaling index (FSI), and approximate entropy (ApEn). Compared to the footswitch (FSR) system, the SPAcc revealed a slight negative bias for all measures except for FSI, demonstrating the SPAcc, in general overestimates measures compared to FSR.

Table 1
Mean (±SD) of linear and nonlinear measures derived from the signals of each system, along with bias, 95% limits of agreement (LOA), and absolute agreement (ICC(2, k)).

Measure	System			Bias (95% Limits of Agreement) [ICC(2,k)]		
	SPAcc	MoCap	FSR	MoCap versus SPAcc	FSR versus SPAcc	MoCap versus FSR
Mean Inter-Stride Interval (ms)	1099.4 (56.9)	1101.4 (56.8)	1101.4 (56.8)	0.02 (−0.90, 0.93) [1.00]	−0.02 (−0.86, 0.83) [1.00]	0.03 (−0.29, 0.35) [1.00]
Stride Time Variability (ms)	13.0 (1.6)	12.7 (1.6)	12.9 (1.8)	−0.25 (−1.15, 0.66) [0.94]	−0.08 (−1.27, 1.12) [0.94]	−0.17 (−1.03, 0.69) [0.98]
Coefficient of Variation of Stride Time (%)	1.18 (0.15)	1.16 (0.15)	1.17 (0.17)	−0.02 (−0.10, 0.06) [0.94]	−0.01 (−0.12, 0.10) [0.94]	−0.02 (−0.10, 0.07) [0.98]
Fractal Scaling Index	0.71 (0.08)	0.72 (0.08)	0.72 (0.09)	0.009 (−0.023, 0.043) [0.96]	0.015 (−0.022, 0.051) [0.93]	−0.005 (−0.036, 0.026) [0.99]
Approximate Entropy	1.24 (0.05)	1.25 (0.05)	1.24 (0.05)	0.004 (−0.029, 0.036) [0.97]	−0.005 (−0.041, 0.033) [0.96]	0.008 (−0.021, 0.037) [0.96]
Sample Entropy	1.43 (0.15)	1.41 (0.15)	1.40 (0.15)	−0.003 (−0.099, 0.094) [0.96]	−0.015 (−0.110, 0.079) [0.95]	0.012 (−0.080, 0.104) [0.97]

Note: SPAcc = smartphone accelerometer system, MoCap = motion capture system, FSR = footswitch system, k = 3. Negative bias [MoCap - SPAcc; FSR - SPAcc; MoCap - FSR] represents an overestimation.

m = 2 (Richman and Moorman, 2000).

2.6. Statistical analyses

Statistical analyses were performed using JMP v.9.0 software (The SAS Institute, NC, USA). Bland-Altman (BA) plots with 95% limits of agreement (LOA) were constructed using the mean of all walking trials for each participant, for each system to assess agreement. The *a priori* defined acceptable LOAs for each measure are defined in supplementary material B. ICC(2,k = 3) assessed absolute agreement between each system (Hartmann et al., 2009). ICC(2,k = 3) also assessed the test–retest reliability of each system using the measures from each walking trial. ICC values of < 0.5, 0.5–0.75, 0.75–0.90, and > 0.90 were interpreted as poor, moderate, good, and excellent, respectively (Koo and Li, 2016). The standard error of measurement (SEM) and the minimal detectable change (MDC) were calculated for each system to quantify absolute reliability (magnitude of measured values spread around the true value) and the amount of change in order to detect a true difference across separate repeated measurements rather than measurement error, respectively (Weir, 2005); lower MDC values indicate better measurement tool responsiveness.

3. Results

3.1. Validity

The 95% LOA calculated for the SPAcc compared to either reference system, and between both reference systems, were found to be within the *a priori* defined acceptable LOA for all dependent measures (Fig. 2). With the exception of stride time COV, the LOA were narrower when the reference systems were compared to one another (Table 1). The ICCs revealed excellent agreement between the SPAcc and both reference systems (Table 1).

3.2. Reliability

Linear and nonlinear measures derived from SPAcc demonstrated moderate-to-excellent reliability (Table 2). The SPAcc revealed ICCs similar to both reference systems across all measures, except for FSI, which was lower for the SPAcc (0.73) compared to MoCap (0.81) and FSR (0.82) systems. The SEM and MDC values were similar across all systems, suggesting absolute reliability and measurement responsiveness of the SPAcc were similar to that of both reference systems (Table 2).

4. Discussion

The aim of this study was to evaluate the agreement and reliability of linear and nonlinear gait measures collected with a SPAcc during treadmill walking. The findings suggest the SPAcc is a valid and reliable method for estimating gait measures during treadmill walking, performing similarly to that of research-grade equipment.

The mean values for xISI across all systems were similar to previous treadmill walking research (Terrier and Dèriaz, 2011) and overground walking while using a smartphone (Proessl et al., 2018). Mean STv and COV derived from the SPAcc were lower compared to previous accelerometer-derived research during treadmill walking (Terrier and Dèriaz, 2011). Mean FSI values in this study were similar to those reported by Terrier and Dèriaz (2011) while using an accelerometer affixed to the low back. The 95% LOA for FSI in the current study were narrower than the LOA reported by Kobsar et al. (2014) who compared an accelerometer to an FSR system during overground walking. However, methodological differences, such as signal filtering, overground walking, population recruited, and number of strides included, may have contributed to the differences in values between the accelerometer and SPAcc. The slight positive bias found for FSI compared to the other reference systems represents a slight underestimation of the SPAcc. These findings suggest a slight systematic adjustment may be required

Table 2
Test-retest reliability (ICC), standard error of measurement (SEM), and minimal detectable change (MDC) results.

	SPAcc				MoCap				FSR			
Measure	ICC(2,k)		SEM	MDC	ICC(2,k)		SEM	MDC	ICC(2,k)		SEM	MDC
Mean Inter-Stride Interval (ms)	0.86	G	12.6	35.0	0.95	E	12.5	34.8	0.95	E	12.6	35.0
Stride Time Variability (ms)	0.95	E	0.73	2.01	0.83	G	0.65	1.81	0.82	G	0.74	2.06
Coefficient of Variation of ISI (%)	0.80	G	0.06	0.17	0.88	G	0.05	0.15	0.85	G	0.06	0.18
Fractal Scaling Index	0.73	M	0.04	0.12	0.81	G	0.04	0.10	0.82	G	0.04	0.10
Approximate Entropy	0.90	E	0.02	0.04	0.87	G	0.02	0.05	0.87	G	0.02	0.05
Sample Entropy	0.86	G	0.06	0.16	0.89	G	0.05	0.14	0.88	G	0.05	0.15

Note: M - moderate, G - good, E - excellent; k = 3; ISI = inter-stride interval.

when estimating the FSI using the SPAcc during treadmill walking. Mean SaEn (1.40–1.43) was found to be greater than mean ApEn (1.24–1.25) for all systems, which is as expected since SaEn does not count self matches and therefore yields values closer to randomness. The ICCs assessing agreement between the SPAcc, and reference systems were found to be similar to those reported by Kobsar et al. (2014) for xISI (1.00), STv (0.94), and FSI (0.95) while comparing an accelerometer to a FSR system. In general, better agreement was found between the SPAcc and MoCap systems, compared to the SPAcc and FSR system, while the two reference systems demonstrated the best agreement to one another.

FSI demonstrated the lowest ICCs for all three systems. This is not surprising due to the sensitivity of nonlinear measures and the between-day design of the current study. Previous research on between-day reliability also suggests that linear measures exhibit high reliability (Stolze et al., 1998) while nonlinear measures reveal lower reliability (Ryan et al., 2021). For example, Raffalt et al. (2018), reported ICCs of $\sim$ 0.38 and $\sim$ 0.6, for SaEn and FSI, respectively. Pierrynowski et al. (2005) also investigated the between-day reliability of FSI and reported an ICC of 0.82, calculated using three six-minute treadmill walking trials while recording the displacement of a right heel marker using a MoCap system to identify heel contact events. The current study used the same number of strides and trials, as recommended by Pierrynowski et al. (2005), to calculate FSI and found similar ICC values for both reference systems (MoCap = 0.81, FSR = 0.82), while the SPAcc revealed an ICC of 0.73. Differences in agreement and reliability of the FSI between the reference systems and the SPAcc might be associated with the locations at which measurements were taken; at the right heel for the MoCap and FSR system, and at the pants pocket for the SPAcc. Any subtle differences in heel contact event locations used to generate the ISI series might be associated with sensor location. Further, to better simulate real-world useability of the smartphone, placement in the pocket was not fixed, allowing the device to move somewhat independently, also potentially affecting the agreement and reliability measures. Previous research suggests pocket tightness does not affect the estimation of linear gait measures using a smartphone (Manor et al., 2018), however, no studies have examined the potential impact on non-linear measures until now.

Interestingly, the entropy measures were more reliable than FSI, suggesting entropy is not as sensitive to between-day differences or that sensor location is not a factor contributing to differences in between-day reliability, as may be the case for FSI. Additionally, perhaps the entropy algorithm itself is not as sensitive to subtle between-day differences. However, only one combination of entropy algorithm parameters was used. Future research should investigate the selection of different input parameters used to calculate entropy and the effect on between-day reliability. A limitation of this study is the absence of a defined control group for interpreting ApEn and SaEn values.

The present study established the utility of a smartphone for estimating gait dynamics among healthy young adults in a controlled environment; enabling future research for evaluating different adult populations (i.e., clinical) and in different settings (i.e., overground walking), however, more work must be done to establish these implications.

CRediT authorship contribution statement

Vincenzo E. Di Bacco: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization. **William H. Gage:** Writing – review & editing, Supervision, Resources, Funding acquisition, 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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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2023.111527.

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