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Metodologia delle misure delle attività sportive

Thursday 17/10/2019 15:45÷17:15

Luca P. Ardigò Ph.D.

A class within an eight-class module

84

Accelerometers

Actiwatch

-> Actical

Actitrac

Biotrainer

Accelerometers

Nokia N79

Carlson Jr et al., 2012

Accelerometers

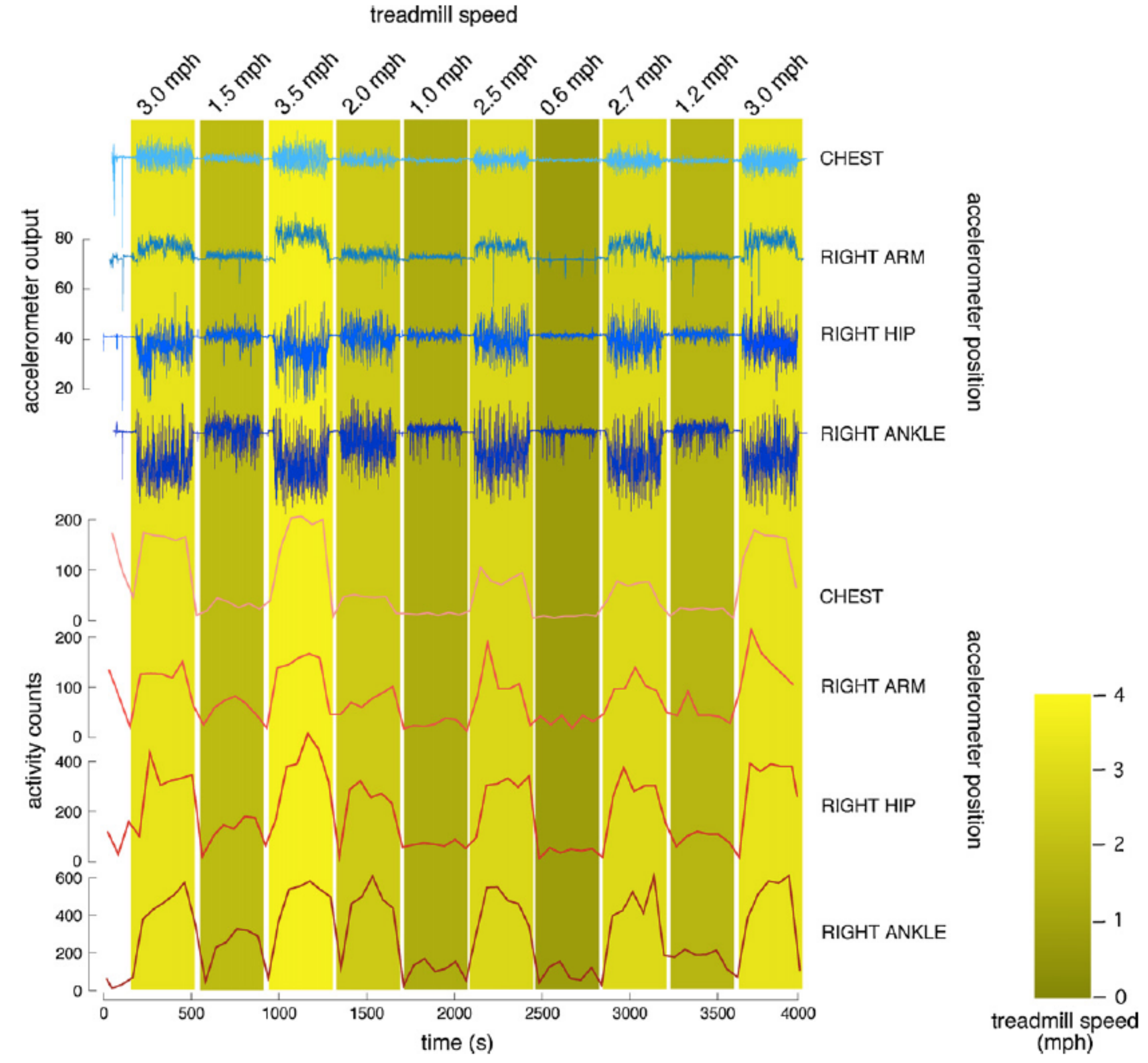

Fig. 1. Activity counts from cell-phone accelerometers provide an accurate measure of treadmill gait speed regardless of where the sensor is worn. The top four traces depict raw data from a representative trial (43 y/o man) showing acceleration magnitude *versus* time for sensors worn at the chest, right arm, right hip, and right ankle (1st through 4th traces from top, respectively). For all traces the baseline is centered at 64 (midscale between sensor output of 0 for −2 g, and 128 for +2 g), the amount of deflection from this baseline is per the common scale provided left of these traces. The bottom four traces show activity counts *versus* time for the sensors worn at the chest, right arm, right hip, and right ankle, respectively. Counts were calculated over 1 min nonoverlapping bins. Treadmill speed is given at the top of each epoch bar.

Accelerometers

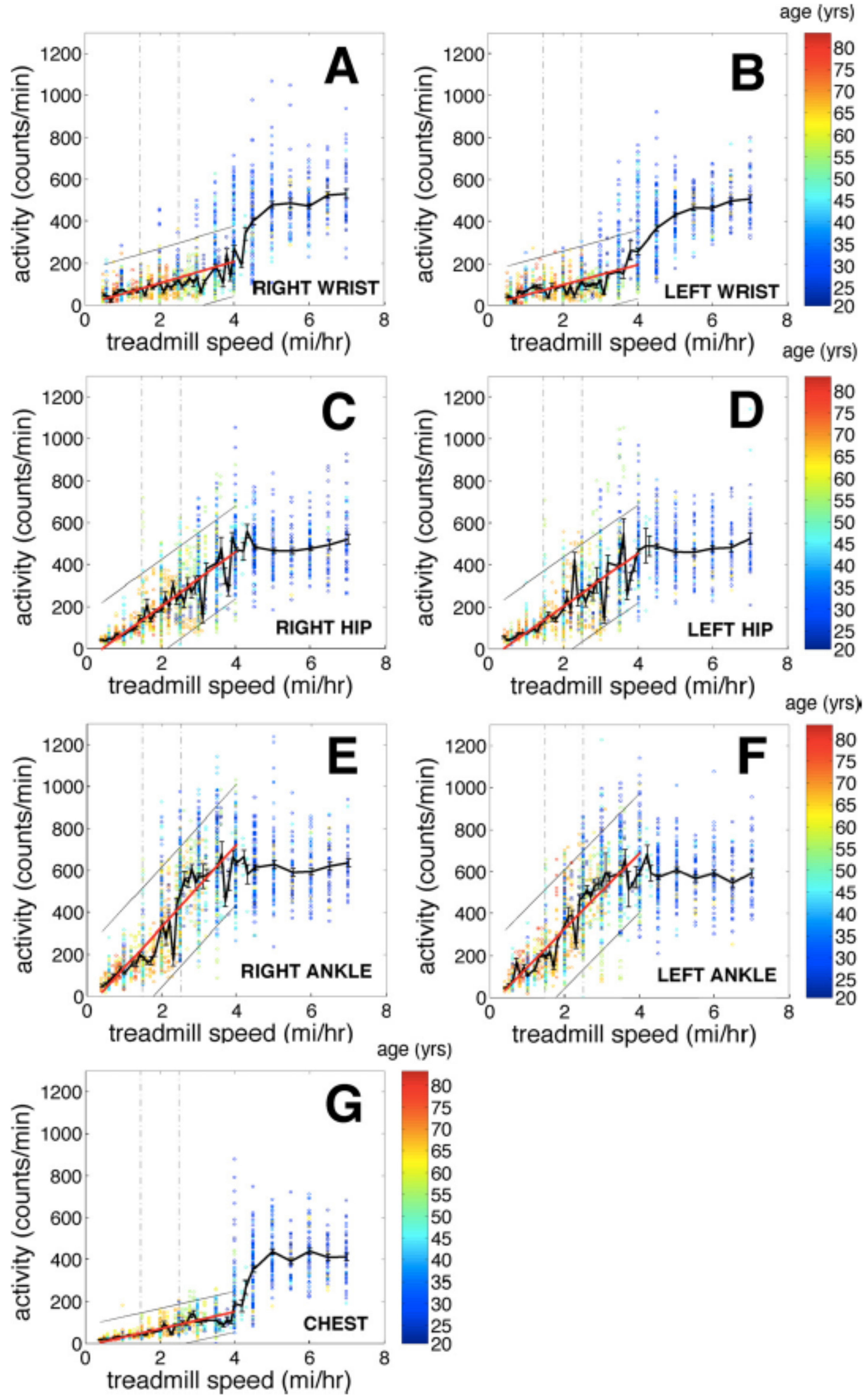

Fig. 3. Activity count versus treadmill speed relationships for all sensor locations. For all figures, the solid red line shows the linear regression between treadmill speed and activity counts (fit for all data between 0.0 and 6.4 km/h (0–4 mi/h) gait speeds); the thin surrounding black lines are 95% confidence boundaries on this regression. The thick black line connects mean activity count values for each of the evaluated treadmill speeds; bars surrounding this point are ±1 standard error of the mean. Individual observations of activity counts are shown as open colored circles. Subject age is color coded as circle color; refer to colorbar at right side for key. The dashed lines at gait speeds of 2.35 km/h (1.46 mi/h) and 4 km/h (2.5 mi/h) highlight system performance at two critical functional thresholds. These relationships come from cell phones placed at the right wrist (A), left wrist (B), right hip (C), left hip (D), right ankle (E), left ankle (F), and neck (G).

Accelerometers

Apple iPod Touch
(iPhone)

Ellis et al., 2015

Accelerometers

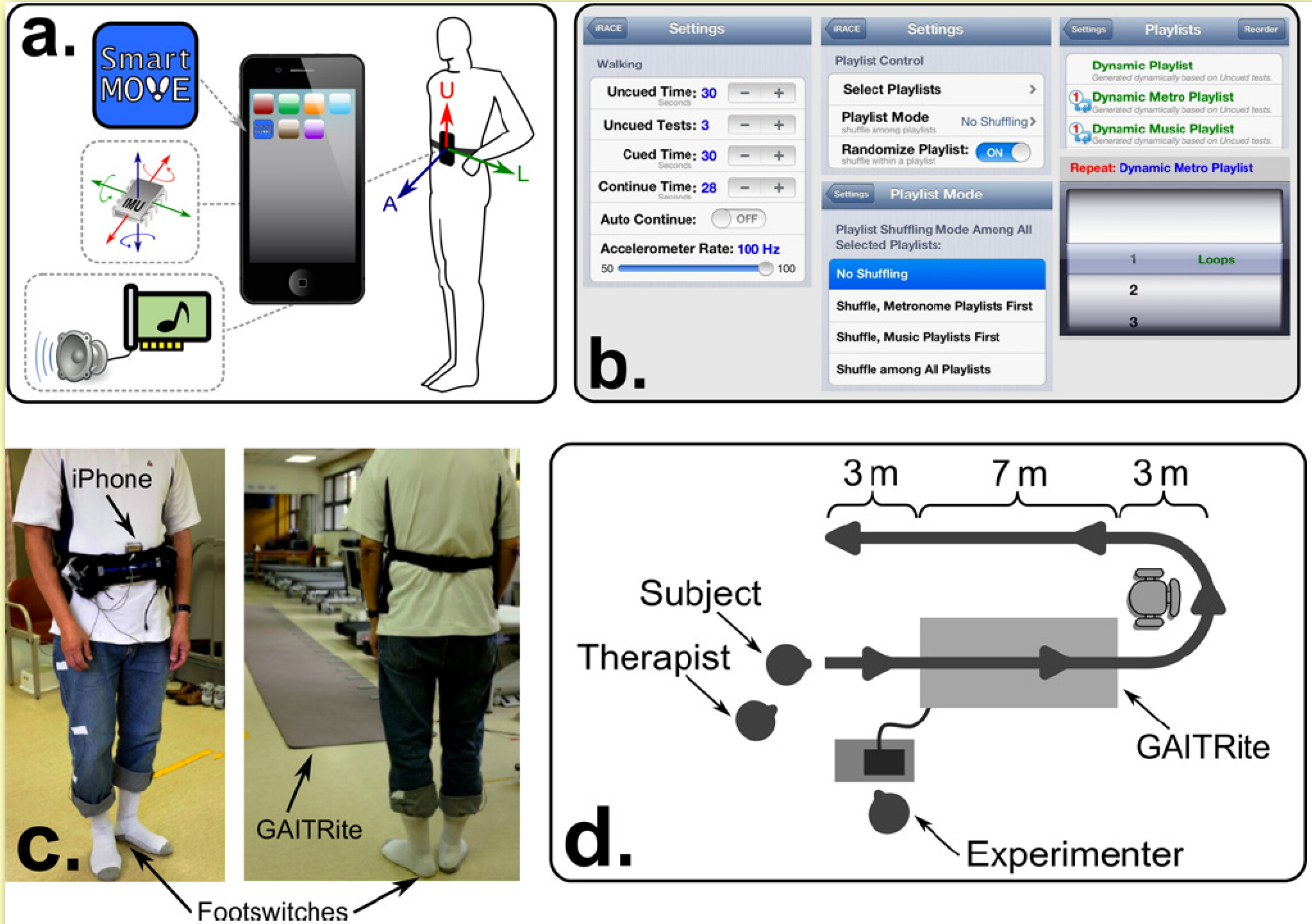

Fig 1. Key experimental features. The SmartMOVE mobile app (a.) utilizes the smartphone's inertial measurement unit to record gait movements during walking. Flexible parameter settings (b.) enable precise control over testing parameters. SmartMOVE outcome measures were validated against heel-mounted footswitches and a GAITRite sensor walkway (c.) while subjects walked along a prescribed path (d.).

Accelerometers

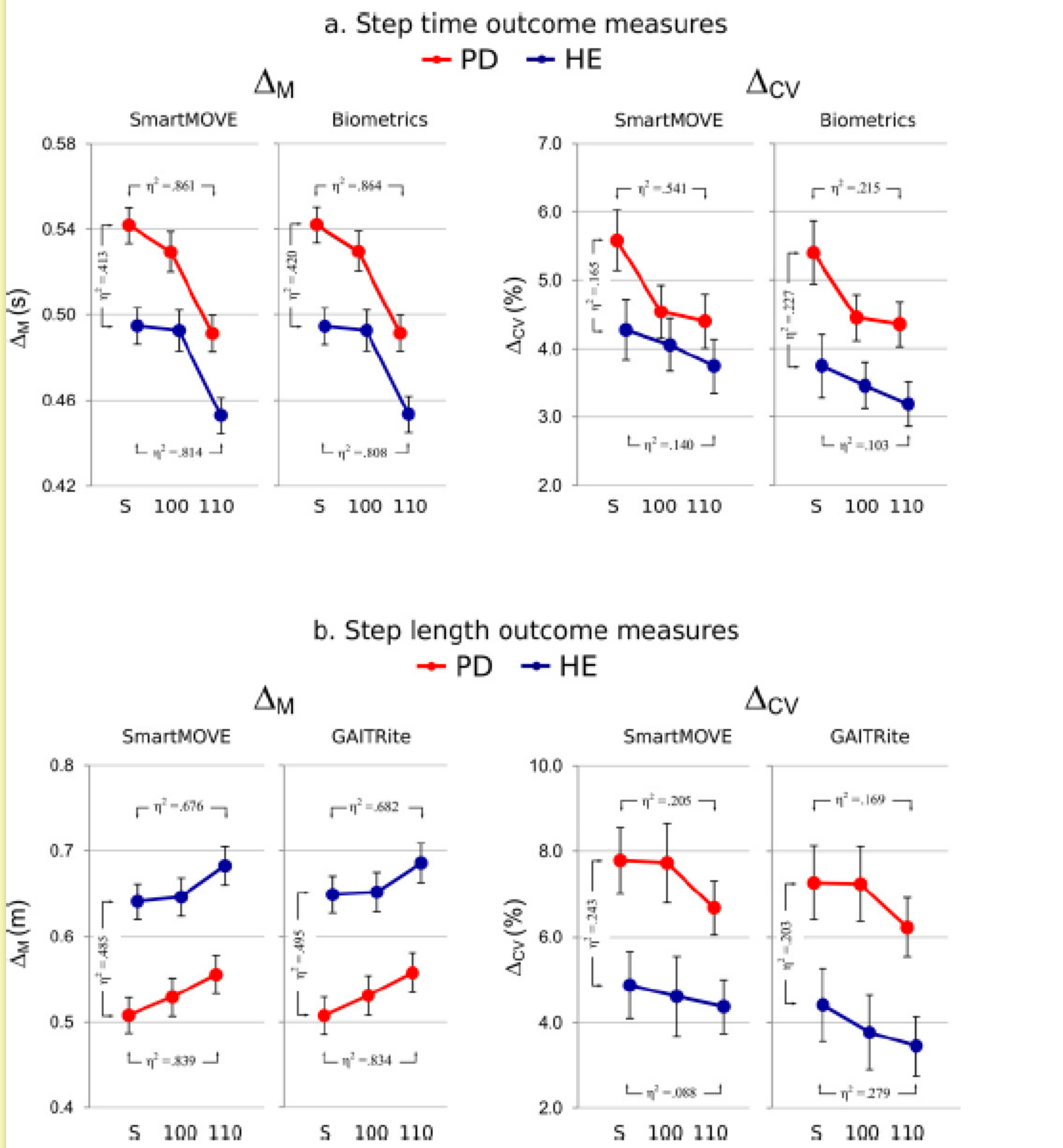

Fig 2. Outcome measure results. Results of the *Group* (separate lines: PD vs. HE) × *Condition* (x-axis: self-paced, 100% RAC, 110% RAC) × *Device* (separate panels: SmartMOVE vs. heel contact–based) ANOVAs for step time (a.) and step length (b.) outcome measures.

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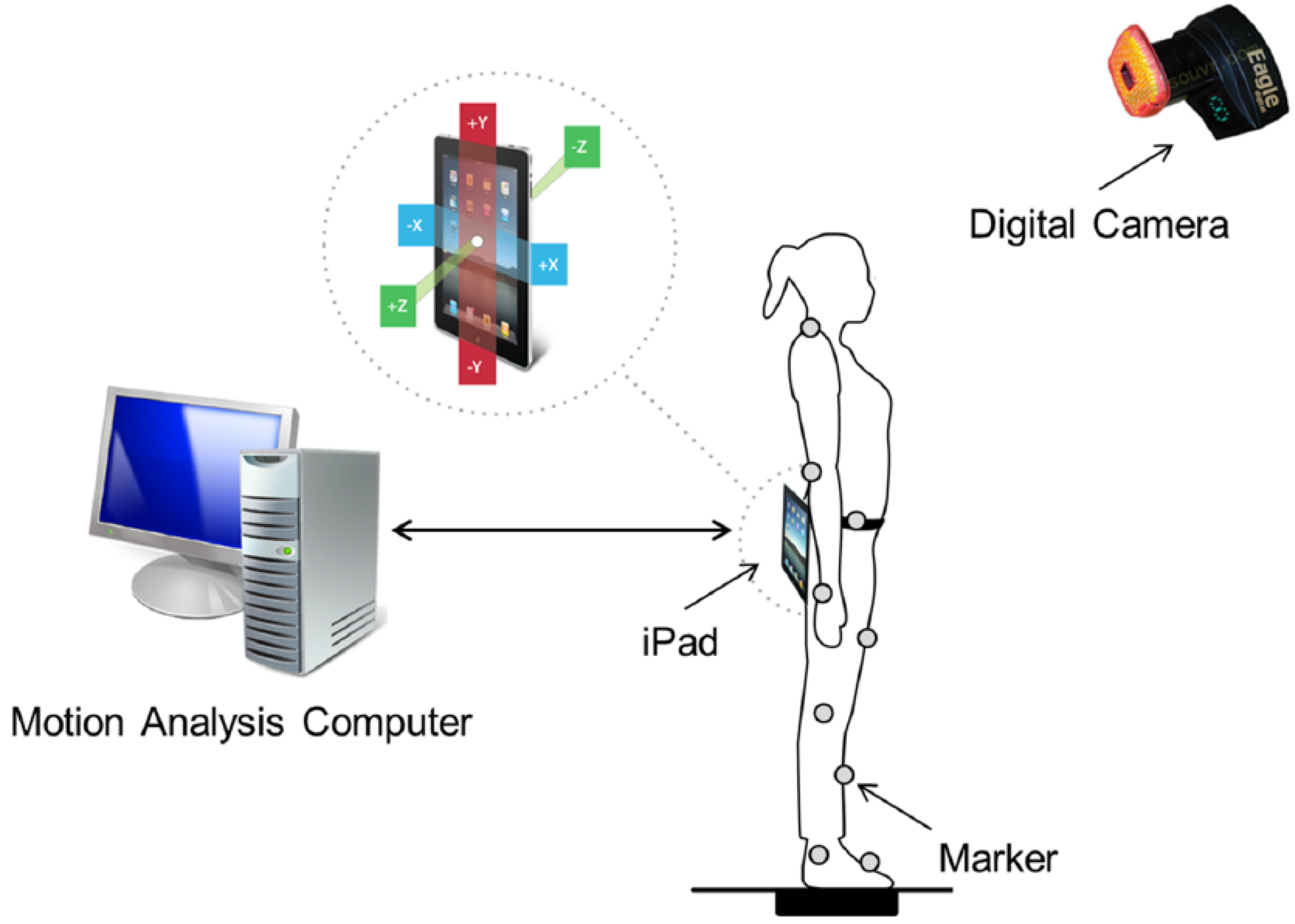
Accelerometers

iPad (third generation)

Ozinga et al., 2014

Fig. 1 Illustration of experimental paradigm and measurement setup



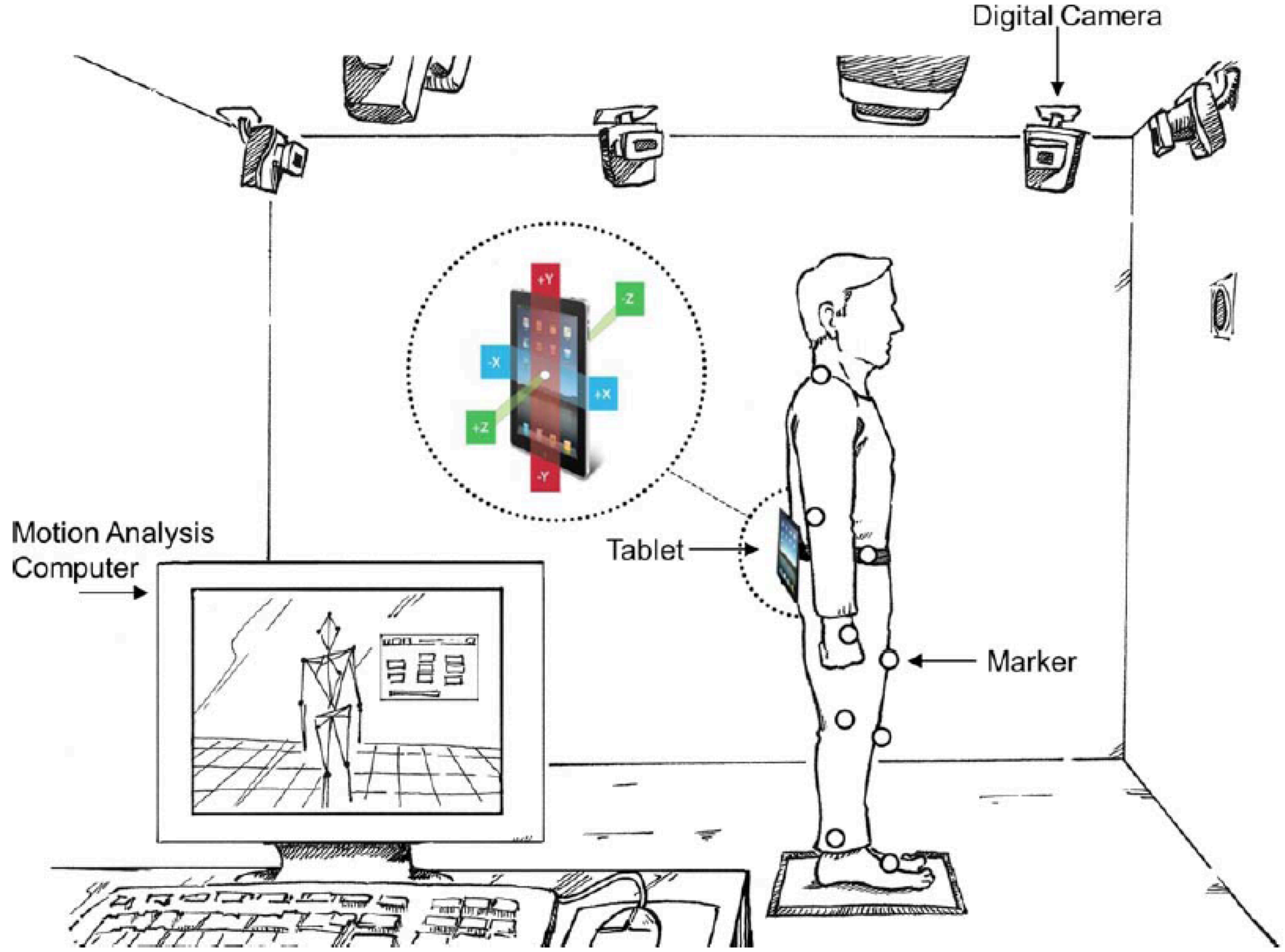


FIG. 1. Illustration of experimental paradigm and measurement setup. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Ozinga et al., 2015

Accelerometers

Samsung Galaxy II

Zhang et al., 2014

Accelerometers

measures

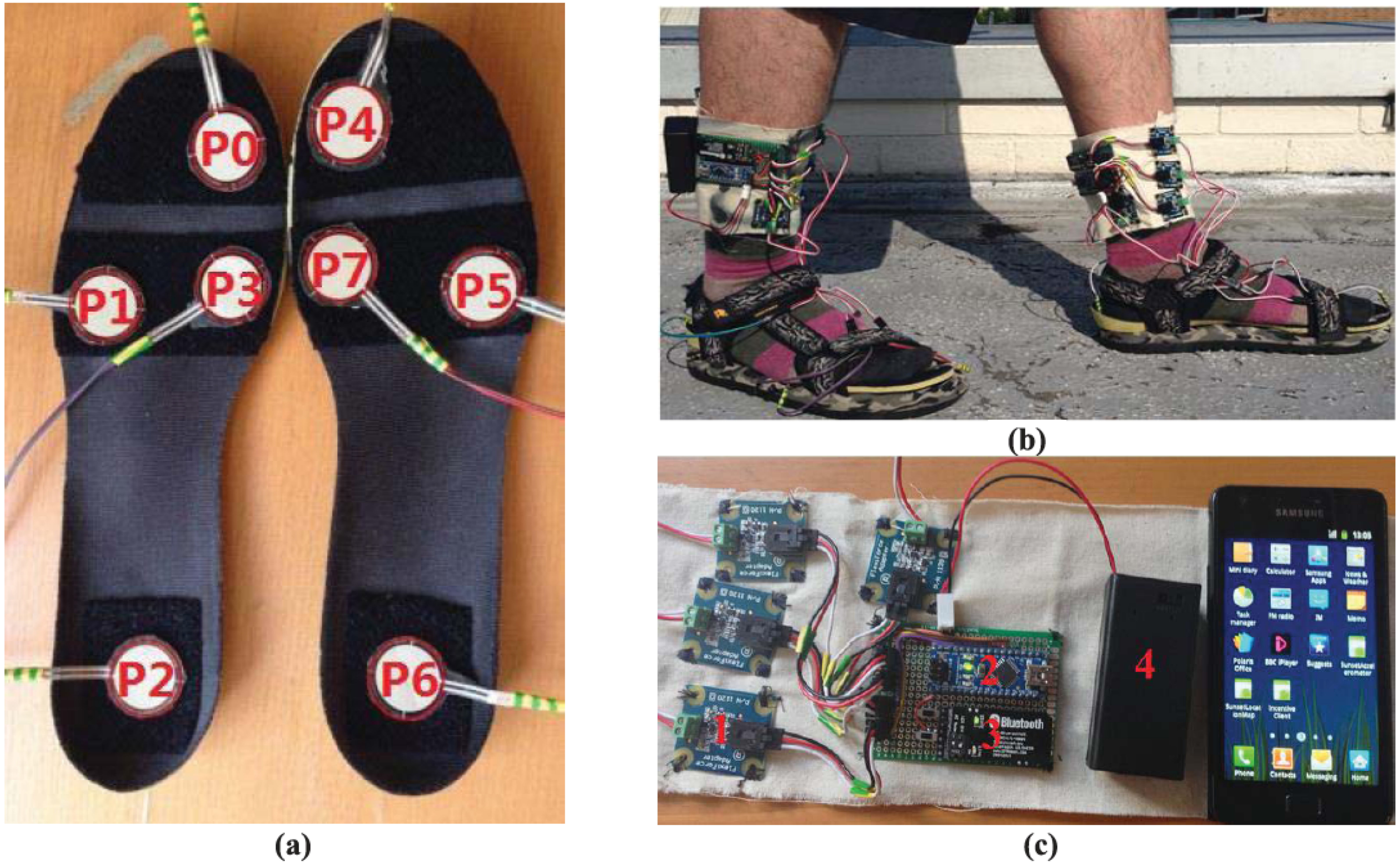


Fig. 2. Experiment equipment: (a) experimental insoles with 8 Flexiforce sensors instrumented; (b) the scene of foot force measurements; and (c) the foot force sensing system and a Samsung galaxy II smart phone.

Accelerometers

measures

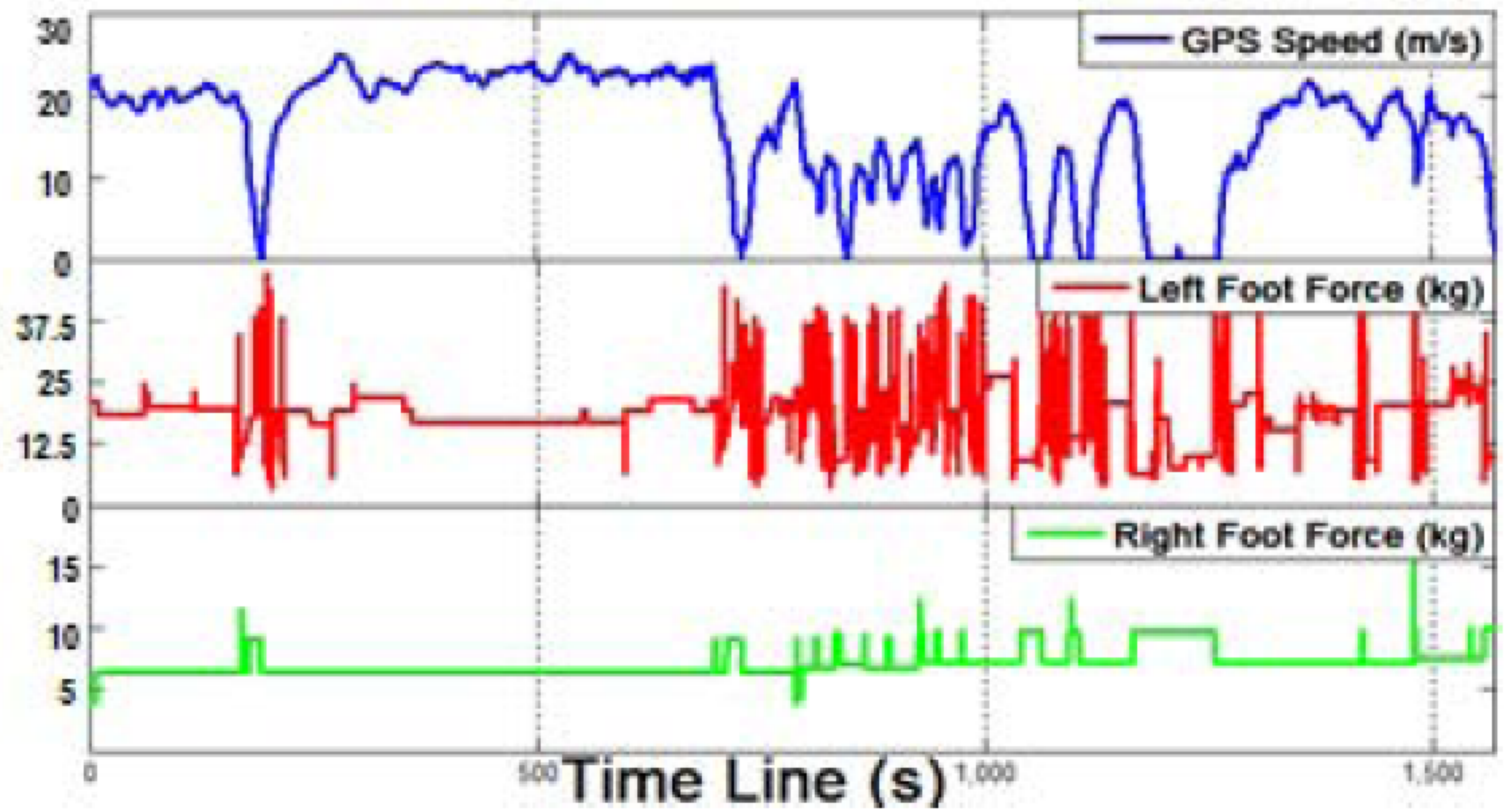


Fig. 8. GPS speed, foot force variations during a 30 minutes driving process.

Cameras

iPhone 4s

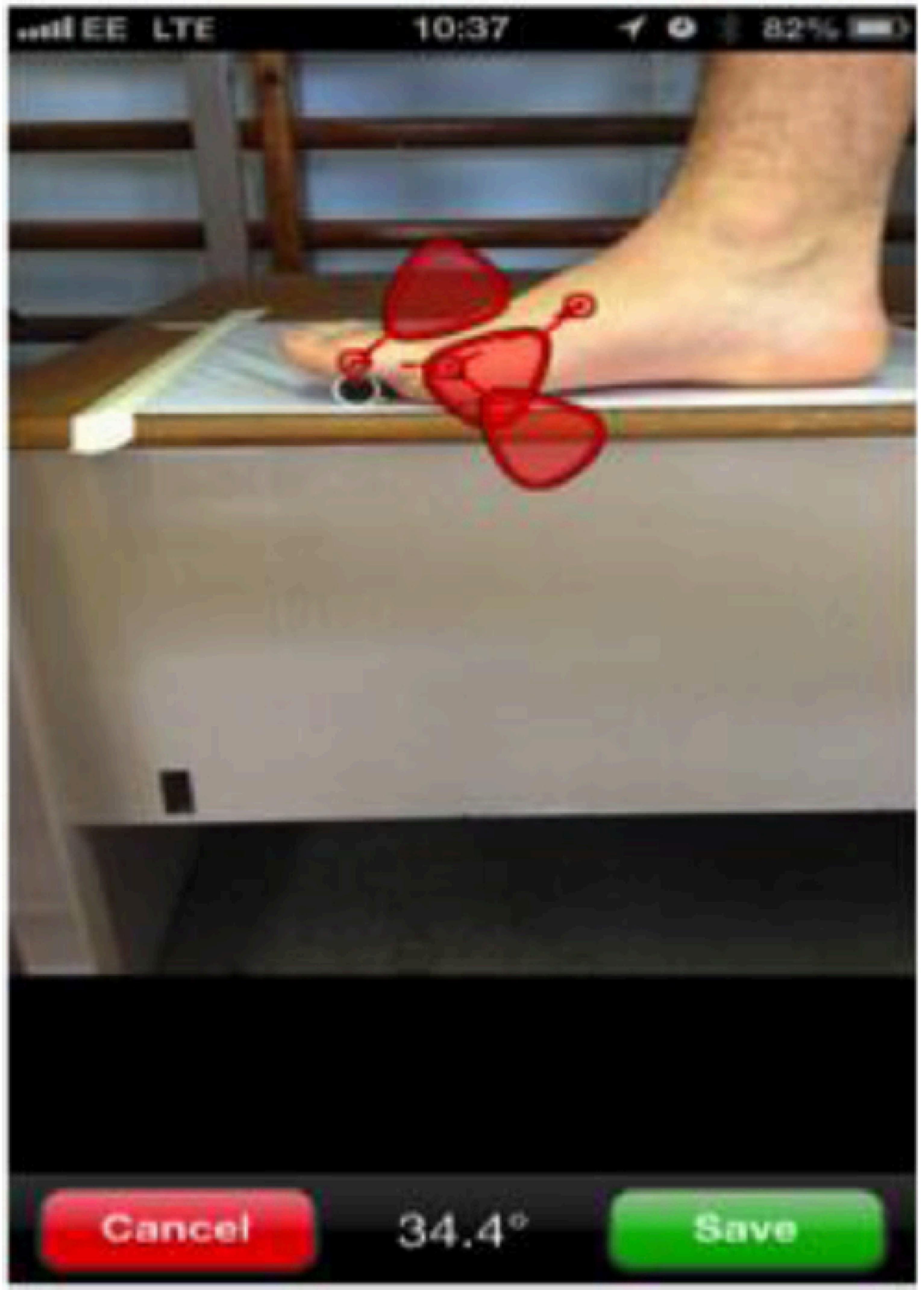


Fig. 2 Screenshot of smartphone app

Otter et al., 2015

Pedometer

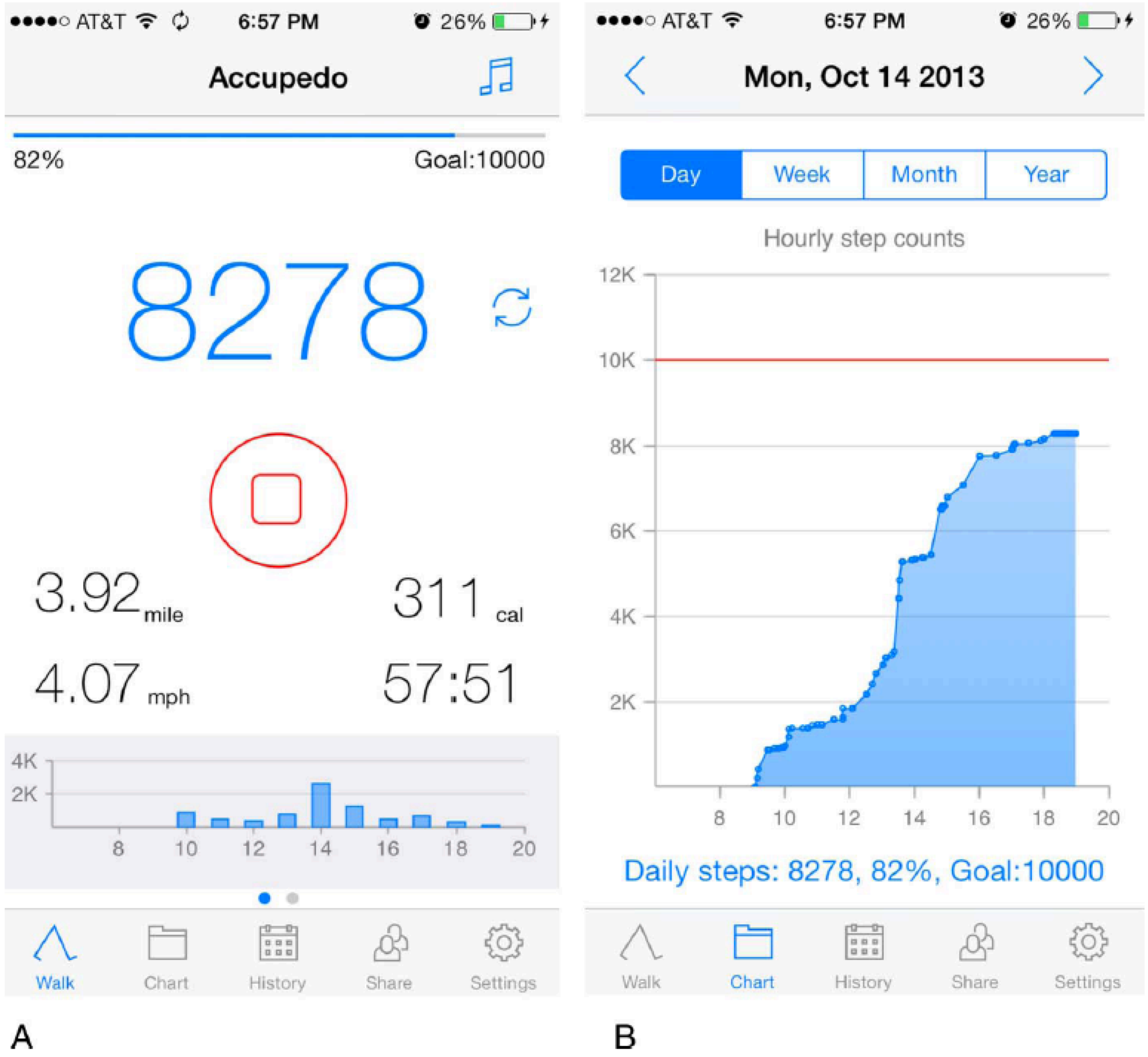


Figure 1 Screenshot of iOS Accupedo-Pro Pedometer user interface: (A) daily log history (step counts, distance, calories and walking time) and (B) charts (daily, weekly, monthly and yearly step counts).

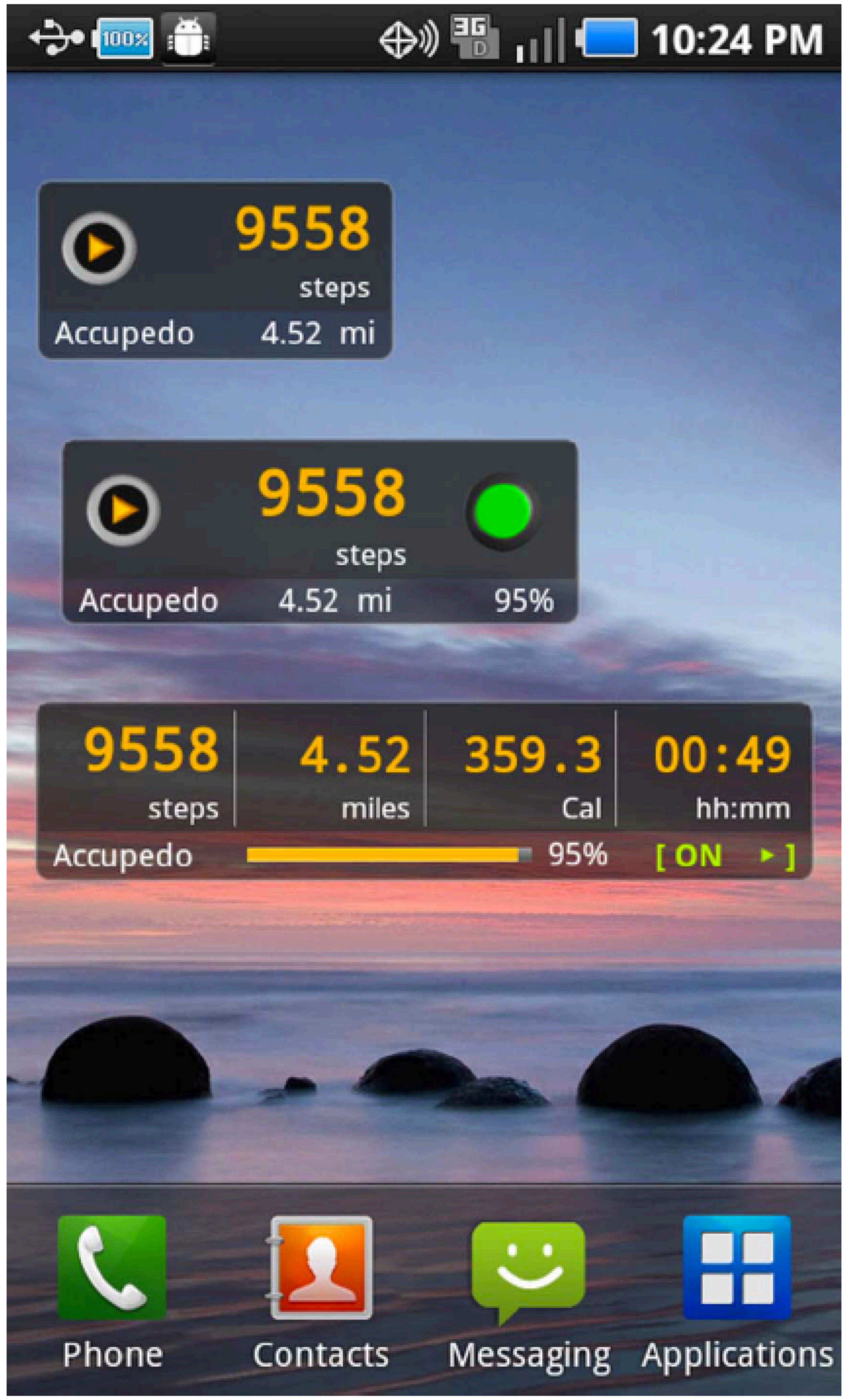


Figure 2 Screenshot of Android Accupedo-Pro Pedometer widget.

Milanović et al., 2016

Smartphone for core stability

2019 study example 1

Test-retest reliability of a smartphone app for measuring core stability for two dynamic exercises

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ABSTRACT

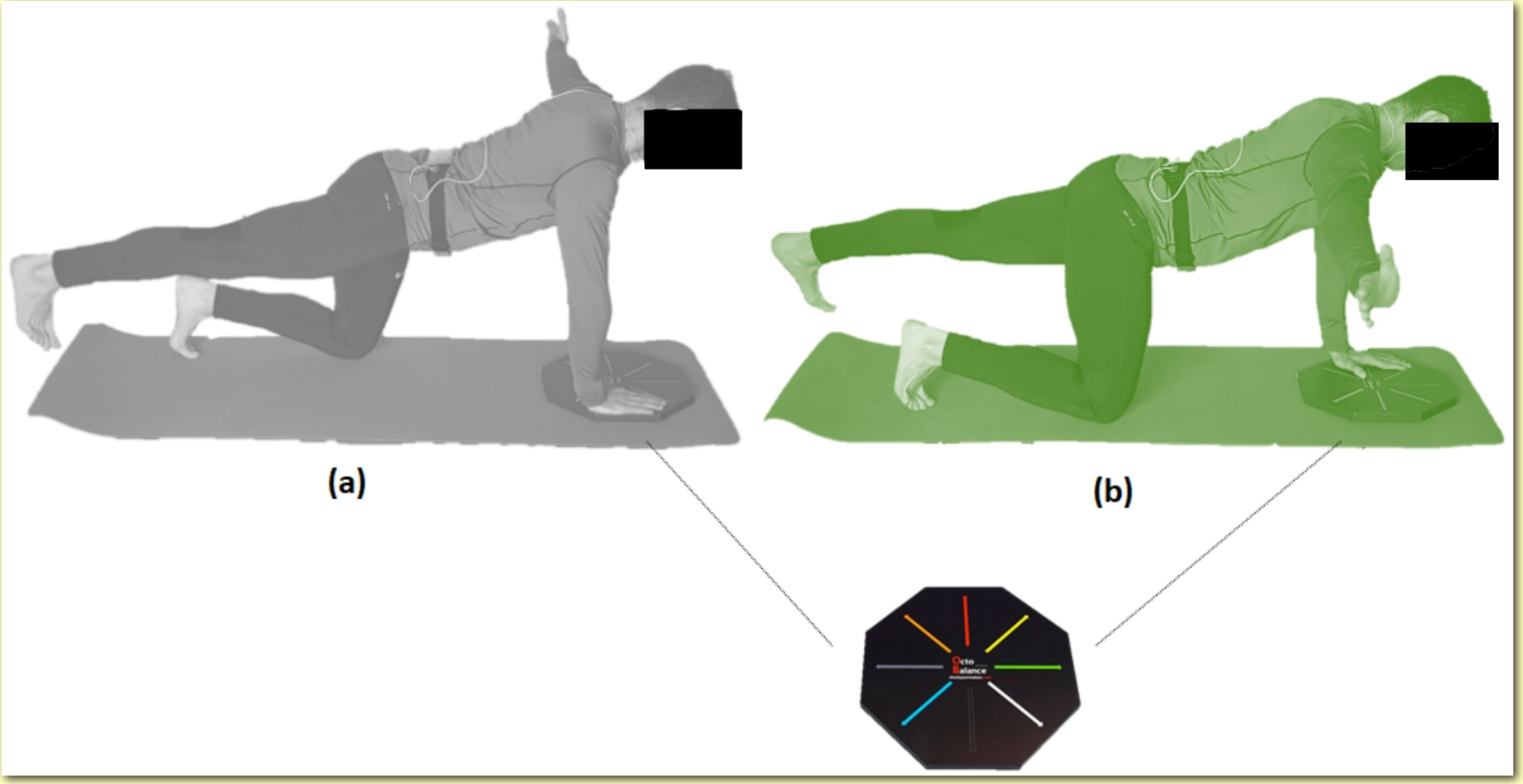
Background. Recently, there has been growing interest in using smartphone applications to assess gait speed and quantify isometric core stability exercise intensity. The purpose of this study was to investigate the between-session reliability and minimal detectable change of a smartphone app for two dynamic exercise tests of the lumbopelvic complex.

Methods. Thirty-three healthy young and active students (age: 22.3 ± 5.9 years, body weight: 66.9 ± 11.3 kg, height: 167.8 ± 10.3 cm) participated in this study. Intraclass correlation coefficient (ICC), coefficient of variation (%CV), and Bland–Altman plots were used to verify the reliability of the test. The standard error of measurement

Smartphone for core stability

Smartphone for core stability

2019 study example 1



Smartphone for core stability

2019 study example 1

Table 1 **Mean values and SD between-session reliability for the two lumbopelvic complex exercises ($n = 33$).**

		Day 1			Day 2									
		mean		**SD**	**mean**		**SD**	***p***	***d***	**CV%**	**ICC**	**95% CI**	**SEM**	**MDD**
Partial range single leg deadlift (SLD)	Right (mm/s-2)	11.8	±	3.0	12.6	±	3.4	0.114	0.3	4.8	0.87	0.75-0.94	1.1	2.9
	Left (mm/s-2)	13.1	±	4.1	12.9	±	3.2	0.934	0.0	0.9	0.87	0.74-0.94	1.5	3.4
	Composite (mm/s-2)	12.4	±	3.2	12.8	±	3.1	0.247	0.1	2.2	0.91	0.82-0.96	1.0	2.7
Variation of bird-dog (BD)	Right (mm/s-2)	9.4	±	3.0	8.9	±	2.9	0.860	−0.2	4.0	0.73	0.45-0.86	1.6	3.5
	Left (mm/s-2)	9.9	±	3.9	9.6	±	4.0	0.103	−0.1	2.2	0.89	0.78-0.95	1.3	3.1
	Composite (mm/s-2)	9.6	±	3.0	9.3	±	2.9	0.243	−0.1	2.5	0.96	0.91-0.98	0.6	2.1

Notes.
SD, standard deviation; *d*, effect size; CV%, coefficient of variation; 95% ICC, intraclass correlation coefficient; CI, confidence intervals; SEM, standard error of measurement; MDD, minimum detectable difference.

Smartphone for core stability

2019 study example 1

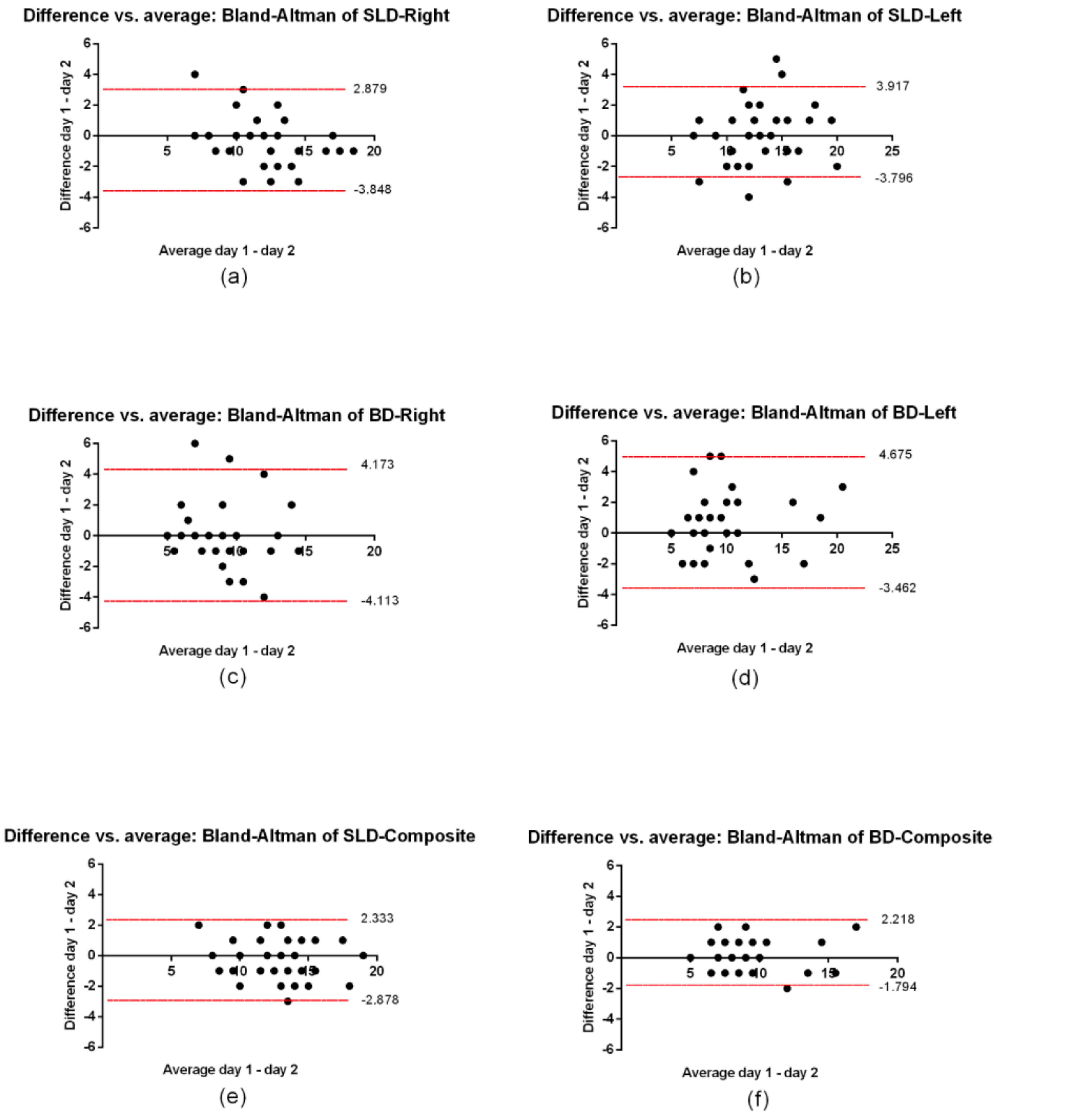


Figure 3 Bland–Altman plots representing mean differences and 95% limits of agreement between Day 1 and Day 2. (A) partial range single leg deadlift (SLD) right leg, (B) partial range single leg deadlift (SLD) left leg, (C) variation of bird-dog (BD) right leg, (D) variation of bird-dog (BD) left leg, (E) partial range single leg deadlift (SLD) composite (right and left), and (F) variation of bird-dog (BD) composite (right and left).

2019 study example 2

Smartphone for change of direction

JOURNAL OF SPORTS SCIENCES
https://doi.org/10.1080/02640414.2019.1640029

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The validity and reliability of a novel app for the measurement of change of direction performance

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[a]Department of Physical Education, Sport and Human Movement, Autonomous University of Madrid, Madrid, Spain; [b]Faculty of Science and Technology, London Sport Institute, Middlesex University, London, UK; [c]University School of Health and Sport (EUSES), University of Rovira Virgili, Amposta, Spain; [d]University School of Health and Sport (EUSES), University of Girona, Girona, Spain

ABSTRACT

The aim of the present investigation was to analyze the validity and reliability of a novel iPhone app (CODTimer) for the measurement of total time and interlimb asymmetry in the 5 + 5 change of direction test (COD). To do so, twenty physically active adolescent athletes (age = 13.85 ± 1.34 years) performed six repetitions in the COD test while being measured with a pair of timing gates and CODTimer. A total of 120 COD times measured both with the timing gates and the app were then compared for validity and reliability purposes. There was an almost perfect correlation between the timing gates and the CODTimer app for the measurement of total time ($r = 0.964$; 95% Confidence interval (CI) = 0.95–1.00; Standard error of the estimate = 0.03 s.; $p < 0.001$). Moreover, non-significant, trivial differences were observed between devices for the measurement of total time and interlimb asymmetry (Effect size < 0.2, $p > 0.05$). Similar levels of reliability were observed between the timing gates and the app for the measurement of the 6 different trials of each participant (Timing gates: Intraclass correlation coefficient (ICC) = 0.651–0.747, Coefficient of variation (CV) = 2.6–3.5%; CODTimer: ICC = 0.671–0.840, CV = 2.2–3.2%). The results of the present study show that change of direction

ARTICLE HISTORY
Accepted 29 June 2019

KEYWORDS
Sprinting; agility; biomechanics; technology; smartphone

Smartphone for change of direction

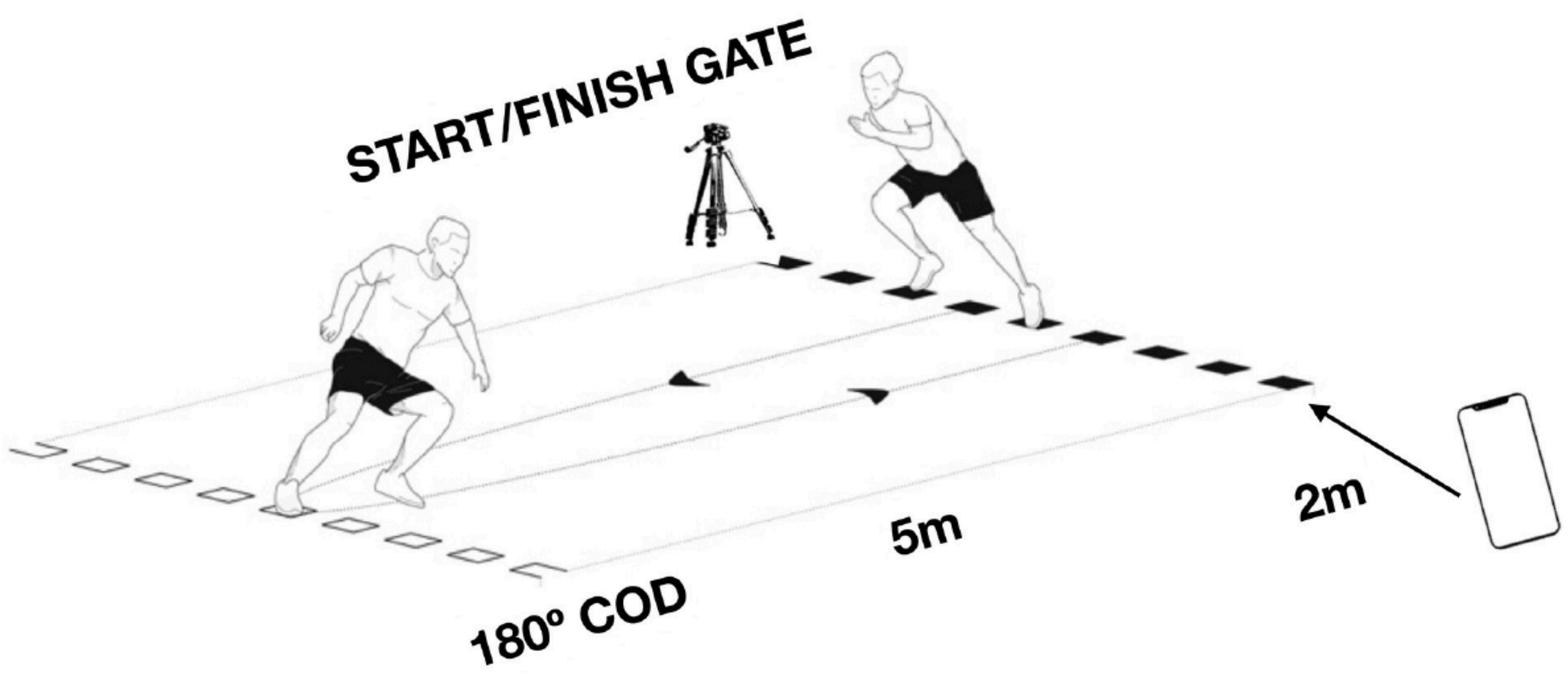
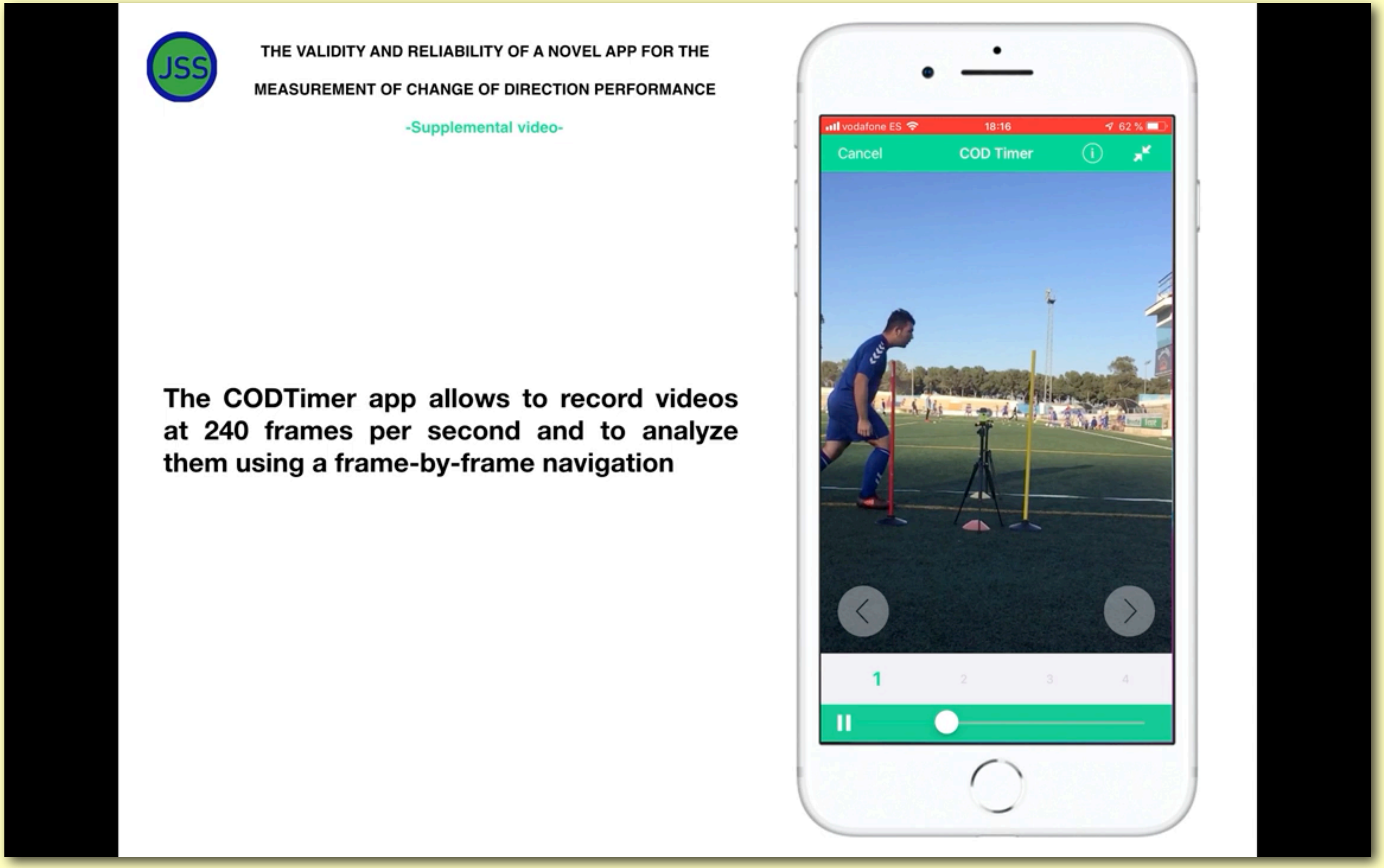


Figure 1. Schematic representation of the 5 + 5 change of direction test, showing were the timing gates and the smartphone were placed.

Smartphone for change of direction



Smartphone for change of direction

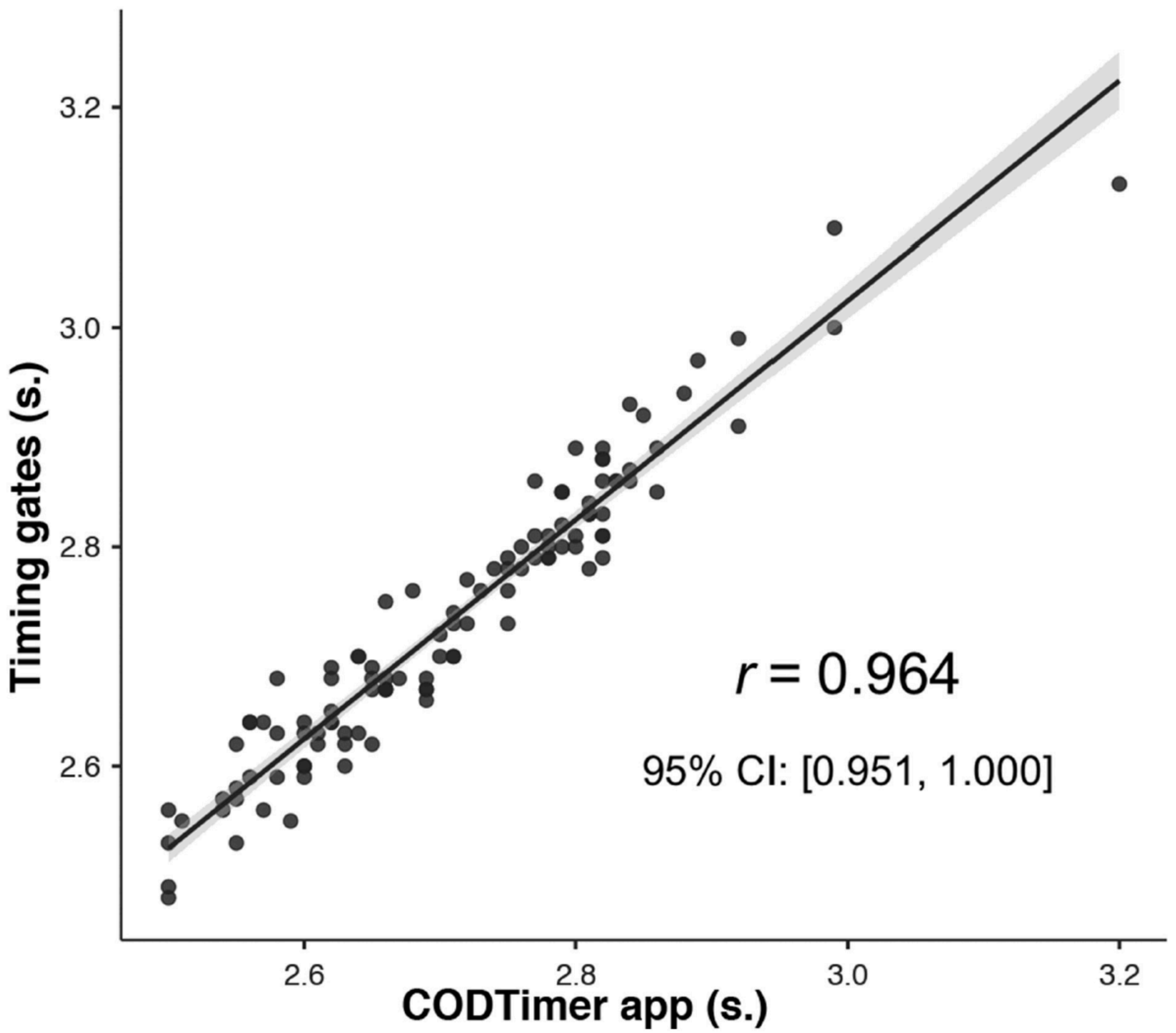


Figure 2. Linear regression between the *CODTimer* app and the timing gates for the measurement of total time in the change of direction test.

Smartphone for change of direction

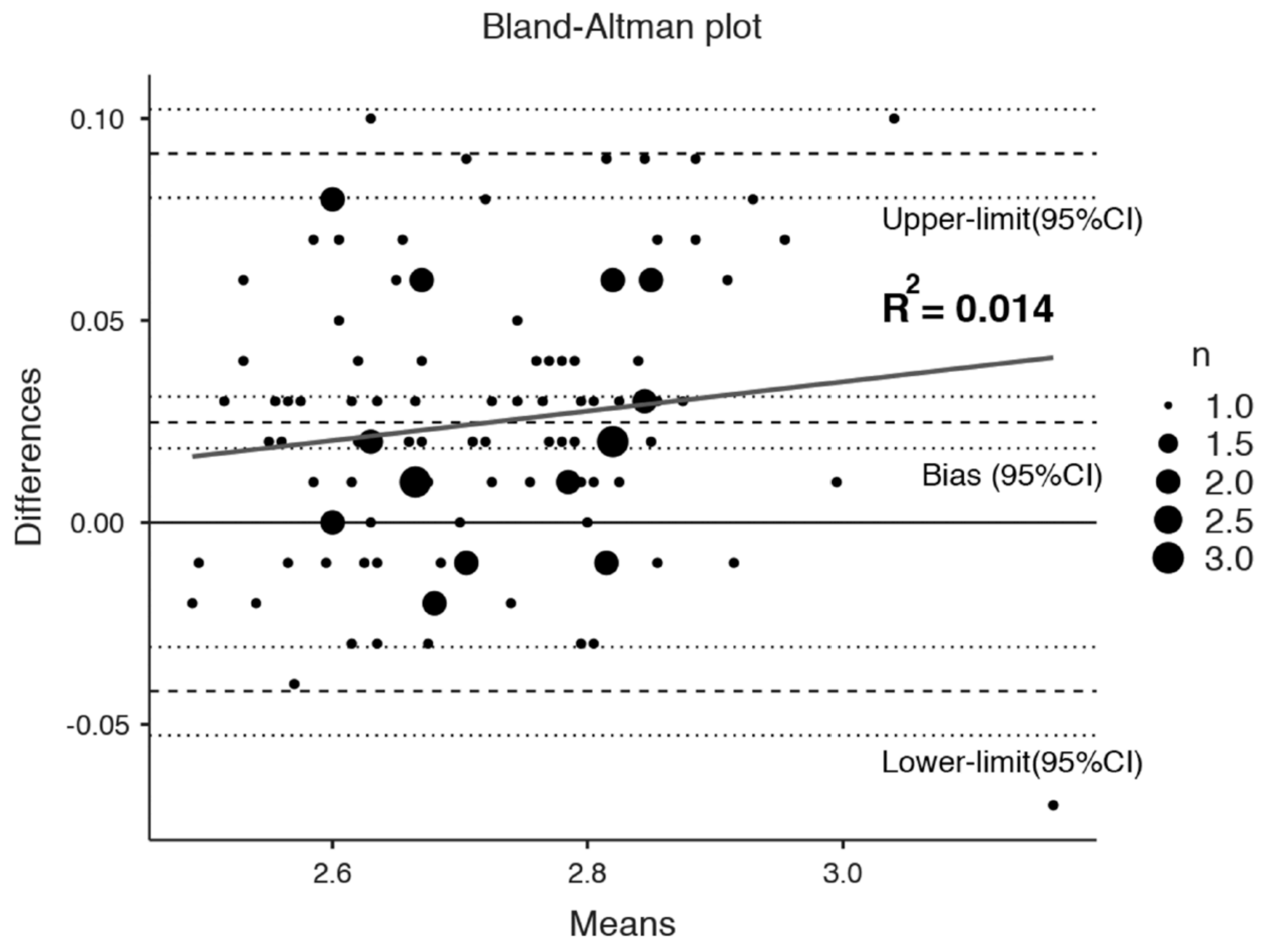


Figure 3. Bland-Altman plot showing the bias (with 95% CI) between instruments, its limits of agreement (±1.96 standard deviations), and the regression line of the residual (bold grey line). Overlapping points are represented with wider circles.

2019 study example 2

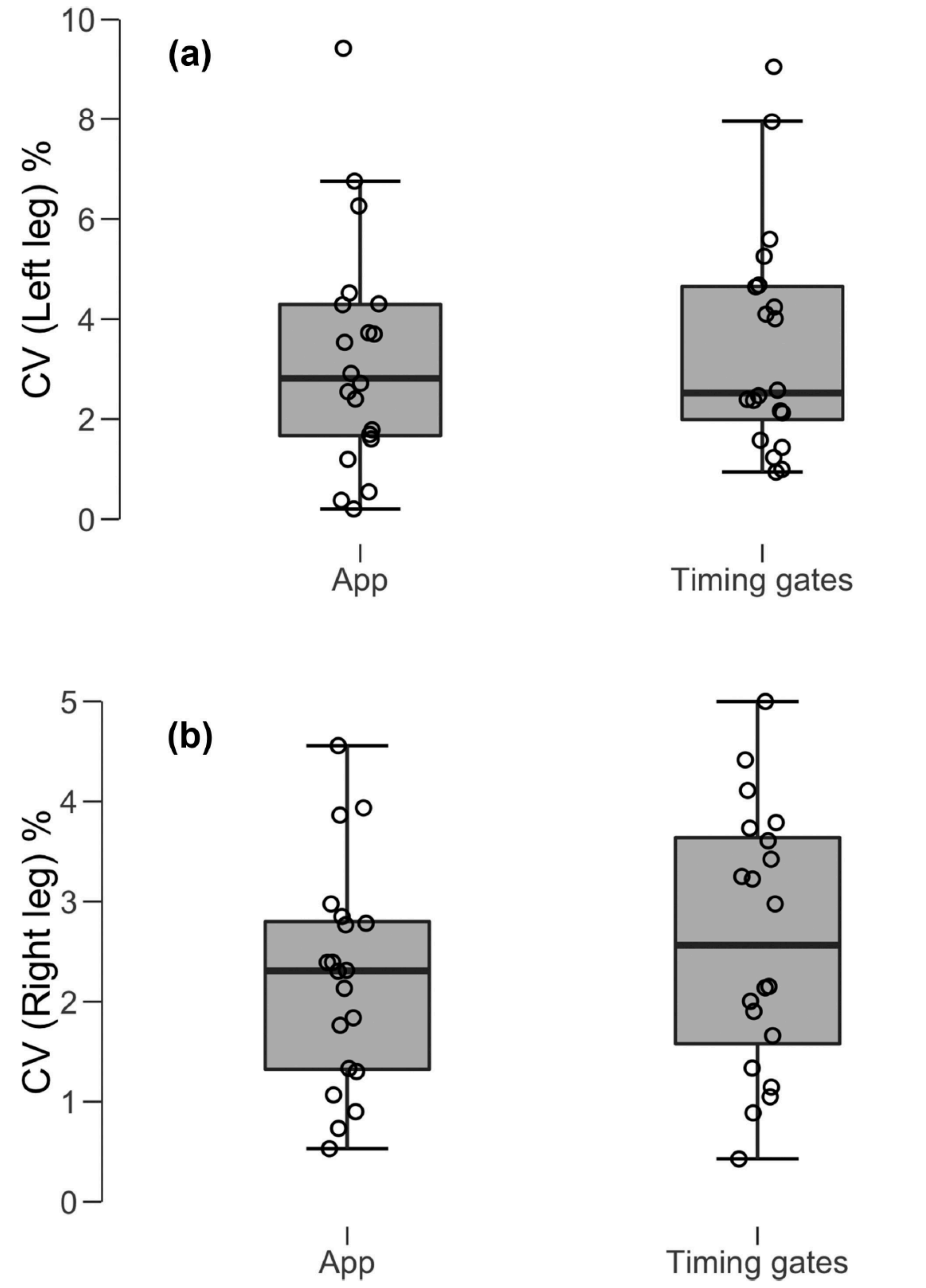


Figure 4. Boxplots with jitter points for the CVs of the different trials performed with each leg, and each instrument.

2019 study example 3

Smartphone for heart rate

INTERNATIONAL JOURNAL OF PERFORMANCE ANALYSIS IN SPORT
https://doi.org/10.1080/24748668.2019.1578097

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External training loads and smartphone-derived heart rate variability indicate readiness to train in elite soccer

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ABSTRACT
Player readiness can affect the ability to perform and tolerate prescribed training load (TL); therefore, in a time-efficient and practice compatible manner, practitioners need objective evidence to inform readiness to train. Six male professional footballers (mean ± standard deviation [SD]; 26 ± 2 years, 79.0 ± 4.9 kg, 1.82 ± 0.05 m) participated. Heart rate variability (HRV) was recorded using a smartphone application prior to the daily training sessions (247 training sessions [41.17 ± 7.41 per player]). External TL was monitored during training using global positioning system devices. Linear mixed models were used to examine variations in HRV and TL across the study period and to determine relationships

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KEYWORDS
Fatigue; performance; autonomic nervous system; recovery; football

Smartphone for heart rate

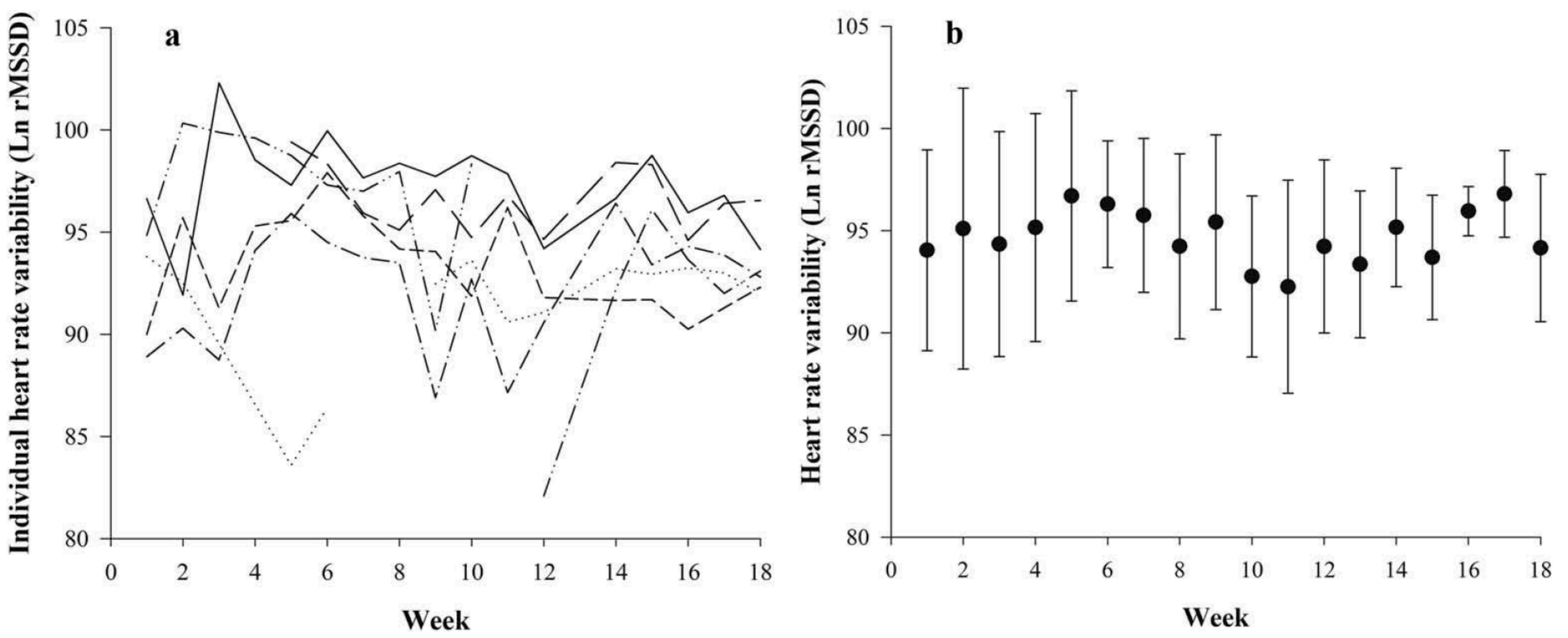


Figure 1. Individual mean weekly (A) and group mean and standard deviation (B) HRV responses across the 18-week study period.

Smartphone for heart rate

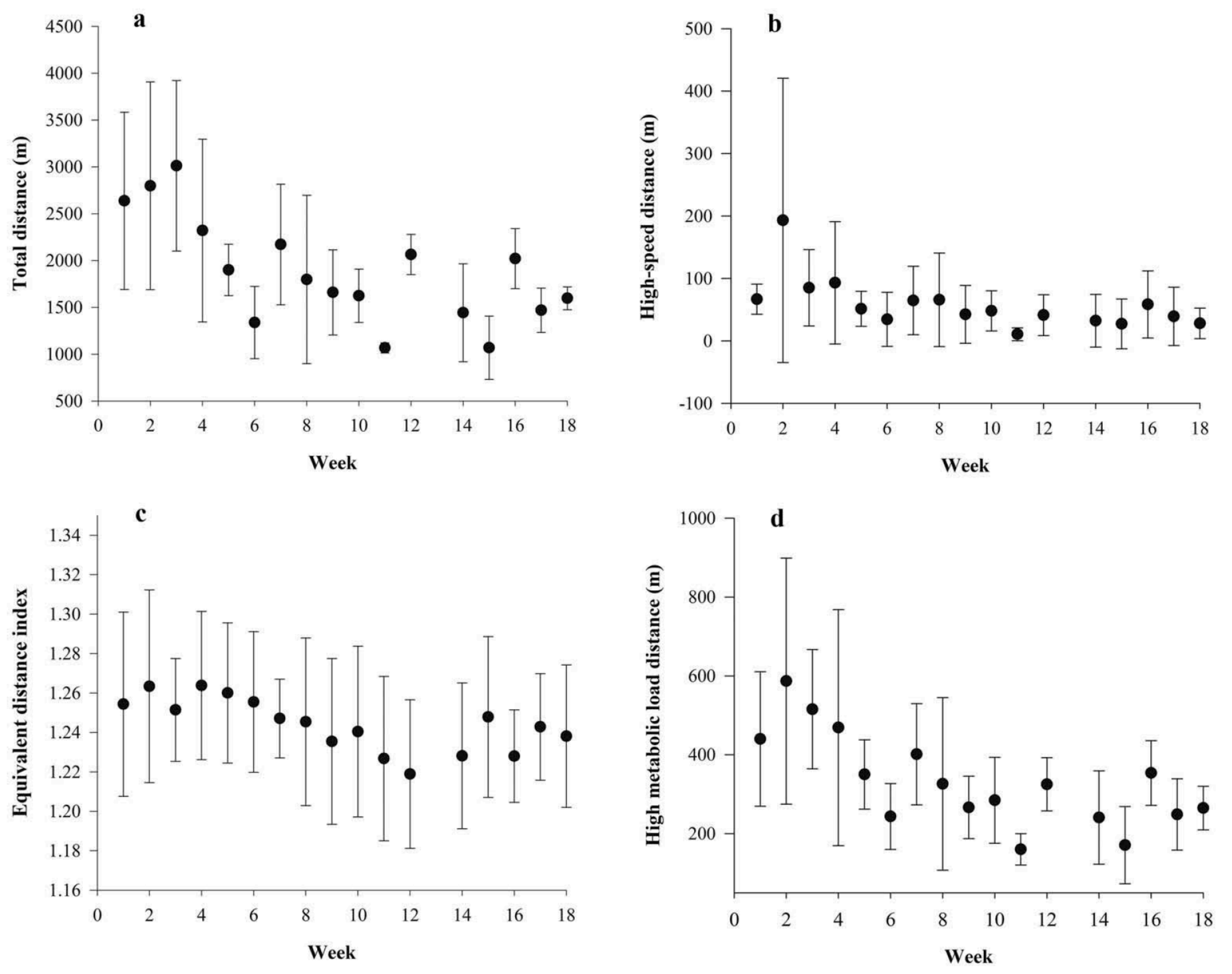


Figure 2. Group mean and standard deviation for external load variables across the 18-week study period. Part (A) Depicts total distance, (B) illustrates high-speed distance, (C) is equivalent distance index and (D) represents high-metabolic load distance.

Smartphone for heart rate

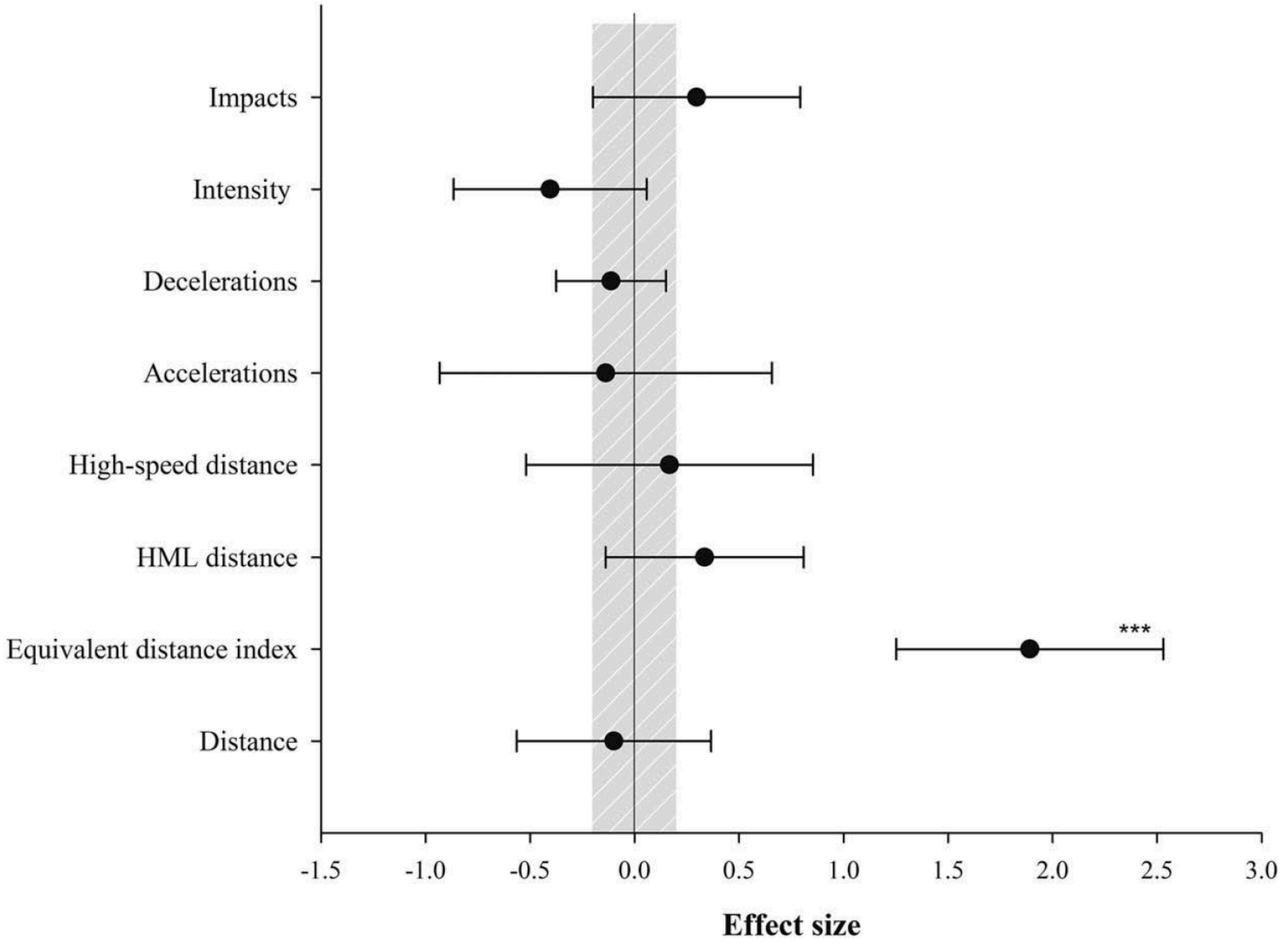
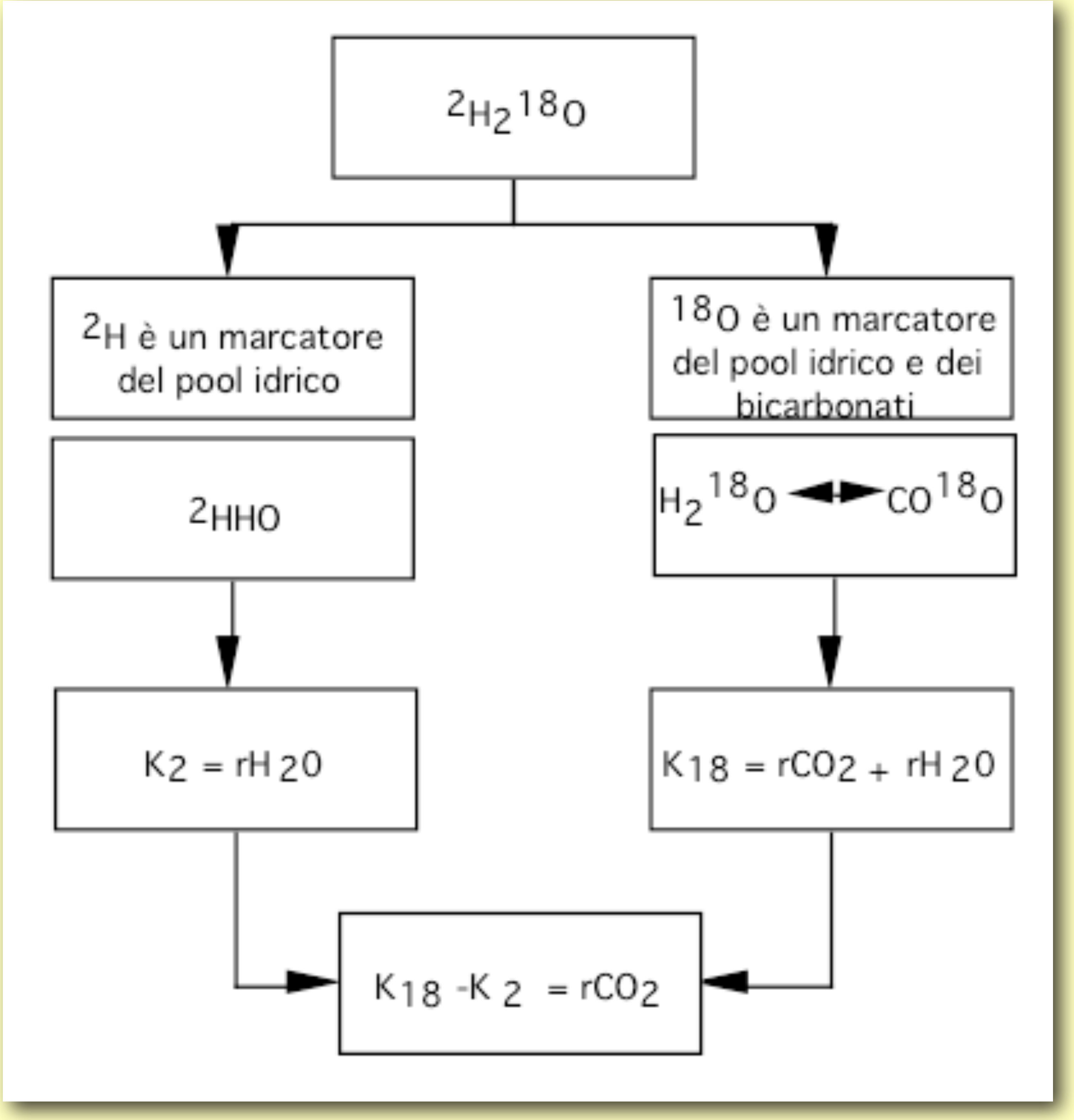


Figure 3. The association between each training load variable and daily heart rate variability. The grey shaded area represents the smallest worthwhile effect (0.2). *** = effect *most likely* >0.2. HML: High-metabolic load.

DLW method

- Lifson et al., 1955;
- (small animals) 1975;
- validation by Scholler et al., 1982;
- (premature infants, children, pregnant and lactating women, elderly, obese people, hospitalized patients);
- subject is administered a dose of stable isotope $^{2}H_2{}^{18}O$, which (^{2}H, ^{18}O) equilibrates relatively quickly with body water (H, O);
- ^{2}H is eliminated as $^{2}H_2O$ (breath, urine, sweat, perspiratio insensibilis), while the ^{18}O is eliminated either as $H_2{}^{18}O$ (breath, …) and as $C^{18}O_2$ (breathe only);
- difference between the two rates of elimination -> V'CO2 -> ME

DLW method


2H2 18O
2H è un marcatore del pool idrico
18O è un marcatore del pool idrico e dei bicarbonati
2HHO
H2 18O CO 18O
K2 = rH 20
K18 = rCO2 + rH 20
K18 -K 2 = rCO2