Innovative Methodology

J Appl Physiol 103: 682–692, 2007.
First published April 26, 2007; doi:10.1152/japplphysiol.00092.2006.

Hierarchy of individual calibration levels for heart rate and accelerometry to measure physical activity

Søren Brage,[1] Ulf Ekelund,[1] Niels Brage,[2] Mark A. Hennings,[1,3] Karsten Froberg,[2] Paul W. Franks,[1,4] and Nicholas J. Wareham[1]

[1]*MRC Epidemiology Unit, Cambridge, United Kingdom;* [2]*Institute of Sports Science and Clinical Biomechanics, University of Southern Denmark, Odense, Denmark;* [3]*Department of Pure Mathematics and Mathematical Statistics, Sydney Sussex College, University of Cambridge, Cambridge, United Kingdom; and* [4]*Genetic Epidemiology and Clinical Research Group, Department of Public Health and Clinical Medicine, Section for Medicine, Umeå University Hospital, Umeå, Sweden*

Submitted 24 January 2006; accepted in final form 23 April 2007

Brage S, Ekelund U, Brage N, Hennings MA, Froberg K, Franks PW, Wareham NJ. Hierarchy of individual calibration levels for heart rate and accelerometry to measure physical activity. *J Appl Physiol* 103: 682–692, 2007. First published April 26, 2007; doi:10.1152/japplphysiol.00092.2006.—Combining accelerometry with heart rate (HR) monitoring may improve precision of physical activity measurement. Considerable variation exists in the relationships between physical activity intensity (PAI) and HR and accelerometry, which may be reduced by individual calibration. However, individual calibration limits feasibility of these techniques in population studies, and less burdensome, yet valid, methods of calibration are required. We aimed to evaluate the precision of different individual calibration procedures against a reference calibration procedure: a ramped treadmill walking-running test with continuous measurement of PAI by indirect calorimetry in 26 women and 25 men [mean (SD): 35 (9) yr, 1.69 (0.10) m, 70 (14) kg]. Acceleration (along the longitudinal axis of the trunk) and HR were measured simultaneously. Alternative calibration procedures included treadmill testing without calorimetry, submaximal step and walk tests with and without calorimetry, and nonexercise calibration using sleeping HR and gender. Reference accelerometry and HR models explained >95% of the between-individual variance in PAI ($P < 0.001$). This fraction dropped to 73 and 81%, respectively, for accelerometry and HR models calibrated with treadmill tests without calorimetry. Step-test calibration captured 62–64% (accelerometry) and 68% (HR) of the variance between individuals. Corresponding values were 63–76% and 59–61% for walk-test calibration. There was only little benefit of including calorimetry during step and walk calibration for HR models. Nonexercise calibration procedures explained 54% (accelerometry) and 30% (HR) of the between-individual variance. In conclusion, a substantial proportion of the between-individual variance in relationships between PAI, accelerometry, and HR is captured with simple calibration procedures, feasible for use in epidemiological studies.

energy expenditure; monitoring; heart rate variability; accelerometry; movement sensor

ACCURATE QUANTIFICATION OF habitual physical activity is important to characterize the relationships between physical activity and health outcomes, to determine the interaction between physical activity and genetic factors, to monitor temporal trends at the population level, and to assess compliance to lifestyle interventions (24, 38, 60).[1] Of the available objective methods, heart rate (HR) monitoring has the advantage that, within an individual, HR displays a strong and relatively universal relationship with physical activity intensity (PAI) across different types of activity, at least at moderate to high intensities (55). However, because the accurate estimation of PAI via HR monitoring may require relatively resource-demanding procedures for individual calibration, this method is less feasible in large-scale studies.

Traditionally, individual calibration has been performed by simultaneously measuring HR and energy expenditure via respiratory gas exchange at rest and during a graded exercise test preferably covering a wide-intensity range. Recently, however, more feasible calibration procedures have been proposed to account for the between-individual variance in HR-PAI relationships (2, 11, 48). Sources of this variance include acute and chronic differences in stroke volume, hemoglobin concentration, and the fraction of hemoglobin saturated with O_2 in both arterial and venous blood. Direct or indirect assessment of these parameters may account for some of the between-individual variance in HR-PAI relationships (28, 29, 32).

In a sample of Caucasian adults, we previously reported that the precision of PAI prediction equations improves by incorporating information obtained from a simple low-to-moderate intensity step test (10). However, the extent to which measurement of respiratory gas exchange during a step test further improves precision remains uncertain. In addition, the utility of a simple walking test has not been fully explored in the context of HR-PAI calibration. It is also unknown whether measures of HR variability account for meaningful fractions of the variance in the HR-PAI relationship. Furthermore, individual calibration of accelerometry (ACC) measures with PAI has not been explored in depth, although the utility of calibrating ACC data to an individually assessed reference activity, such as treadmill walking, has been reported for free-living adolescents (20). The validity of such procedures in other scenarios and populations is, however, uncertain (11, 15).

The objective of this study was to evaluate several procedures for individual calibration, suitable for use in a range of study settings, against the reference procedure: a treadmill test with indirect calorimetric assessment of PAI covering a wide intensity range. We did this for ACC-PAI and HR-PAI relationships separately and also assessed whether combined ACC and HR monitoring improved the estimation of PAI across the

[1] Supplemental material for this article is available online at the *Journal of Applied Physiology* website.

Address for reprint requests and other correspondence: S. Brage, MRC Epidemiology Unit, Elsie Widdowson Laboratory, Fulbourn Road, Cambridge CB1 9NL, UK (e-mail: soren.brage@mrc-epid.cam.ac.uk).

The costs of publication of this article were defrayed in part by the payment of page charges. The article must therefore be hereby marked "*advertisement*" in accordance with 18 U.S.C. Section 1734 solely to indicate this fact.

levels of individual calibration, as this would likely improve precision (3, 10–12, 27, 30, 39, 43, 47, 52, 53, 58, 59).

METHODS

Participants

A total of 26 women and 25 men were recruited from the Cambridge area (UK). Participants were free from cardiopulmonary and metabolic diseases. Ethical approval for the study was obtained from the local research ethics committee. All participants provided written, informed consent.

Study Procedure

Participants were asked to refrain from eating, drinking (except water), smoking, and vigorous exercise for at least 2 h before they arrived at the laboratory. We measured height and weight of subjects in light clothing using a rigid stadiometer and calibrated scales, respectively. Body fat percentage was assessed with the four-compartment model (65) using dual X-ray absorptiometry (Lunar Prodigy; GE Healthcare), air-displacement plethysmography (BodPod; Life Measurement), and heavy water dilution (174 mg of $H_2{}^{18}O$ and 70 mg of ^2H_2O per kg body wt). After light preparation of the skin, ECG electrodes (Red Dot 2570; 3M) were applied on the left side of the chest, with the medial electrode placed just below the apex of the sternum and the lateral electrode placed 12–13 cm horizontally from there [lower position (9)]. Participants were fitted with a combined HR and movement sensor (Actiheart; Cambridge Neurotechnology). The accelerometer in this device has a linear ($R^2 = 0.999$) response to acceleration (10) and was oriented to measure acceleration along the body's longitudinal axis. The HR sensor detects the location of the QRS complex by a differential voltage threshold method and subsequent interpolation and records the intervals between R waves [interbeat interval (IBI)] and average HR, ignoring indiscernible waveforms (10, 44).

Each participant completed four main components of the study, which included a rest test, a step test, a treadmill test, and a free-living observation period for measurement of sleeping HR (SHR). An interval, sufficient to allow HR to return to within 20% of resting HR and lasting no less than 10 min, separated the step and treadmill tests.

Energy Expenditure

Energy expenditure during rest, step, and treadmill tests was measured via indirect calorimetry (Oxycon Pro; Jaeger). Before each test, the vanes that measure respiratory ventilation were calibrated against two known flow rates (0.2 and 2.0 l/s), and gas analyzers were calibrated against gases of known concentration (5% CO_2 and 0% O_2) and room air, as recommended by the manufacturer. This system has been validated previously (49). Energy expenditure was calculated according to Weir (61) (expressed in $J \cdot min^{-1} \cdot kg^{-1}$). Respiratory gas-exchange data were collected on a breath-by-breath basis and initially averaged over 15-s epochs, disregarding the two most extreme values in each interval, which were subsequently smoothed by a three-epoch moving average (except for the last epoch).

Rest Test

Resting HR and resting metabolic rate (RMR) over 45 min were assessed with a ventilated hood with the indirect calorimetry system described above, ~1 h after arrival at the test center. The average of *minutes 7–45* was used in the analyses. Total hemoglobin concentration was measured from a finger-prick blood sample (B-Hemoglobin Analyzer; HemoCue).

Step Test

Participants underwent an 8-min step test as described previously (10). Briefly, participants were instructed to progressively increase their step frequency, dictated by audible metronome (supplied with Actiheart software), ramping up after the first minute from 15 to 32.5 body lifts/min (rate of change: 2.5 body lifts/min^2) on a 215-mm high step. The step test was terminated earlier if HR exceeded 90% of age-predicted maximal HR (56) or if the participant was unable to maintain the prescribed step frequency, even after verbal encouragement from the investigator. After test termination, seated HR recovery was measured for 2 min. The combined sensor was configured to record ACC and ECG waveforms (32 and 128 Hz sampling, respectively), summarized in 15-s epochs. Respiratory gas exchange during the step test and the recovery period was measured with the use of a facemask with the indirect calorimetry system described above. PAI was calculated by subtracting RMR from total energy expenditure (61).

For each individual, two sets of ACC-PAI and HR-PAI slopes (β_{step}) and intercepts (α_{step}) were derived with the use of all data in the test phase except the first minute; one set of parameters [$\beta_{step\ (\dot{V}O_2)}$ and $\alpha_{step\ (\dot{V}O_2)}$, where $\dot{V}O_2$ is oxygen consumption] used the measured PAI during the step test, and a second set of parameters [$\beta_{step\ (no\ \dot{V}O_2)}$ and $\alpha_{step\ (no\ \dot{V}O_2)}$] used estimated PAI for each epoch, based on the average for the whole group, except the individual for whom the calibration was being derived. Thus the latter procedure represents a step-test calibration without measurement of PAI but with knowledge about the "normal" PAI response to this protocol. Fast Fourier transformation of the acceleration waveform for each epoch was used to calculate deviance (Δsteps/min) from the prescribed step frequency, with the assumption that the spectral power peak within four steps per minute of the prescribed frequency represents the actual step frequency. Regressions using estimated PAI were adjusted for the fast Fourier transformation-assessed deviance from the prescribed protocol frequency.

Time- and frequency-domain measures of HR variability [root mean square of successive IBI differences (RMSSD), low-frequency power (LF), high-frequency power (HF), and LF-to-HF ratio] during *minutes 2–5* of the step test were derived as described elsewhere (1). Beat-by-beat HR recovery over 90 s was regressed (quadratic), from which another individual calibration parameter, recovery $HRaS_{step}$, was expressed as the HR above SRH (HRaS) at 1-min recovery time.

Treadmill Test

The Oxycon Pro was configured to control a motorized treadmill (HP Cosmo Pulsar 4.0). A ramped treadmill protocol consisting of three main test phases was used. *Phase 1* (level walking) involved level walking with increasing speed (3 min at 3.2 km/h and then accelerating at 0.33 $km \cdot h^{-1} \cdot min^{-1}$ for the next 6 min), *phase 2* (graded walking) consisted of brisk walking (5.2–5.8 km/h) with increasing gradient (at a rate of 1.7% increased gradient/min for 6 min), and *phase 3* (level running) involved level running with speed increasing from 9 to 12.5 km/h for 4.5 min (average acceleration of 0.78 $km \cdot h^{-1} \cdot min^{-1}$). Transition between *phases 2* and *3* was first a change in gradient by −10.2% over 30 s (now level), followed by a change in speed by +3.2 km/h over 30 s. The treadmill protocol was terminated earlier if the participant wished to stop, if the respiratory exchange ratio exceeded 1.0, or if HR exceeded 90% of the age-predicted maximal HR (56). Energy expenditure, ACC, and HR were measured and summarized as described above for the step test, except that the combined sensor was configured to record all IBIs and to summarize ACC across 15-s epochs.

As for the step test, two sets of calibration parameters for both ACC-PAI and HR-PAI were derived: one set [$\beta_{tread\ (\dot{V}O_2)}$ and $\alpha_{tread\ (\dot{V}O_2)}$] was based on measured PAI. This level represents our reference calibration level (see below). The other parameter set [$\beta_{tread\ (no\ \dot{V}O_2)}$ and $\alpha_{tread\ (no\ \dot{V}O_2)}$] was based on estimated PAI at each time point in the treadmill test, calculated as the average PAI of all individuals except the one for whom the estimate was intended. For individuals without running data, we used the group average for this segment of their ACC-PAI relationship. In addition, we derived sets of individual treadmill calibration parameters, disregarding the running phase of the protocol (models with subscript "excl run").

Walk Test

The first 3 min of the treadmill test was used as an ultrashort walk-test calibration. Average ACC and HRaS of *minute 3* were expressed relative to either measured or estimated PAI ($ACC_{3\text{-min walk}}$ = PAI/ACC and $HRaS_{3\text{-min walk}}$ = PAI/HRaS, respectively). HR variability measures for the walk calibration were derived in the same time interval and as otherwise described for the step test.

Calibration Variables Obtained From Free-Living Data

The combined sensor was configured to record ACC, HR, and the four most extreme IBIs in each 1-min epoch during at least 1 wk of free living. From these data, SHR was derived (10). HR above SHR (HRaS) was calculated as HR minus SHR. It is assumed that information about age, gender, height, weight, and SHR would be available as means of calibration when employing objective monitoring in epidemiological settings.

Calibration Levels

Seven main levels of individual calibration of the ACC-PAI relationship and the HR-PAI relationship were developed: *1*) individually determined ACC-PAI and HR-PAI relationships during treadmill locomotion (reference level), *2*) ACC and HR response to the treadmill protocol without measurement of PAI, assuming that all individuals expend the same amount of physiological energy at any given workload, *3*) measurement of ACC, HR, and PAI during the step test, *4*) ACC and HR responses to the step test without measurement of PAI, *5*) measurement of ACC, HR, and PAI during a 3-min walk, *6*) ACC and HR response to a 3-min walk without measurement of PAI, and *7*) nondynamic calibration where only variables such as age, gender, height, weight, and SHR of the individuals are known. Calibration levels of HR-PAI were extended with hemoglobin concentration.

Calculations and Statistics

HR data were cleaned before analysis (9). IBI data were manually inspected for missed and ectopic beats before measures of HR variability were derived (4, 5); these were subsequently log transformed.

Derivation of models. The first 3 min of the treadmill test and 1 min of phase transition between *phases 2* and *3* were excluded for derivation of PAI models. Segmented linear models for the ACC-PAI relationship were established using level walking and level running data separately, between which interpolation was used to connect the two equations. The ACC-PAI equation was extended downward to a flex movement point equal to 50% of mean ACC at 3.2 km/h. Stepwise multiple linear regression for time series (ANOVA repeated measures with random effects on individual level) was used to derive final prediction PAI models for all levels of individual calibration. Initial models included all terms available for the level in question, including interaction terms (products) for ACC and HRaS with variables that could plausibly influence the ACC-PAI and HRaS-PAI slopes, respectively. Interaction terms were only included together with the singular terms from which they were computed. Exceptions to this rule were β (slope) variables, which were only entered as interaction terms but always accompanied by its corresponding α (intercept) variable (see above). Variables were removed to maximize the explained variance between individuals with the fewest degrees of freedom.

Cross-validation. All derived PAI models and corresponding branched equation estimates (11) for combining HR and ACC were cross-validated separately for each treadmill phase using the Student's Jackknife approach ("leave-one-out"), i.e., calculating predictions of PAI from *n* permutations of the equations derived on the whole sample except data from the individual for whom the equation prediction was intended ($n - 1$) and then comparing this against that observed (26). Branch parameters *x*, *y*, and *z* were set at 0.075 m/s^2, transition HRaS, and flex HRaS, respectively (the latter 2 expressed as functions of SHR), using a priori weightings of the HR-PAI relationship of 90%, 50%, 50%, and 10%, for branch boxes 1–4, respectively (11). The cross-validation of the two equations using calibration via ramped treadmill testing is not an independent cross-validation of these two levels, as each individual's HR data are used in both derivation and validation and for the reference calibration level; this is also true for the PAI data. These two levels of individual calibrations are included in the cross-validation for the purpose of comparison. Bland-Altman plots were produced (7), and the association between estimation error and measured PAI was tested with Pearson correlation. Mean signed error and root mean squared error (RMSE) values were calculated. ANOVA repeated measures were used to test differences between estimated and measured PAI and differences in estimation accuracy (RMSE) between calibration models. Previously published PAI prediction equations (10, 32), combined by branched equation modeling (where applicable), were cross-validated in a similar manner. In addition, the step-test data were used in a different capacity to examine the precision by which the treadmill-derived ACC-PAI and HR-PAI models and their branched model combinations could capture PAI measured during stepping (disregarding the first 3 min). All analyses were conducted with STATA SE 9.2 (StataCorp).

RESULTS

Participant characteristics are shown in Table 1. SHR was higher in women ($P = 0.022$), but neither resting HR nor RMR measured in the laboratory differed by gender ($P \geq 0.42$). The

Table 1. *Participant characteristics*

	Women (n = 26)			Men (n = 25)			All (n = 51)	
	Mean	SD	Range	Mean	SD	Range	Mean	SD
Age, yr	35.1	(9.7)	22–54	34.2	(8.8)	23–49	34.7	(9.2)
Weight, kg	61.7	(9.4)	48–81	78.9*	(12.4)	53–104	70.1	(13.9)
Height, m	1.62	(0.06)	1.5–1.8	1.77*	(0.06)	1.7–1.9	1.69	(0.10)
Body-mass index, kg/m^2	23.7	(3.8)	19–34	25.1*	(3.1)	19–32	24.4	(3.5)
Body fat, %	31.8	(7.5)	15–46	22.0*	(7.9)	8–35	27.0	(9.1)
Sleep HR, beats/min	55.4	(6.9)	39–71	51.3*	(5.4)	40–58	53.4	(6.5)
Rest HR, beats/min	59.9	(8.5)	39–76	58.4	(10.1)	46–93	59.2	(9.2)
Hemoglobin, g/dl	13.5	(1.1)	11–15	15.3*	(0.65)	14–17	14.4	(1.3)
RMR, J$\cdot$min$^{-1}\cdot$kg^{-1}	61.8	(6.3)	50–71	63.5	(8.1)	49–82	62.6	(7.2)
$\dot{V}O_{2max}$, ml$\cdot$min$^{-1}\cdot$kg^{-1}	34.2	(8.0)	21–54	44.4*	(10.9)	24–64	39.2	(10.7)

RMR, resting metabolic rate; HR, heart rate; $\dot{V}O_{2max}$, oxygen consumption at age-predicted maximal HR. *$P < 0.05$ different from women.

relationship between resting HRaS and SHR was 0.066 SHR + 2.2. Both hemoglobin concentration and maximal $\dot{V}O_2$ (estimated by extrapolating the HR-$\dot{V}O_2$ relationship to age-predicted maximum HR) were higher in men ($P < 0.001$).

Step-Test Calibration Parameters

All but five participants completed the 8-min step test. One completed only 5 min, and four individuals completed 7 min. As shown in Fig. 1, PAI increased in a linear fashion after the first minute of stepping [R^2 = 0.72, standard error of the estimate (SEE) = 43 $J \cdot min^{-1} \cdot kg^{-1}$, $P < 0.001$]. The conversion factor between physical lift work rate and PAI was 6.0 and was similar in men and women (P = 0.47). The ACC-PAI relationship during the step test was equal to 129 ACC + 136 (R^2 = 0.42, SEE = 55 $J \cdot min^{-1} \cdot kg^{-1}$, $P < 0.001$). The corresponding HR-PAI relationship during the step test was 4.4 HRaS + 21 gender − 4.2 SHR + 263 (R^2 = 0.43, SEE = 54 $J \cdot min^{-1} \cdot kg^{-1}$, $P < 0.001$). Median (interquartile range) values for LF/HF_{step}, $RMSSD_{step}$, and recovery $HRaS_{step}$ during step test were 2.7 (1.1–5.5), 13.1 (7–26) ms, and 32.9 (19–49) beats/min, respectively, with the latter two being significantly correlated with each other (r = −0.66, $P < 0.001$).

Walk Calibration Parameters

Mean (SD) PAI, ACC, and HRaS values during *minute 3* of treadmill walking were 152 (26) $J \cdot min^{-1} \cdot kg^{-1}$, 0.91 (0.2) m/s^2, and 35 (14) beats/min, respectively, from which the walk-test calibration parameters were computed. Mean (SD) values during $ACC_{3\text{-min walk }(\dot{V}O_2)}$ and $HRaS_{3\text{-min walk }(\dot{V}O_2)}$ were 179 (54) $J \cdot min^{-1} \cdot kg^{-1} \cdot m^{-1} \cdot s^2$ and 4.9 (2) $J \cdot kg^{-1} \cdot beat^{-1}$, respectively. Median (interquartile range) values for walking LF/HF_{walk} and $RMSSD_{walk}$ were 3.1 (1.1–4.9) and 22.1 (14–40) ms, respectively.

Derivation of PAI Models for Walking and Running

Median (range) treadmill test duration was 20 (13.5–20.5) min. All but 3 participants completed the two first treadmill phases, and all but 10 individuals did at least 1 min of running. As shown in Fig. 1, PAI increased continuously throughout the

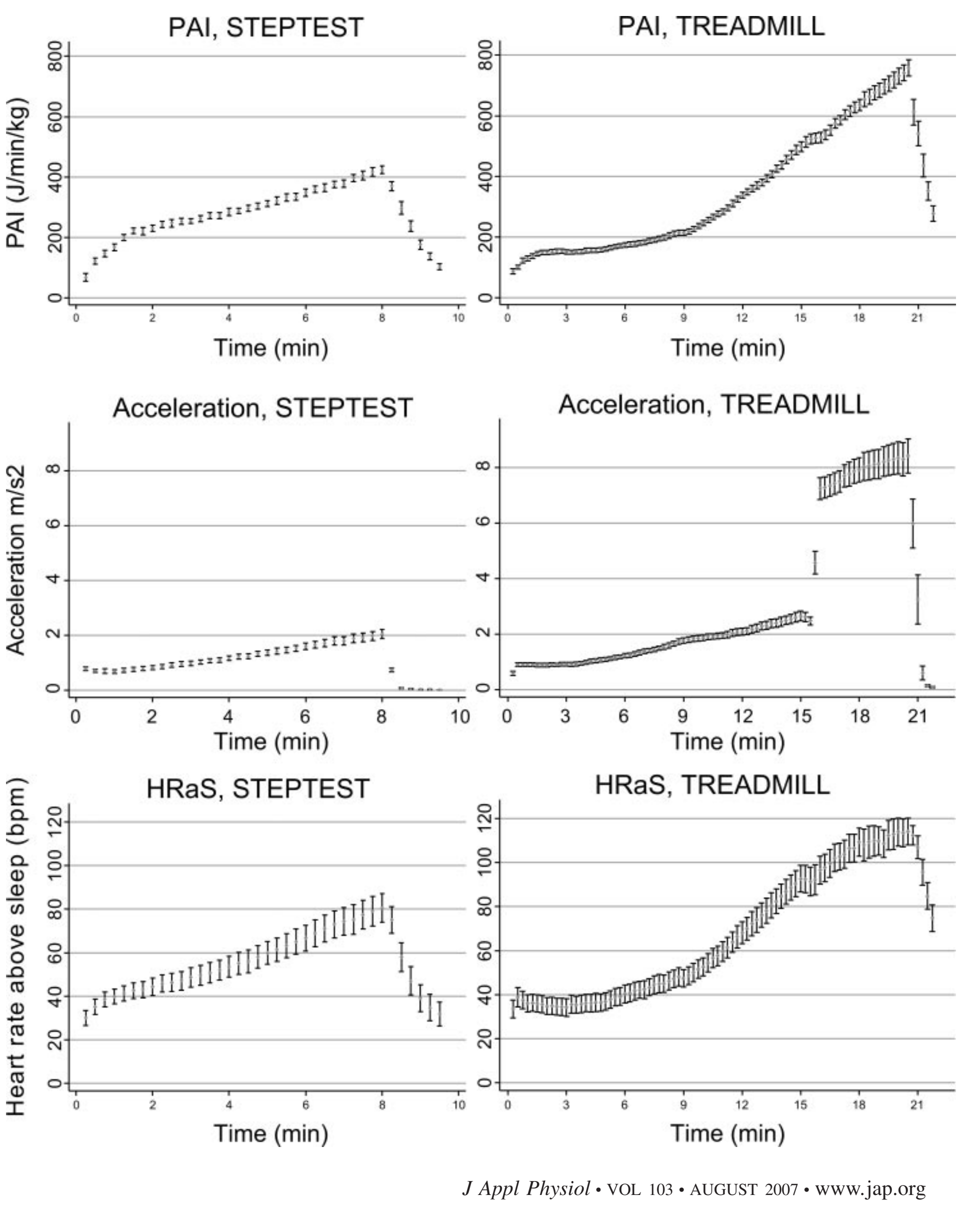

Fig. 1. Mean physical activity intensity (PAI; $J \cdot min^{-1} \cdot kg^{-1}$), trunk acceleration ($m/s^2$), and heart rate above sleep (HRaS; beats/min) response to an 8-min ramped step test (*left*) and a 20.5-min ramped treadmill test (*right*), consisting of level walking (0–9 min, 3.2–5.2 km/h), graded walking (9–15 min, 0–10.2%, 5.2–5.8 km/h), and level running (16–20.5 min, 9–12.5 km/h). bpm, Beats/min. Recovery phase data are included. Error bars are 95% confidence intervals.

treadmill test and more steeply during the graded walking [mean (SD) = 350 (96) $J \cdot min^{-1} \cdot kg^{-1}$] and level running phases [mean (SD) = 651 (82) $J \cdot min^{-1} \cdot kg^{-1}$] than during the level walking phase [mean (SD) = 176 (34) $J \cdot min^{-1} \cdot kg^{-1}$]. HR followed much the same pattern, but ACC displayed more distinct clusters in the three treadmill phases and was closely related to speed ($R^2 = 0.91$). Mean (SD) ACC_{flex} was 0.5 (0.1) m/s^2, flex HRaS was 0.37 SHR − 2.5, and walking/running transition HRaS was 0.80 SHR + 28.3.

Tables 2 and 3 display the derived ACC-PAI and HR-PAI models, respectively. Time shifting ACC one or two epochs in relation to measured PAI had little impact on the derived relationships, with predicted values being 1% higher per 15-s shift (R^2 values similar). Reference level models (*level 1*) using individual calibration of ACC to PAI and HR to PAI with respiratory gas-exchange measurement during the treadmill test both explained ~98% of the overall variance (between $R^2 > 98\%$) with SEE values about one-half of RMR, although only 84% overall variance (between $R^2 = 95\%$) was explained for the ACC model when uphill walking was included in the evaluation. ACC and HR models utilizing individual treadmill calibration parameters obtained in exactly the same way but using only the two walking phases for derivation still explained 85% and 92% of the between-individual variance in PAI, respectively. Full-length treadmill test using estimated PAI as basis for calibration (*level 2*) explained 88% (ACC) and 81% (HR) of the between-individual variance in measured PAI, with 33 and 62% higher SEE values than *level 1*.

Calibration via either a step test or a short walk test captured significant proportions of the between-individual variance in the ACC-PAI and HR-PAI relationships, with little or no benefit of direct measurement of gas exchange for HR models. The walk calibration levels performed slightly better for ACC models, whereas the step test was of greatest utility for HR models. Of all HR variability variables considered, the time-domain variable RMSSD explained most between-individual variance. For step-calibrated models, however, this was only evident when recovery HR was not included (coefficients ~23 $J \cdot min^{-1} \cdot kg^{-1}$ per unit increase in $lnRMSSD_{step}$; models not shown).

Absolute HR on its own explained 61% of the overall variance in PAI (between $R^2 = 0\%$, SEE = 127 $J \cdot min^{-1} \cdot kg^{-1}$), which increased to 64% by including age and gender in the model [between $R^2 = 1\%$, SEE = 120 $J \cdot min^{-1} \cdot kg^{-1}$, age not significant ($P = 0.43$)]. Measures of hemoglobin concentration added <1% to the explained between-individual variance in all models, Hb coefficients ranging between 3.4 and 5.7 $J \cdot min^{-1} \cdot kg^{-1}/(g \cdot dl^{-1})$ for walk and step models and 10 $J \cdot min^{-1} \cdot kg^{-1}/(g \cdot dl^{-1})$ for the nondynamic calibration level (models not shown).

Cross-Validation of Derived PAI Models

The Jackknife cross-validation data of derived ACC and HR models are shown in Table 4, separately for each treadmill phase (level walking, graded walking, and level running). The

Table 2. *Multiple levels of ACC-based individual calibration equations for PAI, derived during treadmill walking and running*

Level	Equation Segment	Equation for PAI, $J \cdot min^{-1} \cdot kg^{-1}$	R^2 Within	R^2 Between	R^2 Overall	SEE, $J \cdot min^{-1} \cdot kg^{-1}$
1	Walk	$1.0 \cdot ACC \times \beta 1_{tread\ (\dot{V}O_2)} + 1.0 \cdot \alpha 1_{tread\ (\dot{V}O_2)}$	0.982	0.986	0.982	36
	Run	$0.97 \cdot ACC \times \beta 2_{tread\ (\dot{V}O_2)} + 0.97 \cdot \alpha 2_{tread\ (\dot{V}O_2)} + 43$	(0.824)	(0.953)	(0.835)	(90)
1$_{excl\ run}$	Walk	$1.0 \cdot ACC \times \beta 1_{tread\ (\dot{V}O_2)} + 1.0 \cdot \alpha 1_{tread\ (\dot{V}O_2)}$	0.941	0.855	0.924	87
	Run	$78 \cdot ACC + 31$	(0.784)	(0.807)	(0.784)	(108)
2	Walk	$5.0 \cdot ACC + 0.91 \cdot ACC \times \beta 1_{tread\ (no\ \dot{V}O_2)} + 0.88 \cdot \alpha 1_{tread (no \dot{V}O_2)} + 13$	0.972	0.884	0.959	48
	Run	$0.88 \cdot ACC \times \beta 2_{tread\ (no\ \dot{V}O_2)} + 0.83 \cdot \alpha 2_{tread\ (no\ \dot{V}O_2)} + 84$	(0.815)	(0.728)	(0.806)	(94)
2$_{excl\ run}$	Walk	$5.0 \cdot ACC + 0.91 \cdot ACC \times \beta 1_{tread\ (no\ \dot{V}O_2)} + 0.88 \cdot \alpha 1_{tread\ (no\ \dot{V}O_2)} + 13$	0.943	0.786	0.916	89
	Run	$78 \cdot ACC + 31$	(0.783)	(0.634)	(0.767)	(111)
3	Walk	$46 \cdot ACC + 0.15 \cdot ACC \times \beta_{step\ (\dot{V}O_2)} + 0.072 \cdot \alpha_{step\ (\dot{V}O_2)} + 81$	0.951	0.803	0.926	86
	Run	$62 \cdot ACC + 0.13 \cdot ACC \times \beta_{step\ (\dot{V}O_2)} + 0.13 \cdot \alpha_{step\ (\dot{V}O_2)} - 21$	(0.787)	(0.644)	(0.772)	(108)
4	Walk	$43 \cdot ACC + 0.18 \cdot ACC \times \beta_{step\ (no\ \dot{V}O_2)} + 0.038 \cdot \alpha_{step\ (no\ \dot{V}O_2)} + 83$	0.950	0.785	0.924	89
	Run	$57 \cdot ACC + 0.18 \cdot ACC \times \beta_{step\ (no\ \dot{V}O_2)} + 0.65 \cdot \alpha_{step\ (no\ \dot{V}O_2)} - 85$	(0.791)	(0.616)	(0.771)	(109)
5	Walk	$43 \cdot ACC + 0.15 \cdot ACC \times ACC_{3\text{-}min\ walk\ (\dot{V}O_2)} + 0.27 \cdot ACC_{3\text{-}min\ walk\ (\dot{V}O_2)} + 42$	0.947	0.852	0.928	78
	Run	$80 \cdot ACC + 0.76 \cdot ACC_{3\text{-}min\ walk\ (\dot{V}O_2)} - 131$	(0.786)	(0.762)	(0.780)	(105)
6	Walk	$43 \cdot ACC + 0.14 \cdot ACC \times ACC_{3\text{-}min\ walk\ (no\ \dot{V}O_2)} + 0.14 \cdot ACC_{3\text{-}min\ walk\ (no\ \dot{V}O_2)} + 65$	0.947	0.794	0.919	82
	Run	$81 \cdot ACC + 0.74 \cdot ACC_{3\text{-}min\ walk\ (no\ \dot{V}O_2)} - 131$	(0.785)	(0.634)	(0.766)	(107)
7	Extrapolation	$248 \cdot ACC$	0.947	0.742	0.912	93
	Walk	$68 \cdot ACC + 90$	(0.785)	(0.538)	(0.756)	(111)
	Interpolation	$64 \cdot ACC + 99$				
	Run	$78 \cdot ACC + 31$				

Models are derived from flat walking ($n = 51$) and flat running ($n = 42$) data only. R^2 and standard error of estimate (SEE) represent goodness of fit for flat treadmill phases, with values in parentheses representing all treadmill phases. *Level 1*: treadmill calibration with indirect calorimetry [reference level, $\alpha 1$ (intercept) and $\beta 1$ (slope) derived from walking segment, and $\alpha 2$ and $\beta 2$ derived from running segment]. *Level 2*: treadmill calibration without indirect calorimetry (assuming same walk-run efficiency for all participants at any given work rate). *Level 3*: step-test calibration with indirect calorimetry. *Level 4*: step-test calibration without indirect calorimetry (assuming same step efficiency for all participants at any given work rate). *Level 5*: 3-min walk calibration with indirect calorimetry. *Level 6*: 3-min walk calibration without indirect calorimetry (assuming same walk efficiency for all participants). *Level 7*: nonexercise calibration. Models with "excl run" subscript do not require running for calibration. ACC, acceleration (in m/s^2) along the longitudinal axis of the trunk; PAI, physical activity intensity.

Table 3. *Multiple levels of HR-based individual calibration equations for PAI, derived during treadmill walking and running*

Level	Equation for PAI, $J \cdot min^{-1} \cdot kg^{-1}$	R^2 Within	R^2 Between	R^2 Overall	SEE, $J \cdot min^{-1} \cdot kg^{-1}$
1	$1.0 \cdot HRaS \times \beta_{tread\ (\dot{V}O_2)} + 1.0 \cdot \alpha_{tread\ (\dot{V}O_2)}$	0.975	0.999	0.977	26
1$_{excl\ run}$	$1.4 \cdot HRaS + 0.78 \cdot HRaS \times \beta_{tread\ (\dot{V}O_2)} + 0.85 \cdot \alpha_{tread\ (\dot{V}O_2)} - 1.6 \cdot SHR + 76$	0.961	0.917	0.956	35
2	$1.0 \cdot HRaS \times \beta_{tread\ (no\ \dot{V}O_2)} + 0.89 \cdot \alpha_{tread\ (no\ \dot{V}O_2)} - 1.1 \cdot SHR + 49$	0.963	0.808	0.947	42
2$_{excl\ run}$	$2.4 \cdot HRaS + 0.65 \cdot HRaS \times \beta_{tread\ (no\ \dot{V}O_2)} + 0.76 \cdot \alpha_{tread\ (no\ \dot{V}O_2)} - 3.3 \cdot SHR + 147$	0.946	0.700	0.923	49
3	$3.4 \cdot HRaS + 0.51 \cdot HRaS \times \beta_{step\ (\dot{V}O_2)} + 0.27 \cdot \alpha_{step\ (\dot{V}O_2)} + 8.5 \cdot test\ duration_{step} - 1.8 \cdot recHRaS_{step} - 71$	0.947	0.676	0.913	55
4	$3.3 \cdot HRaS + 0.52 \cdot HRaS \times \beta_{step\ (no\ \dot{V}O_2)} + 0.30 \cdot \alpha_{step\ (no\ \dot{V}O_2)} + 4.9 \cdot test\ duration_{step} - 1.3 \cdot recHRaS_{step} - 0.85 \cdot SHR - 13$	0.948	0.675	0.919	57
5	$5.1 \cdot HRaS + 0.21 \cdot HRaS \times HRaS_{3\text{-}min\ walk\ (\dot{V}O_2)} + 23 \cdot HRaS_{3\text{-}min\ walk\ (\dot{V}O_2)} + 30 \cdot lnRMSSD_{walk} + 39 \cdot gender - 1.2 \cdot SHR - 230$	0.928	0.614	0.888	61
6	$5.0 \cdot HRaS + 0.23 \cdot HRaS \times HRaS_{3\text{-}min\ walk\ (no\ \dot{V}O_2)} + 22 \cdot HRaS_{3\text{-}min\ walk\ (no\ \dot{V}O_2)} + 9.2 \cdot lnRMSSD_{walk} + 31 \cdot gender - 2.6 \cdot SHR - 82$	0.928	0.590	0.892	60
7	$5.5 \cdot HRaS + 1.6 \cdot HRaS \times gender - 7.8 \cdot SHR \times gender + 338 \cdot gender - 4.7 \cdot SHR - 207$	0.941	0.302	0.812	85

HRaS, HR above sleep; SHR, sleeping heart rate; RMSSD, root mean square of successive differences in interbeat intervals during calibration test; β, slope for HR-PAI in calibration test; α, intercept for HR-PAI in calibration test; $recHRaS_{step}$, HRaS reached 1 min after termination of the step test (based on quadratic regression of 90-s recovery HR data).

ACC models (derived from data from level walking and running) displayed no mean bias in level treadmill activity but underestimated graded walking by ~30%. HR models displayed little or no mean bias on all levels of calibration. For all models, we observed negative correlations between estimation error and measured PAI. By contrast, the HR model derived by Keytel et al. (32) overestimated PAI during all treadmill phases by 17–36% with larger scatter around the mean but showed a positive trend for the signed error to depend on PAI. For all models, magnitude of estimation error increased with increasing PAI. This was also the case for ACC models when error magnitude was expressed relative to PAI, whereas a decrease was observed for the HR models.

RMSE of the reference calibration level for ACC (*level 1*) was 7% of measured PAI during level walking, 37% during graded walking, and 8% during running (Table 4). For level walking and running, respective RMSE values were 115% and 36% higher on the calibration level utilizing treadmill testing

Table 4. *Cross-validation of ACC- and HR-based calibration equations for PAI*

Level	Phase	ACC Models PAI	ACC Models MSE (95% CI)	ACC Models 95% LoA	ACC Models RMSE	HR Models PAI	HR Models MSE (95% CI)	HR Models 95% LoA	HR Models RMSE
1	Level walking	176	0 (0; 0)	−25; 25	13‡	177	1 (−1; 3)	−45; 47	23‡§
	Graded walking	244	−107 (−114; −100)	−258; 44	131‡	353	2 (−2; 6)	−51; 55	27‡§
	Level running	651	1 (−12; 14)	−110; 112	55‡	643	−7 (−13; −1)	−84; 70	39‡
2	Level walking	176	0 (−7; 7)	−57; 57	28†‡	176	0 (−8; 7)	−68; 67	34†‡§
	Graded walking	244	−107 (−117; −96)	−268; 55	134‡	356	5 (−3; 13)	−72; 82	39†‡§
	Level running	652	2 (−19; 23)	−148; 151	75†‡	641	−10 (−29; 10)	−140; 121	66†‡
3	Level walking	176	0 (−7; 8)	−61; 62	31†	178	2 (−12; 15)	−102; 105	52†‡§
	Graded walking	238	−112 (−123; −101)	−279; 55	140	355	4 (−7; 16)	−92; 101	48†‡§
	Level running	646	−4 (−39; 31)	−226; 218	111†	631	−20 (−46; 6)	−182; 142	83†‡
4	Level walking	176	0 (−8; 8)	−64; 64	32†	177	1 (−12; 14)	−100; 102	51†‡§
	Graded walking	239	−111 (−123; −100)	−278; 55	139	355	4 (−8; 16)	−97; 106	51†‡§
	Level running	649	−1 (−37; 35)	−229; 226	114†	629	−22 (−45; 2)	−172; 129	78†‡
5	Level walking	176	0 (−5; 5)	−45; 45	23†‡	178	2 (−10; 15)	−96; 100	49†‡§
	Graded walking	239	−112 (−121; −103)	−271; 47	137	361	10 (−6; 25)	−117; 136	64†‡§
	Level running	648	−2 (−38; 34)	−225; 222	112†	619	−31 (−60; −3)	−210; 147	95†‡
6	Level walking	176	0 (−7; 7)	−60; 60	30†	179	3 (−10; 15)	−94; 99	48†‡§
	Graded walking	238	−112 (−123; −102)	−277; 52	139	360	10 (−5; 24)	−112; 131	61†‡§
	Level running	650	−2 (−37; 38)	−231; 232	116†	622	−28 (−58; 1)	−209; 153	95†‡
7	Level walking	176	0 (−8; 8)	−66; 66	33†	177	1 (−21; 23)	−161; 163	81†‡§
	Graded walking	238	−113 (−125; −101)	−282; 57	141†	359	8 (−17; 33)	−179; 194	93†‡§
	Level running	647	−2 (−40; 36)	−238; 234	118†	616	−35 (−64; −7)	−226; 155	102†‡
EJCN a+d (10)	Level walking	147	−29 (−41; −17)	−120; 62	54†‡	160	−16 (−32; −0)	−136; 103	62†‡
	Graded walking	211	−139 (−154; −125)	−316; 37	165†‡	334	−17 (−33; −1)	−139; 106	64†‡§
	Level running	620	−30 (−62; 2)	−234; 174	106†	600	−51 (−73; −29)	−202; 100	91†‡
Keytel, et al. (32)	Level walking					239	63 (23; 103)	−226; 353	158†§
	Graded walking					465	114 (69; 159)	−213; 441	199†‡
	Level running					764	113 (58; 169)	−240; 466	210†‡

Values are in $J \cdot min^{-1} \cdot kg^{-1}$. MSE, mean signed error; CI, confidence intervals; LoA, limits of agreement; RMSE, root mean square error. †Significantly different from *level 1* ($P < 0.05$). ‡Significantly different from *level 7* ($P < 0.05$). §Significantly different from corresponding ACC model on same level ($P < 0.05$). EJCN a (ACC) and EJCN d (HR) represent levels of individual calibration equivalent to *level 7* and *level 4*, respectively.

without direct PAI measurement as calibration (*level 2*). This error increased only marginally during walking when using less intense forms of individual calibration (*levels 3–7*), whereas the error in running was further inflated by ~50% on these calibration levels.

RMSE of the reference HR model (*level 1*) was 13% of measured PAI during level walking, 8% during graded walking, and 6% during running, thus being less precise than the reference ACC model (*level 1*) in level walking but more precise in graded walking and running. The errors of the HR model using full-length treadmill calibration without PAI measurement (*level 2*) were 44–69% larger than reference model errors. HR models incorporating step-test parameters (*levels 3* and *4*) had errors about twice the reference level error. Models using short-walk calibration (*levels 5* and *6*) were also half as accurate as the reference model for level walking but less accurate during graded walking and level running. Errors for the nonexercise calibrated HR model (*level 7*) and the model by Keytel et al. (32) were about three- and fivefold as large as reference calibration level errors, respectively.

PAI estimates from a combination of the ACC-PAI and HR-PAI equations on each of the levels of individual calibration using the branched modeling approach were also cross-validated (Table 5). Proportions of observations quantified by the four branches (branch utilizations with regard to time) were 3/97/0/0%, 44/56/0/0%, and 99/1/0/0% for level walking, graded walking, and level running, respectively. In general, ACC models improved precision during graded walking and running by combining with HR, but error tended to increase for level walking. In parallel, most HR-based models improved accuracy during level walking and running phases by combining with ACC, with the greatest benefit occurring during level walking and in models with lower degree of individual calibration. By contrast, errors during graded walking increased by combining HR with ACC with the set of branched equation parameters used here. For the previously published values of "flex HRaS" and "transition HRaS" (10), branch utilizations were 2/98/0/0%, 26/74/0/0%, and 94/6/0/0% for level walking, graded walking, and level running, respectively, which in conjunction with the equations from the same study resulted in underestimation of PAI during all treadmill phases.

Validation of PAI Models During Stepping

The step-test data were also utilized to examine the effect of combining ACC with HR for estimating PAI during this activity. The derived ACC-PAI equations all significantly underestimated PAI during the step test by ~41% ($P < 0.001$). Underestimation of PAI was also evident in some of the HR models, although to a lesser degree (≤6%). Combined models generally underestimated step PAI by 17%.

DISCUSSION

The advantages of objective measurement of physical activity in large-scale epidemiological studies are becoming increasingly acknowledged, but employment of these methods may be limited by the need for individual calibration. As with all measurements, there is a trade-off between validity and feasibility, and individual calibration should be viewed as a matter of degree, rather than an all-or-nothing determination of whether all between-individual variance has been accounted for. This study aimed to quantify the loss of validity that would follow the use of more feasible, less intensive methods for individual calibration in a heterogeneous sample of adult men and women, covering a wide range in age, fitness, and anthropometric characteristics. Our results show that reasonably precise estimates of walking and running intensity may be obtained with ACC and HR monitoring. Models based on HR alone are more sensitive to loss of information through simplifying individual calibration. Validity of combined models was generally higher and less susceptible to loss of calibration information. Measured RMR agreed well with predicted values using only age, gender, height, and weight (42), which is consistent with a study comparing several prediction equations (23). Thus estimates of total metabolic rate may be easily obtained from the PAI equations derived here.

ACC-PAI Relationship

None of the routinely available variables (age, gender, and height) contributed significantly to the ACC models. Variance in the ACC-PAI relationship would be expected to stem from sources different from those affecting the HR-PAI relationship, mainly because ACC is a biomechanical measure and also because the translation into physiological PAI makes additional assumptions about the efficiency with which physical work is performed. The difference in precision, with which PAI was predicted from calorimetry- and noncalorimetry-calibrated models, illustrates the impact of efficiency. Some of the residual variance in the ACC-PAI relationship during treadmill activity was accounted for by including information obtained during a short walk or step test. In particular, the 3-min walk calibration with indirect calorimetry captured 85% of the between-individual variance in PAI during flat treadmill activity (76% with graded walking). Our observations concur with those of Ekelund et al. (20), who used individual ACC responses during treadmill walking to account for between-individual variance in free-living energy expenditure. By contrast, individual calibration of the ACC-PAI relationship during treadmill walking and running did not improve measurement precision of physical activity energy expenditure measured by whole-body direct calorimetry in 12 young men. This may be because of the greater homogeneity of that sample (11), although Chen and Sun (15) also reported only small improvements in accuracy when using individualized ACC-PAI curves for triaxial ACC to estimate energy expenditure in a large, heterogeneous sample.

The benefits of individually calibrating the walking-running ACC-PAI relationship may, however, be of minor importance, considering the nonuniversal nature of the ACC-PAI relationship across activity types. Acceleration along the longitudinal axis of the trunk is unlikely to relate similarly to PAI of biomechanically different forms of activity. In line with this, ACC-PAI relationships differ between level and graded walking (46, 57), and ACC models may also not fully capture the increased energy expenditure associated with stair climbing (13, 50). Not surprisingly, ACC-PAI models derived from level treadmill activity significantly underestimated PAI during both graded walking and stepping in the present study. In addition, one would expect cycling and swimming PAI to be greatly underestimated with treadmill-derived ACC-PAI equations. To capture differences in PAI in a range of biomechani-

Table 5. *Cross-validation of branched equations for PAI*

Level	Phase	PAI	MSE (95% CI)	95% LoA	RMSE
1	Level walking	177	1 (−1; 2)	−29; 31	17*‡§
	Graded walking	325	−26 (−33; −19)	−103; 51	47*‡§
	Level running	644	−6 (−12; −1)	−79; 66	37*‡§
2	Level walking	177	1 (−6; 7)	−56; 57	28*†
	Graded walking	328	−23 (−33; −14)	−115; 68	51*‡§
	Level running	642	−8 (−27; 11)	−136; 120	64*†‡
3	Level walking	179	2 (−6; 11)	−66; 71	35*†‡
	Graded walking	327	−24 (−35; −13)	−128; 80	57*†‡§
	Level running	632	−18 (−42; 5)	−166; 129	76*†
4	Level walking	178	2 (−6; 10)	−64; 68	33*†
	Graded walking	327	−24 (−36; −12)	−130; 83	58*†‡§
	Level running	631	−20 (−40; 1)	−158; 119	72*†‡
5	Level walking	179	3 (−5; 11)	−63; 69	33*†‡
	Graded walking	333	−18 (−32; −3)	−144; 108	65†‡§
	Level running	622	−28 (−54; −3)	−191; 134	85*†
6	Level walking	179	3 (−6; 12)	−66; 73	35*†
	Graded walking	333	−18 (−32; −4)	−142; 106	65†§
	Level running	625	−25 (−52; 1)	−192; 142	87*†
7	Level walking	180	4 (−10; 19)	−102; 110	53*†
	Graded walking	336	−15 (−37; 7)	−187; 158	87†§
	Level running	619	−32 (−58; −6)	−207; 143	93*†
EJCN a+d (10)	Level walking	156	−20 (−34; −7)	−120; 79	54*†
	Graded walking	297	−54 (−70; −39)	−189; 80	87*†§
	Level running	604	−47 (−67; −27)	−188; 94	85*†
EJCN a+b (10)	Level walking	157	−19 (−36; −2)	−143; 105	65*†‡
	Graded walking	305	−47 (−70; −24)	−235; 141	105†‡§
	Level running	584	−67 (−95; −40)	−260; 125	117*†

Values are in $J \cdot min^{-1} \cdot kg^{-1}$. EJCN a+d and EJCN a+b represent levels of individual calibration equivalent to *level 4* and *level 6*, respectively. *Significantly different from corresponding noncombined HR-model ($P < 0.05$). †Significantly different from *level 1* ($P < 0.05$). ‡Significantly different from *level 7* ($P < 0.05$). §Significantly different from corresponding noncombined ACC-model ($P < 0.05$).

cally diverse activities with movement sensing alone, it may be necessary to combine several movement sensors placed on different parts of the body for movement signature recognition (66, 67), which highlights the issue of validity vs. feasibility and may present additional challenges with regard to behavior alterations due to monitoring (64).

HR-PAI Relationship

Theoretically, instantaneous $\dot{V}O_2$ and carbon dioxide production ($\dot{V}CO_2$) should be proportional to instantaneous cardiac output (HR times stroke volume) and also arterial $\dot{V}O_2$ and $\dot{V}CO_2$ differences, respectively, where arterial $\dot{V}O_2$ difference depends on hemoglobin and PO_2 and arterial $\dot{V}CO_2$ difference depends on factors such as hemoglobin content, pH, temperature, O_2 saturation, and PCO_2 (18, 22, 36). Within individuals, HR is the most variable factor over time (minutes, hours) and may increase three- to fivefold from rest to maximal exercise. Because changes in arterial $\dot{V}O_2$ difference and stroke volume usually occur simultaneously, although not always proportionally, with changes in HR, the use of an instantaneous measure of HR is a good starting point for indirect estimation of PAI. However, as this and many other studies have shown, the between-individual variance in HR-PAI relationships is often so large that simply using a raw measure of HR may not be meaningful. Previously, this has been overcome by individual calibration with direct measurement of PAI over a wide intensity range (60). As our and other analyses have shown, some of this variance can be accounted for simply by using HR above resting level and adjusting for gender (2, 10, 11, 19). These two factors may capture variance in stroke volume and oxygen transport capacity of the blood. Nonetheless, it was surprising that the hemoglobin level did not explain more variance in the HR-PAI relationships, but this may be because of a lack of heterogeneity in this parameter (17, 37, 40). Similarly, some of the variance in fitness level, a factor known to have a profound impact on the HR-PAI relation (32), may be captured by SHR, but this is clearly better done by assessing the HR response to a dynamic stress test, even short ones. Markers of vagal activity during or immediately after exercise had some utility in the present study, although the physiological significance of HR variability measures is uncertain (45). To this end, it is worth noting that RMSSD during the step test explained very little of the variance when recovery HR was also included, owing in part to the high intercorrelation. We speculate, therefore, that including a measure of HR recovery may increase validity of walk calibration, considering the greater robustness of such a measure over measures of HR variability (5, 41). Models including step- or walk-test parameters were still relatively accurate, with errors roughly two to three times the error observed for the reference calibration level. Benefits of direct measurement of PAI during the walk and step tests were marginal, suggesting that either between-individual differences in walk and step efficiency were small compared with random error in the individual measurement of PAI during calibration or was compensated for by other covariates. Across calibration procedures, reliance on individually derived slopes and intercepts was greater for longer and more intense forms of calibration.

The equation developed by Keytel et al. (32) using steady-state work rates generally overestimated PAI during the ramped treadmill test used in the present study. Because differences in kinetics of HR and respiratory gas exchange when work rate is increasing would be negligible considering the relatively small ramp slope (rate of change in work rate) used in the present study, the discordance in PAI estimates is most likely explained by real differences in the two study populations. The observed bias may have been reduced, had Keytel's equation been expressed as HR above resting (2, 10, 11, 19).

For epidemiological research, it is worth noting that an estimate of cardiorespiratory fitness, which is strongly related to metabolic health (6, 25, 33), may be obtained by inserting maximum HRaS (predicted or measured) in derived HR-PAI equations. The validity of such fitness estimates should be evaluated by maximal exercise testing but would likely depend on the accuracy of the maximum HR estimate (56), on exercise intensity range of the individual calibration test in question, and possibly also on availability of respiratory gas-exchange parameters (8, 16, 34, 62, 63).

Combined HR and ACC Models

As mentioned above, the relationship between ACC and PAI lacks universality across activity types, and a well-recognized limitation to HR monitoring, even when individually calibrated, is poorer specificity at very low PAI levels. It is generally agreed that at least some of these limitations may be overcome by combining HR and movement sensing (10–12, 30, 47, 52–54, 58), which we could generally confirm in the present study. Specifically, when ACC-PAI models were combined with HR-PAI models, estimation error was reduced during graded walking, stepping, and running, but this benefit was absent in level walking. Most level walking observations were quantified with a 90% reliance of the ACC-PAI relationship, which would explain the similarity in PAI estimates. HR models, especially those incorporating less intense individual calibration, improved accuracy by being combined with ACC and mainly in level walking. Overall, the negative correlation of error from ACC and HR supports differential weighting modeling approaches, such as branched equation modeling (11).

Limitations

It is possible that the walk calibration may have been performed differently and perhaps been more practical if not undertaken on treadmill but rather during self-paced walking over a set distance and with subsequent HR recovery measurement. Although a substantial part of the between-individual variance in PAI was accounted for, even with more parsimonious calibration techniques, it is unknown how error may propagate in other types of activities. Therefore, a key objective for future research on physical activity assessment would be to examine the error structure of models combining ACC and HR in diverse settings. Although HR-based methods have established validity across a wide range of activities, and HR-PAI equations from the present study therefore may generalize equally to those scenarios, there is less evidence of potential benefits for using some level of individual calibration for ACC-PAI (20). Derived HR-PAI equations may, however, overestimate sedentary behavior, even when used with the highest level of individual calibration. Traditionally, the flex HR approach has been employed to overcome this (14, 35). When combining HR with ACC, other options exist to overcome the lower validity of the HR-PAI relationship at low intensity, such as branched equation modeling (11, 30, 54, 58). This requires complete continuous calibration curves for both ACC and HR, constructed by extrapolating the derived relationship downward to the respective flex points, below which relationships are forced through their origins.

In conclusion, it is possible to obtain reasonably precise estimates of walking and running intensity with ACC and HR monitoring, the latter being most sensitive to loss of information through simplifying individual calibration. Simpler methods for calibration, already proven feasible for fitness testing in epidemiological settings (6, 21, 31, 51), can be performed with acceptable accuracy to consider combined HR and movement sensing as an objective measure of physical activity in population-based studies.

ACKNOWLEDGMENTS

We thank all participants for willingness to contribute to this research. Rosalind Stevenson, Ema de Lucia-Rolfe (MRC Epidemiology Unit), Samantha Northcott, and Peter R. Murgatroyd (Wellcome Trust Clinical Research Facility, Addenbrooke's Hospital) are acknowledged for assistance in data collection and equipment checks. We thank Antony Wright, Cheryl Kidney, and Andy Coward (MRC Collaborative Centre for Human Nutrition Research) for $^2H^{18}O_2$ preparation and analyses.

The results of the present study do not constitute endorsement by the authors of the products described.

GRANTS

This study received financial support from the Medical Research Council UK, Wellcome Trust, and Unilever UK.

REFERENCES

1. Heart rate variability: standards of measurement, physiological interpretation, and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. *Eur Heart J* 17: 354–381, 1996.
2. **Andrews RB.** Net heart rate as a substitute for respiratory calorimetry. *Am J Clin Nutr* 24: 1139–1147, 1971.
3. **Avons P, Garthwaite P, Davies HL, Murgatroyd PR, James WP.** Approaches to estimating physical activity in the community: calorimetric validation of actometers and heart rate monitoring. *Eur J Clin Nutr* 42: 185–196, 1988.
4. **Berntson GG, Quigley KS, Jang JF, Boysen ST.** An approach to artifact identification: application to heart period data. *Psychophysiology* 27: 586–598, 1990.
5. **Berntson GG, Stowell JR.** ECG artifacts and heart period variability: don't miss a beat! *Psychophysiology* 35: 127–132, 1998.
6. **Blair SN, Kohl HW 3rd, Paffenbarger RS Jr, Clark DG, Cooper KH, Gibbons LW.** Physical fitness and all-cause mortality. A prospective study of healthy men and women. *JAMA* 262: 2395–2401, 1989.
7. **Bland JM, Altman DG.** Statistical methods for assessing agreement between two methods of clinical measurement. *Lancet* 1: 307–310, 1986.
8. **Bogaard HJ, Woltjer HH, van Keimpema AR, Postmus PE, de Vries PM.** Prediction of peak oxygen uptake in men using pulmonary and hemodynamic variables during exercise. *Med Sci Sports Exerc* 32: 701–705, 2000.
9. **Brage S, Brage N, Ekelund U, Luan J, Franks PW, Froberg K, Wareham NJ.** Effect of combined movement and heart rate monitor placement on physical activity estimates during treadmill locomotion and free-living. *Eur J Appl Physiol* 96: 517–524, 2006.
10. **Brage S, Brage N, Franks PW, Ekelund U, Wareham NJ.** Reliability and validity of the combined heart rate and movement sensor Actiheart. *Eur J Clin Nutr* 59: 561–570, 2005.
11. **Brage S, Brage N, Franks PW, Ekelund U, Wong MY, Andersen LB, Froberg K, Wareham NJ.** Branched equation modeling of simultaneous accelerometry and heart rate monitoring improves estimate of directly measured physical activity energy expenditure. *J Appl Physiol* 96: 343–351, 2004.

12. **Brage S, Wedderkopp N, Franks PW, Andersen LB, Froberg K.** Reexamination of validity and reliability of the CSA monitor in walking and running. *Med Sci Sports Exerc* 35: 1447–1454, 2003.
13. **Campbell KL, Crocker PR, McKenzie DC.** Field evaluation of energy expenditure in women using Tritrac accelerometers. *Med Sci Sports Exerc* 34: 1667–1674, 2002.
14. **Ceesay SM, Prentice AM, Day KC, Murgatroyd PR, Goldberg GR, Scott W, Spurr GB.** The use of heart rate monitoring in the estimation of energy expenditure: a validation study using indirect whole-body calorimetry. *Br J Nutr* 61: 175–186, 1989.
15. **Chen KY, Sun M.** Improving energy expenditure estimation by using a triaxial accelerometer. *J Appl Physiol* 83: 2112–2122, 1997.
16. **Cox MH, Thomas SG, Weller IM, Corey P.** Reliability and validity of a fitness assessment for epidemiological studies. *Can J Sport Sci* 17: 49–55, 1992.
17. **Dempsey JA, Reddan WG, Birnbaum ML, Forster HV, Thoden JS, Grover RF, Rankin J.** Effects of acute through life-long hypoxic exposure on exercise pulmonary gas exchange. *Respir Physiol* 13: 62–89, 1971.
18. **Douglas AR, Jones NL, Reed JW.** Calculation of whole blood CO_2 content. *J Appl Physiol* 65: 473–477, 1988.
19. **Dugas LR, van der ML, Odendaal H, Noakes TD, Lambert EV.** A novel energy expenditure prediction equation for intermittent physical activity. *Med Sci Sports Exerc* 37: 2154–2161, 2005.
20. **Ekelund U, Aman J, Westerterp K.** Is the ArteACC index a valid indicator of free-living physical activity in adolescents? *Obes Res* 11: 793–801, 2003.
21. **Ekelund U, Brage S, Franks PW, Hennings S, Emms S, Wareham NJ.** Physical activity energy expenditure predicts progression toward the metabolic syndrome independently of aerobic fitness in middle-aged healthy Caucasians: the Medical Research Council Ely Study. *Diabetes Care* 28: 1195–1200, 2005.
22. **Fick A.** über die Messung des Blutquantums in den Herzventrikeln. *Würzburg Physikalische Medizinische Gesellschaft* 2: 16, 1870.
23. **Frankenfield DC, Rowe WA, Smith JS, Cooney RN.** Validation of several established equations for resting metabolic rate in obese and nonobese people. *J Am Diet Assoc* 103: 1152–1159, 2003.
24. **Franks PW, Barroso I, Luan J, Ekelund U, Crowley VEF, Brage S, Sandhu MS, Jakes RW, Middelberg RPS, Harding AH, Brage S, Schafer AJ, O'Rahilly S, Wareham N.** PGC-1α genotype modifies the relationship between volitional energy expenditure and $\dot{V}O_{2\,max}$. *Med Sci Sports Exerc* 35: 1998–2004, 2003.
25. **Franks PW, Ekelund U, Brage S, Wong MY, Wareham NJ.** Does the association of habitual physical activity with the metabolic syndrome differ by level of cardiorespiratory fitness? *Diabetes Care* 27: 1187–1193, 2004.
26. **Harrell FEJ.** *Regression Modeling Strategies. With Application to Linear Models, Logistic Regression, and Survival Analysis*. Berlin: Springer, 2001.
27. **Haskell WL, Yee MC, Evans A, Irby PJ.** Simultaneous measurement of heart rate and body motion to quantitate physical activity. *Med Sci Sports Exerc* 25: 109–115, 1993.
28. **Hiiloskorpi HK, Pasanen ME, Fogelholm MG, Laukkanen RM, Manttari AT.** Use of heart rate to predict energy expenditure from low to high activity levels. *Int J Sports Med* 24: 332–336, 2003.
29. **Hiiloskorpi H, Fogelholm M, Laukkanen R, Pasanen M, Oja P, Manttari A, Natri A.** Factors affecting the relation between heart rate and energy expenditure during exercise. *Int J Sports Med* 20: 438–443, 1999.
30. **Johansson PH, Rossander-Hulthen L, Slinde F, Ekblom B.** Accelerometry combined with heart rate telemetry in the assessment of total energy expenditure. *Br J Nutr* 95: 631–639, 2006.
31. **Katzmarzyk PT, Perusse L, Rao DC, Bouchard C.** Familial risk ratios for high and low physical fitness levels in the Canadian population. *Med Sci Sports Exerc* 32: 614–619, 2000.
32. **Keytel LR, Goedecke JH, Noakes TD, Hiiloskorpi H, Laukkanen R, van der ML, Lambert EV.** Prediction of energy expenditure from heart rate monitoring during submaximal exercise. *J Sports Sci* 23: 289–297, 2005.
33. **Laaksonen DE, Lakka HM, Salonen JT, Niskanen LK, Rauramaa R, Lakka TA.** Low levels of leisure-time physical activity and cardiorespiratory fitness predict development of the metabolic syndrome. *Diabetes Care* 25: 1612–1618, 2002.
34. **Latin RW, Elias BA.** Predictions of maximum oxygen uptake from treadmill walking and running. *J Sports Med Phys Fitness* 33: 34–39, 1993.
35. **Livingstone MB, Prentice AM, Coward WA, Ceesay SM, Strain JJ, McKenna PG, Nevin GB, Barker ME, Hickey RJ.** Simultaneous measurement of free-living energy expenditure by the doubly labeled water method and heart-rate monitoring. *Am J Clin Nutr* 52: 59–65, 1990.
36. **Loeppky JA, Luft UC, Fletcher ER.** Quantitative description of whole blood CO_2 dissociation curve and Haldane effect. *Respir Physiol* 51: 167–181, 1983.
37. **Lonsdorfer J, Bogui P, Otayeck A, Bursaux E, Poyart C, Cabannes R.** Cardiorespiratory adjustments in chronic sickle cell anemia. *Bull Eur Physiopath Respir* 19: 339–344, 1983.
38. **Lucia A, Gomez-Gallego F, Barroso I, Rabadan M, Bandres F, San Juan AF, Chicharro JL, Ekelund U, Brage S, Earnest CP, Wareham NJ, Franks PW.** PPARGC1A genotype (Gly^{482}Ser) predicts exceptional endurance capacity in European men. *J Appl Physiol* 99: 344–348, 2005.
39. **Luke A, Maki KC, Barkey N, Cooper R, McGee D.** Simultaneous monitoring of heart rate and motion to assess energy expenditure. *Med Sci Sports Exerc* 29: 144–148, 1997.
40. **Lundby C, Calbet JA, van HG, Saltin B, Sander M.** Pulmonary gas exchange at maximal exercise in Danish lowlanders during 8 wk of acclimatization to 4,100 m and in high-altitude Aymara natives. *Am J Physiol Regul Integr Comp Physiol* 287: R1202–R1208, 2004.
41. **McNames J, Aboy M.** Reliability and accuracy of heart rate variability metrics versus ECG segment duration. *Med Biol Eng Comput* 44: 747–756, 2006.
42. **Mifflin MD, St Jeor ST, Hill LA, Scott BJ, Daugherty SA, Koh YO.** A new predictive equation for resting energy expenditure in healthy individuals. *Am J Clin Nutr* 51: 241–247, 1990.
43. **Moon JK, Butte NF.** Combined heart rate and activity improve estimates of oxygen consumption and carbon dioxide production rates. *J Appl Physiol* 81: 1754–1761, 1996.
44. **Pan J, Tompkins WJ.** A real-time QRS detection algorithm. *IEEE Trans Biomed Eng* 32: 230–236, 1985.
45. **Parati G, Mancia G, Rienzo MD, Castiglioni P, Taylor JA, Studinger P.** Point/counterpoint: cardiovascular variability is/is not an index of autonomic control of circulation. *J Appl Physiol* 101: 676–682, 2006.
46. **Perrin O, Terrier P, Ladetto Q, Merminod B, Schutz Y.** Improvement of walking speed prediction by accelerometry and altimetry, validated by satellite positioning. *Med Biol Eng Comput* 38: 164–168, 2000.
47. **Rennie K, Rowsell T, Jebb SA, Holburn D, Wareham NJ.** A combined heart rate and movement sensor: proof of concept and preliminary testing study. *Eur J Clin Nutr* 54: 409–414, 2000.
48. **Rennie KL, Hennings SJ, Mitchell J, Wareham NJ.** Estimating energy expenditure by heart-rate monitoring without individual calibration. *Med Sci Sports Exerc* 33: 939–945, 2001.
49. **Rietjens GJ, Kuipers H, Kester AD, Keizer HA.** Validation of a computerized metabolic measurement system (Oxycon-Pro) during low and high intensity exercise. *Int J Sports Med* 22: 291–294, 2001.
50. **Schmitz KH, Treuth M, Hannan P, McMurray R, Ring KB, Catellier D, Pate R.** Predicting energy expenditure from accelerometry counts in adolescent girls. *Med Sci Sports Exerc* 37: 155–161, 2005.
51. **Siconolfi SF, Garber CE, Lasater TM, Carleton RA.** A simple, valid step test for estimating maximal oxygen uptake in epidemiologic studies. *Am J Epidemiol* 121: 382–390, 1985.
52. **Strath SJ, Bassett DR Jr, Swartz AM, Thompson DL.** Simultaneous heart rate-motion sensor technique to estimate energy expenditure. *Med Sci Sports Exerc* 33: 2118–2123, 2001.
53. **Strath SJ, Bassett DR Jr, Thompson DL, Swartz AM.** Validity of the simultaneous heart rate-motion sensor technique for measuring energy expenditure. *Med Sci Sports Exerc* 34: 888–894, 2002.
54. **Strath SJ, Brage S, Ekelund U.** Integration of physiological and accelerometer data to improve physical activity assessment. *Med Sci Sports Exerc* 37: S563–S571, 2005.
55. **Strath SJ, Swartz AM, Bassett DR, O'Brien WL, King GA, Ainsworth BE.** Evaluation of heart rate as a method for assessing moderate intensity physical activity. *Med Sci Sports Exerc* 32: S465–S470, 2000.
56. **Tanaka H, Monahan KD, Seals DR.** Age-predicted maximal heart rate revisited. *J Am Coll Cardiol* 37: 153–156, 2001.
57. **Terrier P, Aminian K, Schutz Y.** Can accelerometry accurately predict the energy cost of uphill/downhill walking? *Ergonomics* 44: 48–62, 2001.

58. **Thompson D, Batterham AM, Bock S, Robson C, Stokes K.** Assessment of low-to-moderate intensity physical activity thermogenesis in young adults using synchronized heart rate and accelerometry with branched-equation modeling. *J Nutr* 136: 1037–1042, 2006.
59. **Treuth MS, Adolph AL, Butte NF.** Energy expenditure in children predicted from heart rate and activity calibrated against respiration calorimetry. *Am J Physiol Endocrinol Metab* 275: E12–E18, 1998.
60. **Wareham NJ, Hennings SJ, Prentice AM, Day NE.** Feasibility of heart-rate monitoring to estimate total level and pattern of energy expenditure in a population-based epidemiological study: the Ely Young Cohort Feasibility Study 1994–5. *Br J Nutr* 78: 889–900, 1997.
61. **Weir JB.** New methods for calculating metabolic rate with special reference to protein metabolism. *J Physiol* 109: 1–9, 1949.
62. **Weller IM, Thomas SG, Corey PN, Cox MH.** Prediction of maximal oxygen uptake from a modified Canadian aerobic fitness test. *Can J Appl Physiol* 18: 175–188, 1993.
63. **Weller IM, Thomas SG, Gledhill N, Paterson D, Quinney A.** A study to validate the modified Canadian Aerobic Fitness Test. *Can J Appl Physiol* 20: 211–221, 1995.
64. **Wickstrom G, Bendix T.** The "Hawthorne effect"—what did the original Hawthorne studies actually show? *Scand J Work Environ Health* 26: 363–367, 2000.
65. **Withers RT, LaForgia J, Pillans RK, Shipp NJ, Chatterton BE, Schultz CG, Leaney F.** Comparisons of two-, three-, and four-compartment models of body composition analysis in men and women. *J Appl Physiol* 85: 238–245, 1998.
66. **Zhang K, Pi-Sunyer FX, Boozer CN.** Improving energy expenditure estimation for physical activity. *Med Sci Sports Exerc* 36: 883–889, 2004.
67. **Zhang K, Werner P, Sun M, Pi-Sunyer FX, Boozer CN.** Measurement of human daily physical activity. *Obes Res* 11: 33–40, 2003.