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Branched equation modeling of simultaneous accelerometry and heart rate monitoring improves estimate of directly measured physical activity energy expenditure

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Brage, Søren, Niels Brage, Paul W. Franks, Ulf Ekelund, Man-Yu Wong, Lars Bo Andersen, Karsten Froberg, and Nicholas J. Wareham. 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. First published September 12, 2003; 10.1152/japplphysiol.00703.2003.—The combination of heart rate (HR) monitoring and movement registration may improve measurement precision of physical activity energy expenditure (PAEE). Previous attempts have used either regression methods, which do not take full advantage of synchronized data, or have not used movement data quantitatively. The objective of the study was to assess the precision of branched model estimates of PAEE by utilizing either individual calibration (IC) of HR and accelerometry or corresponding mean group calibration (GC) equations. In 12 men (20.6–25.2 kg/m^2), IC and GC equations for physical activity intensity (PAI) were derived during treadmill walking and running for both HR (Polar) and hip-acceleration [Computer Science and Applications (CSA)]. HR and CSA were recorded minute by minute during 22 h of whole body calorimetry and converted into PAI in four different weightings ($P_{1–4}$) of the HR vs. the CSA ($1\text{-}P_{1–4}$) relationships: if CSA $> x$, we used the P_1 weighting if HR $> y$, otherwise P_2. Similarly, if CSA $\leq x$, we used P_3 if HR $> z$, otherwise P_4. PAEE was calculated for a 12.5-h nonsleeping period as the time integral of PAI. A priori, we assumed $P_1 = 1$, $P_2 = P_3 = 0.5$, $P_4 = 0$, $x = 5$ counts/min, $y =$ walking/running transition HR, and $z =$ flex HR. These parameters were also estimated post hoc. Means ± SD estimation errors of a priori models were -4.4 ± 29 and 3.5 ± 20% for IC and GC, respectively. Corresponding post hoc model errors were -1.5 ± 13 and 0.1 ± 9.8%, respectively. All branched models had lower errors ($P \leq 0.035$) than single-measure estimates of CSA (less than or equal to −45%) and HR (≥39%), as well as their nonbranched combination (≥25.7%). In conclusion, combining HR and CSA by branched modeling improves estimates of PAEE. IC may be less crucial with this modeling technique.

validity; intensity; epidemiology; calorimetry; movement sensor; activity monitor; energy expenditure; individual calibration

PHYSICAL ACTIVITY IS A COMPLEX BEHAVIOR and difficult to measure precisely at population level. The reasons that precise estimates of physical activity are important include clarification of which dimension of activity is most strongly associated with a particular health outcome, understanding dose-response relationships, improving the ability to monitor secular trends in activity level and the compliance to intervention programs, cross-cultural comparisons, and optimization of sample size for the detection of gene-environment interactions (21, 38). Accelerometry and heart rate (HR) monitoring are among the available objective methods. There are, however, limitations associated with both methods when used alone for the assessment of physical activity energy expenditure (PAEE) and its first time derivative, physical activity intensity (PAI). The limitations of HR monitoring are largely due to biological variance. For example, the HR-PAI relationship is affected by age, sex, training state, stroke volume, hemoglobin concentration of the blood and its O_2 saturation, mental stress, ambient temperature, hydration, and quantity of muscle mass involved in the activity (20, 36, 41). Some of these limitations can be overcome by individual calibration. In contrast, the limitations of accelerometry are primarily biomechanical in that the accelerometry-PAI relationship during different activities, such as walking on the level and incline, when running, stepping, and cycling, and during load-bearing activities, is highly variable (2, 5, 6, 9, 10, 15, 18, 24, 31, 33). Thus it is difficult to accurately translate epidemiological accelerometry data directly into units of intensity or expended energy. Because the errors associated with the two methods are not positively correlated, the combination of HR and accelerometry should theoretically yield a more precise estimate of PAEE and PAI than either used independently (5, 6, 11, 14, 22, 25, 28, 34, 35, 37). Many of the studies in which the validity of combined HR monitoring and accelerometry has been assessed have used multiple regression techniques, which produce weighted averages. These depend on the protocol used and, consequently, may not perform well in other diverse scenarios. Moreover, this approach does not exploit the time synchronization between the accelerometry and HR to estimate the model coefficients. The selective use of data derived from either HR or accelerometry, depending on the characteristics of the activity assessed, may improve the generalizability of PAEE and PAI

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estimates to the free-living scenario. Some investigators have adopted this approach (28, 34, 35), although they have not explored the potential use of body movement data in a quantitative manner when the two data sources are combined. Combining the methods in this way may provide more robust estimates of intensity and energy expenditure in the intensity region around the flex HR, a HR used to discriminate between activity and nonactivity. Definition of flex HR is critical, because the majority of time is spent in this intensity region (28). Although Rennie et al. (28) demonstrated the utility of a single piece combined monitor, this device is not commercially available. Other studies involved equipping subjects with a Polar HR monitor and two Computer Science and Applications (CSA) accelerometers, model 7164 (now also known as MTI Actigraphs; Manufacturing Technology, Fort Walton Beach, FL), one on the arm and one on the leg (34, 35). This combination performed better for the prediction of energy expenditure than when HR monitors, hip-mounted CSAs, or hip-mounted pedometers were used separately. However, as with the study by Rennie et al. (28), this combined method did not use the accelerometer data quantitatively and required even more individual calibration than is commonly undertaken in the epidemiological setting. Additional potential problems with the use of three separate measurement units in epidemiological studies include lower response rates and increased Hawthorne effect. Although the combination of a Polar HR monitor and a hip-mounted CSA accelerometer is not perfect, it is more feasible and is currently being used in larger cohorts. Additionally, the precision of any objective assessment method, especially energy expenditure estimated from HR, is dependent on some level of individual calibration. However, this procedure places additional demands on both experimenter and participant. Thus a key question is whether the combination of HR and accelerometry will be sufficiently precise to preclude the need for individual calibration. Therefore, the aim of this study was to compare the time integral of minute-by-minute estimated PAI (in kJ·kg^{-1}·min^{-1}) from the combination of a hip-mounted CSA accelerometer and a Polar HR monitor against whole body calorimetry PAEE (in kJ/kg). This was done by using both accelerometry and HR data in a quantitative manner, and with and without individual calibration.

METHODS

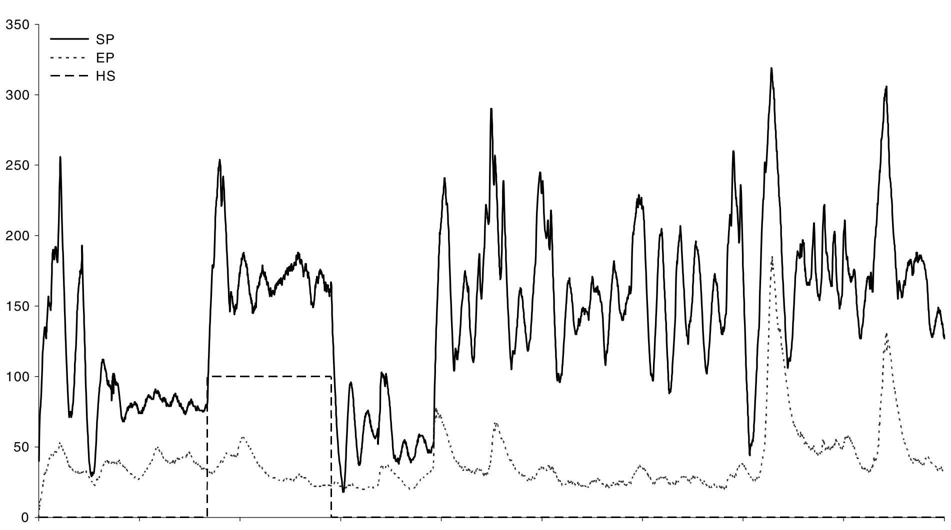
Subjects

Twelve male subjects (22.7–30.0 yr, 63.9–91.2 kg, 169–199 cm, 20.6–25.2 kg/m^2) performed individual calibration on a treadmill, after which they spent 22 h in a whole body heat-sink calorimeter, in which they performed various activities of daily living. All subjects were healthy and well trained with a mean peak O_2 uptake ($\dot{V}O_2$) (fitness) of 61.5 ml·min^{-1}·kg^{-1} (range: 51.0–71.5 ml·min^{-1}·kg^{-1}). Informed, written consent was obtained from each participant on entry to the study, which was approved by the local research ethics committee (Denmark).

Calorimetry Study

Calorimeter. The calorimeter protocol has been described in detail previously (17). In brief, the method relies on the principle that all expended energy is converted to heat (sensible power) or used to evaporate water (evaporative power). An example of the calorimeter output is shown in Fig. 1. The sum of the two time integrals of the sensible and the evaporative power represents the overall energy production for the time interval. Because of the large volume of this heat-sink calorimeter, the response time of the two power readings, e.g., after an activity bout, is rather slow, and thus data must be analyzed in extended epochs. Nonetheless, the energy expenditure measurements from these epochs are precise within ±2%, owing to high precision of the sensible and evaporative power (±1.4 and ±4.0%, respectively) (17).

The total energy expenditure (TEE) is composed of three main components. These are resting energy expenditure (REE), diet-induced thermogenesis (DIT), and PAEE. To assess the predictive capabilities for PAEE of CSA and HR used independently and in combination, PAEE was calculated as TEE − (REE + DIT) and expressed in kilojoules per kilogram body weight. The data were



22.00	23:00	07:30	08.45	10.00	11.20	12.20	14.40	15.30	16.30	18.15	20.00
Entry	Bed time	Get up	15 min cycling 1W·kg^{-1} 60 rpm	10 min walk	3 min step test (90 step·min^{-1})	10 min walk	10 min walk	15 min jog	5x3 min step test (75-135 step·min^{-1})	20 min cycling 1W·kg^{-1} 60 rpm	Exit

Fig. 1. Protocol for the calorimeter study with example of calorimeter data output. SP, sensible power; EP, evaporative power; HS, heat source.

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analyzed in two epochs: a nighttime period from 0000 to 0700 and a daytime period from 0730 to 2000.

HR and movement measurement. During both sleeping and waking hours, subjects wore a Polar Vantage NV HR monitor (Polar Electro, Kempele, Finland), set to measure HR (in beats/min) every 15 s, and two CSA accelerometers on each hip, sampling at 15- and 60-s epochs, respectively. All CSA and HR data were compiled to a minute-by-minute file for each individual. We used the mean of four CSA monitors to make our estimates more generalizable, because differences between CSA monitors and sites of placement on the hip have been reported (4, 39). We defined resting HR (RHR) as the 10th lowest HR observed during sleeping to obtain a robust estimate of this key parameter.

Study protocol. Each subject was instructed not to exercise during the 2 h immediately preceding his arrival at the laboratory at 2130 and to refrain from eating and drinking (other than water) from 2030 onward. Height and body weight were assessed by standard anthropometric methods. Body composition was assessed by the impedance technique (TBF-300, Tanita Europe) by using an average between the standard and the athlete settings on the impedance scale. Subjects entered the calorimeter at 2200 and left the calorimeter 22 h later. Figure 1 shows the overall activity protocol for the 22 h of calorimetry. Each subject performed a standardized protocol, which aimed to emulate the types of activity the subjects would undertake during a typical day. This involved periods of rest/reading and bouts of different forms of exercise. During periods when no activity other than reading was scheduled, subjects were allowed to use the telephone in the calorimeter. Of the 12.5 h when subjects were awake, they spent 13.1% on regular physical activity, which comprised 4.7% cycling, 4% walking, 2.4% stepping, and 2% jogging. The subjects went to bed at 2300 and were woken at 0730. Breakfast was served at 0815, lunch at 1330, and snacks (fruit or chocolate) at 1015, 1545, and 1730. Ad libitum quantities and compositions of breakfast and lunch were selected by the subject from a limited menu.

DIT. All consumed foods were registered and analyzed by a national food database (DanKost 2000, Dansk Catering Service), to yield energy intake (EI) and macronutrient composition. DIT was estimated from the absolute energy yield (in kJ) of the three macronutrients, according to the equation DIT = 0.025·fat EI + 0.07·carbohydrate EI + 0.275·protein EI (19).

REE. A heat source yielding exactly 6 kJ/min was introduced from 0200 to 0500 as a means of internal validation. This procedure enables the examination of the precision of the calorimeter's response to an increase in energy expenditure. The sleeping metabolic rate (SMR) was calculated for the periods 0000–0200 (SMR_1) and 0500–0700 (SMR_3) and then averaged (SMR_{1+3}). This was compared with the calculated SMR from 0200 to 0500 (SMR_2), which ideally should be 6 kJ/min higher if the calorimeter were 100% accurate, assuming that SMR_{1+3} did indeed approximate SMR during the heat supplementation. The total heat supplement was 1,080 kJ, so the SMR for the whole night was calculated as SMR = ($TEE_{0000-0700}$ − 1,080 kJ)/7 h. The resting metabolic rate (RMR) was assumed to equal 105% SMR (13). The RMR value was used as a baseline in derivation of the calibration equations (see *Calibration Study*). REE during time awake was obtained by integrating RMR over 12.5 h. This was also obtained by prediction equations using the impedance-derived body composition data (16).

Calibration Study

The calibration procedure was carried out in duplicate on a treadmill approximately 4 mo before the calorimetry study, as described previously (6). The subjects did not change their overall (self-reported) physical activity level during this interim period. Briefly, the calibration protocol consisted of 5-min intervals (continuous) at the following treadmill velocities: 3 and 6 km/h of walking and 8, 9, 10, 12, 14, 16, 18, and 20 km/h of running until volitional exhaustion. On both of these treadmill tests, $\dot{V}O_2$ was measured by an automated system (EO Sprint, Erich Jaeger). Aerobic fitness (peak $\dot{V}O_2$) was determined as the maximal observed value in either of the two treadmill tests. For each velocity, steady-state $\dot{V}O_2$ and HR were calculated as the mean of *minutes 3.5–5* after change of speed, and CSA output was expressed as the mean of 4 min, i.e., four epochs not overlapping different speeds. Body mass-specific PAI was calculated as $\dot{V}O_2$ minus measured RMR from the calorimeter and expressed in kilojoules per kilogram per minute by assuming an energetic value of 1 liter of oxygen = ~20.35 kJ (7). This value assumes that energy is derived equally from fat and carbohydrate and has been used elsewhere (28). Parallel estimates of PAI were also obtained by using predicted RMR. All HR values are expressed as absolute values minus RHR.

The calibration equations for PAI (calculated by using both measured and predicted RMR) were derived at group level (n = 12) and individual level for CSA, HR, and their combination as follows.

CSA to PAI conversion. One-dimensional accelerometers, such as the CSA, record virtually the same value across running speeds but increases linearly across walking through to jogging speeds (6, 12, 26). Therefore, we used linear regression to produce prediction equations for the CSA-PAI relationship in the 3–9 km/h range of CSA output (2 walking and 2 running speeds). This relationship was extrapolated to a CSA flex point, defined as 50% of the mean CSA output at 3 km/h. Between this flex point and the origin (0 counts/min, 0 kJ·kg^{-1}·min^{-1}), we assumed a straight line.

HR to PAI conversion. All subjects completed the calibration protocol, including the 16 km/h interval. Therefore, prediction equations for the HR-PAI relationship were produced by using only data in the 3–16 km/h intervals by quadratic regression (8). This regression was forced through the origin (0 beats/min, 0 kJ·kg^{-1}·min^{-1}), thus effectively assuming that the energy expenditure is equal to REE when the absolute HR is equal to RHR. In the flex HR method, this relationship was used for all HR values above the flex HR (defined as 10 beats/min + the average of RHR and the mean HR at 3 km/h). For HR values below the flex HR, we assumed PAI to be 0 kJ·kg^{-1}·min^{-1}. This approach is similar to the one used by Spurr et al. (32).

Nonbranched CSA + HR to PAI conversion. Multiple linear regression on the treadmill data in the 3–9 km/h range was used to produce a nonbranched equation containing both CSA and HR.

Branched CSA + HR to PAI conversion (a priori). We constructed a branched model, the structure of which is shown in Fig. 2. A priori, we assumed values of y = the walking/running transition HR (mean HR between the fastest walking and the slowest running on the treadmill), z = flex HR, P_1 = 100%, P_2 = P_3 = 50%, and P_4 = 0%. Pilot testing indicated that 5 counts/min is moderately exceeded in cycling activity; so to ensure that cycling was not quantified by *box 4* in Fig. 2, we set x = 5 counts/min.

Conversion of Calorimeter CSA and HR into PAEE

The daytime period in the calorimeter lasted 750 min, and for each minute we converted the CSA and HR into PAI (kJ·kg^{-1}·min^{-1}) by using the derived calibration equations. Estimates of PAEE were obtained as the sum (time integral) of the 750 estimated values of PAI. This produced estimates of PAEE (in kJ/kg) for each individual, which were then compared with the measured value. A priori, a total of eight models using measured RMR in the calibration and eight models using predicted RMR in the calibration were tested against measured PAEE.

Post Hoc Branched CSA + HR Model Estimation

According to the branched model (Fig. 2), we also estimated the parameters x, y_{1-2}, z_{1-2}, and P_{1-4} by using both the individually calibrated conversion equations and the group mean calibration equations. This estimation was done by minimizing the standard error of

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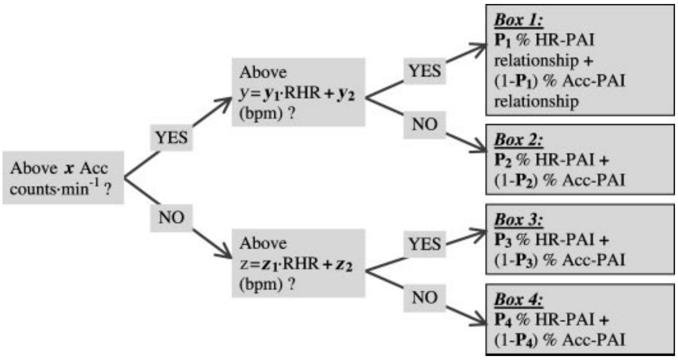

Fig. 2. Equation structure for the combination of accelerometry (Acc) and heart rate (HR). All HR values are absolute HR minus resting HR (RHR). All physical activity intensity (PAI) relationships are determined by calibration. Therefore, this study has 2 equation complexes, depending on whether individual or group calibration is used. The equation complexes translate minute-by-minute data into PAI as follows. If the Computer Science and Applications (CSA) value is above x, we use *box 1* (with P_1) if the HR value is above y; otherwise we use *box 2* (with P_2). Similarly, if the CSA value is $\leq x$, we use *box 3* (with P_3) if the HR value is above z; otherwise we use *box 4* (with P_4). Physical activity energy expenditure (PAEE) is obtained by integrating PAI with respect to time. The parameters x, y_{1-2}, z_{1-2}, and P_{1-4} are either assumed a priori or can be estimated post hoc by simulation of all possible models, while the standard error between predicted and measured PAEE is minimized. bpm, Beats/min.

the estimates (SEE), calculated as the square root of the mean squared error between the estimated and the measured PAEE for all potential models. This is essentially normal linear regression; i.e., all possible combinations of the parameters x, y_{1-2}, z_{1-2}, and P_{1-4} are considered and their time integrals (PAEE) of the resulting minute-by-minute PAI are then compared with the measured PAEE. Indeed, this procedure would be preferred if the criterion measure were minute-by-minute PAI, but since this is not the case, it is necessary to restrict the flexibility of the model to only move within reasonable boundaries around the parameters set in the CSA + HR (a priori) model. Thus constraints of parameters were specified as follows: x range 0–60 counts/min, y range 24–105 beats/min, z range 5.5–34 beats/min (both obtained with the y_1 and z_1 range $\pm$ 5.0, and the y_2 and z_2 range $\pm$ 250 beats/min), and $P_1 \geq P_2 \geq P_3 \geq P_4$ (all range 0–100%). The y and z ranges were determined by a 50% expansion of the ranges of transition HR and flex HR, respectively. To assess the robustness of the estimated model parameters, the standard error minimization procedure was rerun, disregarding the maximum and the minimum error, which resulted in a different set of parameters with a trimmed standard error. The relative contribution from HR and CSA was calculated as the fraction of observations being quantified by *boxes 1–4* in Fig. 2 times their weighting (P_{1-4} and 1-P_{1-4} for HR and CSA, respectively).

Statistics

Mean CSA output and mean HR during daytime were calculated and denoted CSA_{day} and HR_{day}, respectively. CSA_{night} and HR_{night} were calculated in a similar manner. For comparison purposes, the associations between PAEE and either CSA_{day}, HR_{day}, or their combination were also modeled by linear regression.

Agreement between the estimates of PAEE and the measured PAEE values was assessed in multiple ways. First, differences were calculated and tested with Student's paired *t*-tests. Differences are expressed as percentages of the measured PAEE and TEE values. Second, heteroscedasticity was explored by inspection of modified Bland-Altman plots (errors plotted against measured PAEE) and quantified with Pearson's correlation (1, 3). Third, precision of the models was assessed by the SEE. Difference in model precision was tested with Student's paired *t*-tests on the squared estimation errors. To test for bias and confounding, Pearson's correlation was used to test whether estimation errors could be explained by weight changes, aerobic fitness, body composition, RMR, or EI. The agreement between SMR_{1+3} and SMR_2 was tested with Student's paired *t*-test. Statistical significance was set at the 0.05 level. All analyses were performed with STATA version 7.0 (Stata), except the parameter estimation for the post hoc models, for which we used a macro (available on request), programmed in JAVA version 1.4.1 (Sun Microsystems).

RESULTS

Internal Validation of the Calorimeter

During the night, SMR decreased by 14.4% ($P < 0.001$) when SMR_1 and SMR_3 were compared. Mean $\pm$ SD difference between SMR_{1+3} and SMR_2 was 6.2 $\pm$ 0.6 kJ/min, which was not significantly different ($P = 0.31$) from the 6 kJ/min supplied by the heat source.

Calibration Equations

CSA flex was 497 counts/min at group level (range: 432–563 counts/min). The group calibration equations for the prediction of PAI were PAI = 0.053·CSA + 47.88 for CSA values above CSA flex and PAI = 0.15·CSA for CSA values below. The PAI-HR relationship was PAI = 0.011 HR^2 + 5.82 HR, and the nonbranched CSA + HR model was PAI = 0.028·CSA + 4.04·HR − 38.3, with all HR values expressed as beats per minute above RHR. There was no difference between the two treadmill tests for any of these relationships ($P \geq 0.80$).

Summary Statistics for Calorimetry Study

Mean $\pm$ SD percent body fat was 9.8 $\pm$ 2.1%. Mean $\pm$ SD values of REE, PAEE, and EI were 52.4 $\pm$ 7.4, 33.6 $\pm$ 7.0, and 153.5 $\pm$ 17.8 kJ/kg, respectively, for the 12.5 h when subjects were awake. Mean predicted REE was not significantly different from mean measured REE ($P = 0.538$), but there was a negative trend ($r = -0.73$, $P = 0.007$) in the Bland-Altman plot (not shown). Energy expenditure from physical activity accounted for an average $\pm$ SD of 33 $\pm$ 5.8% of TEE. DIT accounted for 12 $\pm$ 1.3%, and REE for the remaining 55 $\pm$ 5.2%. Mean $\pm$ SD RHR was 43.6 $\pm$ 6.3 beats/min. Average daytime HR ranged from 14.9 to 27.9 beats/min above RHR, with a mean $\pm$ SD of 21.5 $\pm$ 3.8 beats/min above RHR. All observed CSA values were in the range of 0–14,636 counts/min, with a third of the daytime observations being 0 or 1 count/min and 1% above 7,500 counts/min. Average daytime CSA output had a group mean $\pm$ SD of 290.2 $\pm$ 64.3 counts/min, whereas means for each subject ranged from 173.6 to 397.3 counts/min.

PAEE Estimated From CSA, flex HR, CSA + HR (MLR), and CSA + HR (a priori)

Measured PAEE was significantly correlated with CSA_{day} ($R^2 = 0.55$, $P = 0.006$, SEE = 4.96 kJ/kg), HR_{day} ($R^2 = 0.35$, $P = 0.044$, SEE = 5.95 kJ/kg), and their combination ($R^2 = 0.78$, $P = 0.001$, SEE = 3.67 kJ/kg).

Use of the treadmill calibration on both individual and group levels produced the estimates of PAEE from CSA, flex HR, and their combinations that are shown in Table 1. The mean $\pm$

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Table 1. *Estimates of PAEE from CSA, HR, and their combination in nonbranched (MLR) and branched models (a priori and post hoc)*

		Estimated PAEE, Using Individual Calibration					Estimated PAEE, Using Group Calibration				
		Nonbranched			Branched		Nonbranched			Branched	
ID	PAEE	CSA	Flex HR	MLR CSA + HR	A priori CSA + HR	Post hoc CSA + HR	CSA	Flex HR	MLR CSA + HR	A priori CSA + HR	Post hoc CSA + HR
1	26.9	15.7	57.4	61.5	37.6	31.4	15.9	35.2	39.9	25.5	30.4
2	41.5	17.6	77.6	84.8	47.3	42.7	18.6	66.9	51.8	42.1	37.4
3	28.2	8.6	62.2	57.0	36.2	33.6	12.9	56.8	44.3	36.0	32.3
4	41.2	19.4	22.2	9.7	20.8	34.2	19.7	63.0	52.7	41.5	39.4
5	42.6	18.6	41.1	54.5	29.3	32.3	21.8	49.2	41.3	35.0	36.8
6	33.4	14.3	47.0	27.9	33.1	33.3	18.0	41.2	33.9	31.0	30.3
7	26.9	14.8	19.7	26.8	17.2	21.9	16.5	24.5	24.5	20.5	24.6
8	36.9	16.0	55.0	53.6	37.0	37.8	19.1	58.8	52.3	40.7	38.7
9	42.6	19.9	91.3	97.8	57.4	44.2	25.5	90.6	64.0	57.6	45.8
10	28.0	15.8	33.3	11.4	24.6	28.4	16.3	46.3	39.6	32.4	29.6
11	30.7	21.0	29.2	25.1	24.3	30.4	21.5	52.6	43.9	39.2	33.1
12	24.1	13.4	25.7	22.2	19.6	23.4	13.2	24.4	20.3	18.8	22.6
Mean ± SD	33.6±7.0	16.3±3.4	46.8±22.7	44.4±28.4	32.0±12.0	32.8±6.7	18.3±3.6	50.8±18.7	42.4±12.3	35.0±10.6	33.4±6.6
SEE	0	18.2§‡	23.7‡	26.9§‡	10.0†	4.4†‡	16.0‡*	21.8†‡*	11.9‡*	6.6†	3.2†
SEE_{pred}	0	18.2§‡	20.7	25.0‡	9.7†	5.8†	15.8‡	18.2‡	12.7‡	6.0†	3.5†
R^2	1	0.37	0.20	0.23	0.27	0.61	0.61	0.59	0.53	0.61	0.78
P value		0.037	0.143	0.116	0.086	0.003	0.003	0.003	0.004	0.003	0.000

Values are in kJ/kg, except for R^2 and *P* values [strength of association between measured and estimated physical activity energy expenditure (PAEE)]. ID, subject identification; CSA, Computer Science and Applications method; flex HR, heart rate method; MLR, multiple linear regression method; SEE, the standard error of the estimate using measured resting metabolic rate (RMR) in the calibration; SEE_{pred}, corresponding SEE when predicted RMR is used in the calibration. *Significantly different from corresponding model using predicted instead of measured RMR values in the calibration ($P < 0.05$). †Significantly different from nonbranched (MLR) CSA + HR model on the same calibration level ($P < 0.05$). ‡Significantly different from branched CSA + HR (a priori) model on the same calibration level ($P < 0.05$). §Significantly different from corresponding model using group calibration ($P < 0.05$).

SD (*P* value for difference from measured value) percentage errors of the CSA estimates of PAEE were −50.8 ± 10.0% ($P < 0.001$) and −45.1 ± 7.3% ($P < 0.001$) for the individually calibrated and the group-calibrated estimates, respectively. Corresponding values were 39.1 ± 58.0% ($P = 0.047$) and 48.8 ± 37.7% ($P = 0.001$) for flex HR, 29.9 ± 71.8% ($P = 0.176$) and 25.7 ± 25.6% ($P = 0.004$) for the nonbranched CSA + HR model, and −4.4 ± 29.0% ($P = 0.612$) and 3.5 ± 20.1% ($P = 0.477$) for the branched CSA + HR (a priori) model.

The modified Bland-Altman plots (Fig. 3, *A* and *B*) illustrated that differences between CSA estimates and measured values of PAEE were negatively correlated with PAEE ($r = -0.88$, $P < 0.001$ for both individual and group calibration estimates). Estimation errors from flex HR demonstrated a different relationship (Fig. 3, *C* and *D*), with $r = 0.15$ ($P = 0.631$) and $r = 0.53$ ($P = 0.079$) for individual and group calibration estimates, respectively. For the two nonbranched CSA + HR models (Fig. 3, *E* and *F*), corresponding values were $r = 0.25$ ($P = 0.426$) and $r = 0.28$ ($P = 0.387$), and for the two branched CSA + HR (a priori) models (Fig. 3, *G* and *H*), values were $r = -0.08$ ($P = 0.803$) and $r = 0.19$ ($P = 0.561$). For all eight a priori models, estimation errors were not significantly related to weight change between the calibration and the calorimeter test ($P \geq 0.40$), weight change during the calorimeter test ($P \geq 0.07$), fitness ($P \geq 0.17$), body composition ($P \geq 0.10$), RMR ($P \geq 0.10$), or EI ($P \geq 0.21$).

As indicated by the differences in SEE (Table 1), the branched CSA + HR (a priori) models were more precise than both the corresponding single-measure models and the nonbranched CSA + HR models ($P = 0.035$ and $P = 0.007$ for the models using individual and group calibration, respectively). Of all four single-measure models, only the flex HR model using group calibration was significantly less precise than the nonbranched CSA + HR model at the same level of calibration ($P = 0.048$). Only the nonbranched model of CSA + HR using group calibration lost a statistically significant amount of precision when utilizing predicted RMR instead of measured RMR in the calibration. Other models were either unaffected or showed improvement.

PAEE Estimated from Branched CSA + HR (Post Hoc)

The PAEE estimates of the two branched post hoc models are shown in Table 1, together with the a priori model estimates. The branched model parameters underlying these results are displayed in Table 2. The mean ± SD (*P* for difference from measured PAEE) percentage errors of the estimates were −1.5 ± 13.0% ($P = 0.452$) and 0.1 ± 9.8% ($P = 0.843$) for the individually calibrated and the group calibrated estimates, respectively. Mean error in percent was −2.36% for the individual calibration model (individual estimates from −24 to 16%) and 0.54% (individual estimates ranging within ±14%) for the group calibration model, corresponding to ~0.18 ± 4.6% of TEE. The branched post hoc models were also more precise than their nonbranched counterparts ($P = 0.026$ and $P = 0.007$ for the models using individual and group calibration, respectively). The Bland-Altman plots (Fig. 3, *I* and *J*) illustrated that estimation errors were not significantly correlated with measured PAEE ($r = -0.40$, $P = 0.202$, and $r = -0.36$, $P = 0.244$ for individual and group calibration, respectively). Estimation errors of the two post hoc models were not significantly related to weight change between the calibration and the calorimeter test ($P \geq$

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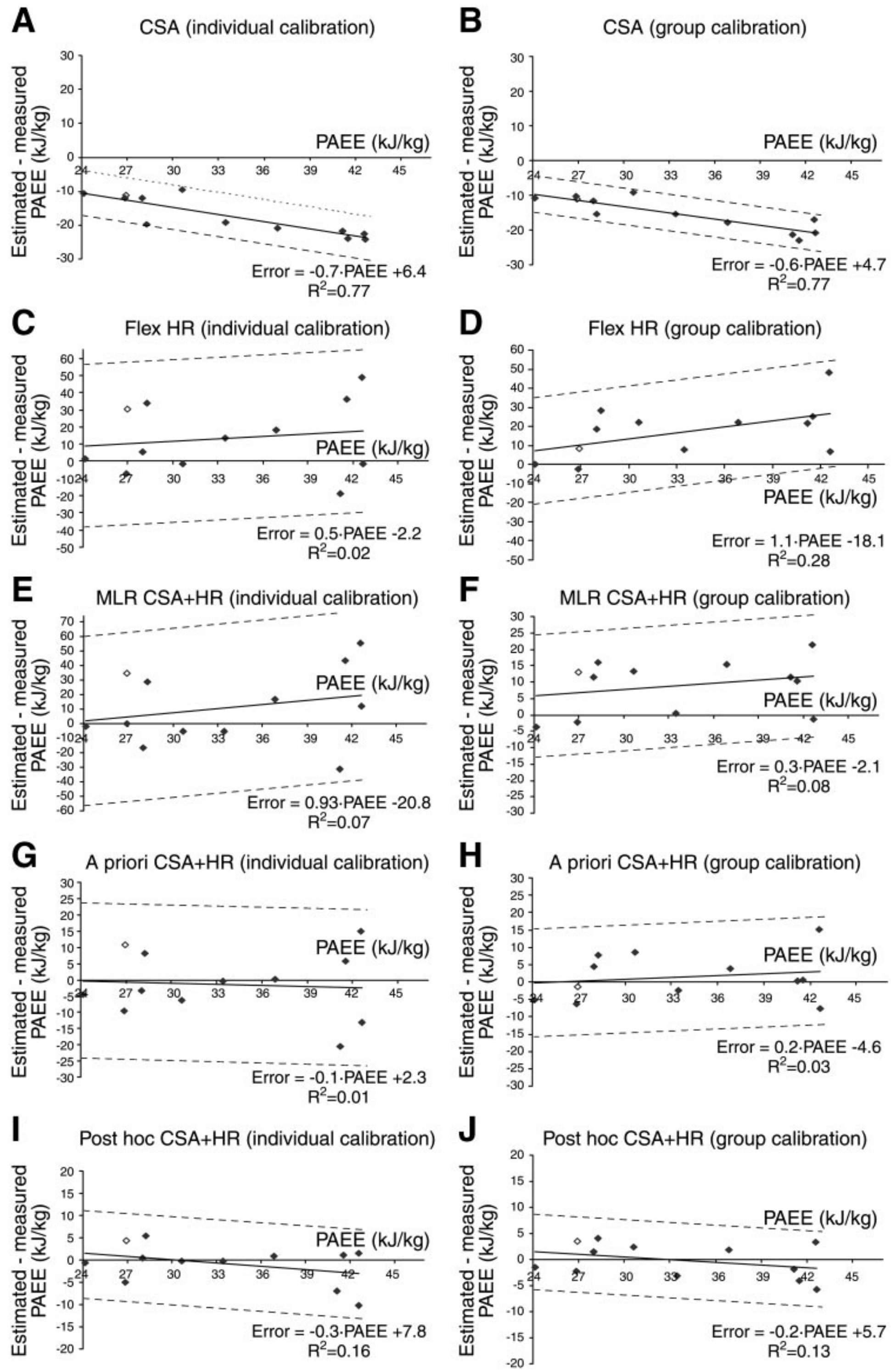

Fig. 3. Bland-Altman plots of differences between measured and estimated PAEE. *A* and *B*: CSA estimates. *C* and *D*: flex HR estimates. *E* and *F*: CSA + HR [multiple linear regression (MLR)] estimates. *G* and *H*: branched CSA + HR (a priori) estimates. *I* and *J*: branched CSA + HR (post hoc) estimates. *Left*: results of models using individual calibration. *Right*: models using group calibration. Lines are regression of the errors against measured PAEE with 95% error bands (dashed lines).

0.51), weight change during the calorimeter test ($P \geq 0.08$), fitness ($P \geq 0.16$), body composition ($P \geq 0.24$), RMR ($P \geq 0.27$), or EI ($P \geq 0.24$).

DISCUSSION

The calorimeter used in this study has been previously shown to measure energy expenditure with a precision of ±2% (17). This level of precision is similar to that estimated through our internal validation using the fixed heat source. For the calculation of the criterion measure PAEE, it was necessary to make assumptions on the magnitude to which diet increases TEE. There is some controversy about the magnitude of DIT for a given individual, but it is generally agreed that DIT is modified by age, gender, obesity, and macronutrient intake (19, 23, 27, 29, 40). With the exception of macronutrient intake, our sample was relatively homogeneous with regard to these mod-

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Table 2. *Estimated parameters in the branched CSA + HR post hoc models with the utilization of individual and group calibration, respectively*

	Individual Calibration	Group Calibration
x	4 (4)	35 (6)
y_1	2.6 (2.5)	0.4 (−3.5)
y_2	−63 (−62)	50 (224)
z_1	−1.1 (−1.0)	−1.0 (−1.0)
z_2	70 (68)	60 (64)
P_1	0.61 (0.64)	1.00 (1.00)
P_2	0.32 (0.27)	0.21 (0.21)
P_3	0.18 (0.26)	0.21 (0.21)
P_4	0.0 (0.0)	0.10 (0.10)
Utilization (1/2/3/4)	282/4,260/768/3,690 (408/4,134/389/4,069)	80/2,869/2,922/3,129 (230/4,022/1,468/3,280)
HR/CSA contribution	22%/78% (16%/84%)	18%/82% (19%/81%)

Parameters are obtained by minimizing the SEE or the trimmed SEE (in parentheses). Utilization is the number of observations that end up being quantified by *boxes 1, 2, 3,* and *4* in the equation structure. HR/CSA contribution is the sum of the fraction of observations being quantified by *boxes 1–4* (Fig. 2) times their weighting (P_{1-4} and 1-P_{1-4} for HR and CSA, respectively).

ifying parameters, which helps justify our choice of method to calculate DIT in the present study. Furthermore, DIT estimated in this way was comparable to the more simplistically calculated and widely used value of 0.1·TEE (30). Although the results of the present study change with different assumptions of DIT, the relative differences between the models persist, therefore demonstrating the utility of combining accelerometry with HR.

The CSA accelerometer and the Polar HR monitor are among the most widely used physical activity monitors. Although this combination has been studied previously, the specific modeling techniques described in the present study have not been reported (5, 6, 34, 35). The combination method used here is based on three assumptions. The first is that RHR is measured, preferably overnight. The second is that some level of calibration has been undertaken. And the third is that a valid measure of REE is obtained to provide a base for the PAI calculations. Our measurement of REE was obtained by the gold standard technique of whole body calorimetry, including overnight assessment. This procedure is infeasible for large-scale population studies but was appropriate in this study for the purpose of validating the method we describe. An alternative to our procedure would have been measurement of REE with indirect calorimetry as a part of the calibration or by calculating REE from prediction equations. Although the latter showed regression to the mean in our study, this did not significantly affect the precision of the branched models. Additionally, we used four CSA accelerometers in this study to correct for unit differences (4) and effect of placement on the hip (39), but this is not necessary in the epidemiological setting if CSA units are thoroughly calibrated before use and consistently placed on the same site.

Our main finding was that the combination of HR and accelerometry improves the estimates of PAEE when treadmill-derived calibration equations were used in a branched model. This is mainly because estimates of PAEE derived by using the CSA are usually underestimates of the true value, whereas the flex HR method usually overestimates PAEE. The group level calibration equations used individually in this study are not independent of the subjects because each of them is represented by a weight of 0.083 in the equations. Therefore, the comparisons between the estimates with and without individual calibration should be interpreted with some caution and merely taken as an indicator of how the error structure and optimal weighting between accelerometry and HR data changes as one moves away from individual calibration. Nonetheless, moving toward a higher degree of individual calibration resulted in a slightly more precise group mean and less heteroscedasticity (correlation between estimation error and PAEE) only for the flex HR method, although the standard error tended to increase (nonsignificant). For all other models, the group mean estimate and standard error tended to decrease (only significant for the CSA and CSA + HR models). Although HR is expressed in beats above resting, which reduces a considerable amount of the interindividual variance in the HR-PAI relationships, this was not anticipated. Even though genetic and other nonvariable components of the interindividual variance in the PAI relationships would be removed by individual calibration, it is possible that drift between the calibration and validation parts of the study due to changes in fitness and/or weight may explain this observation. However, even though small weight changes occurred, this is largely accounted for by expressing all values relative to body weight. Furthermore, the estimation errors were not significantly related to weight changes, fitness (at the time of calibration), body composition, RMR, or EI, making (residual) bias less likely. The greater variance of the PAEE estimation errors for the models incorporating individual calibration suggests that errors in the calibration procedure are greater than errors resulting from interindividual variance, with the possible exception of the HR-PAI relationships. If this is true, it highlights the importance of choosing an appropriate calibration procedure. This is probably more of an issue for the interpolations that were employed to infer energy expenditure at the lowest levels of activity. In this study, the interpolated part of the CSA-PAI relationship is used >90% of the time, reflecting the relatively long periods of low or no activity in the calorimeter. Indeed, a large proportion of time was spent in the intensity region around the flex HR, as was also observed by Rennie et al. (28).

Ultimately, any calibration procedure should reflect the activity most commonly engaged in by the population in which it is being employed. But this is often hard to define in the free-living scenario, especially when one is mindful of minimizing the burden placed on the experimenter and participants. Although, in the interest of precision, a representative calibration procedure should perhaps involve 24-h whole body calorimetry for each individual (25, 37), this is unfeasible in large-scale epidemiological studies in which access to the participant and to the laboratory is often limited.

The precision of the CSA + HR (a priori) model using individual calibration is comparable to that level reported by Rennie et al. (28) when expressed in the same way (i.e., relative to TEE). The levels of energy expenditure were also similar in our study and theirs (7.6 vs. 8.0 kJ $\cdot kg^{-1} \cdot h^{-1}$; $P = 0.25$), although the protocols differed. However, as already highlighted, the CSA + HR (a priori) model using the group calibration, which we report in this study, was more precise than the method reported by Rennie et al., although this may be attributable to our more homogeneous sample. Irrespective of

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this, the high precision of the CSA + HR (post hoc) models is encouraging; in theory, the model using group calibration could predict PAEE within 0.54% on group level, with the individual estimates within ±14%, corresponding to ~0.18 ± 4.6% of TEE. Interestingly, the partial contributions of HR and CSA were virtually reversed in the branched models compared with multiple linear regression-derived equations on walking and running alone (5, 6, 22). Although this is partially due to the absence of high-intensity exercise in the protocol, it supports the potential utility of the branched modeling technique, particularly in populations in whom high-intensity exercise is uncommon. However, there was some variation in the estimated parameters compared with their trimmed counterparts. This was especially the case for *x* and *y* in the model using group calibration, suggesting that these parameters may lack robustness. In contrast, the *z* and P parameters were comparable between the individual- and group-calibrated models. Nonetheless, these models should only be used in other populations, bearing in mind that the data for these models are derived from a relatively small and homogeneous sample of young men, who undertook a fixed activity protocol in a calorimeter. For example, these branched models are likely to underestimate activities that are characterized by more static types of activity or arm-only work, as opposed to dynamic leg exercise. Moreover, because the ability to obtain a precise estimate of PAEE is an important factor in accurately establishing dose-response relationships between physical activity and disease and because heat-sink calorimeters provide an accurate measure of PAEE but not minute-by-minute PAI, we used PAEE as the criterion measure, as opposed to PAI. The estimated values for PAEE correlated with the measured PAEE values on the same level ($R^2 = 0.78$) as the multiple regression model that used average daytime HR and CSA. However, further validation in a more heterogeneous sample, and preferably against doubly labeled water-derived estimates of TEE, is needed before any of these methods can confidently be applied to free-living populations. The branched model was designed as a framework to interpret simultaneous HR and accelerometry data into minute-by-minute PAI. This is in contrast to the multiple regression model of PAEE (with CSA_{day} and HR_{day}), which can only be used to estimate PAEE. Thus the logical progression would be to validate the branched model for combining accelerometry with HR data as a measure of PAI in a range of activities by using a similar experimental design as Strath et al. (35). It would also be valuable to know how branched models perform in common occupational settings and activities that predominantly involve arm work or static work. The method proposed in this paper to estimate parameters in branched models is based on the same mathematical principle as normal regression, i.e., minimizing the SEEs. This approach would, however, improve substantially by increasing the volume of data. Preferably, the data would also be derived from a range of different activity modes and intensities. Frequency, duration, and TEE of physical activity can be derived from such an intensity measurement, provided the time resolution is sufficiently high to capture the changes in intensity.

In conclusion, the combination of HR and CSA data in a branched equation model improves the estimate of PAEE in a population of trained young men compared with either method used alone or when the traditional nonbranched combination is used. Our results also suggest that individual calibration may not be as necessary when branched modeling is employed. We hypothesize from these observations that, in larger heterogeneous populations, more parsimonious calibration procedures may be sufficiently precise when utilized in conjunction with equations derived in smaller samples.

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