Brage S, Brage N, Franks PW, Ekelund U, Wong MY, Andersen LB et al.. Branched equation modeling of simultaneous accelerometry and heart rate monitoring improves estimate of directl...

Article *in* Journal of Applied Physiology · February 2004

Impact Factor: 3.06 · DOI: 10.1152/japplphysiol.00703.2003 · Source: PubMed

Articles in PresS. J Appl Physiol (September 12, 2003). 10.1152/japplphysiol.00703.2003

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

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Running head: Simultaneous accelerometry and HR to estimate PAEE

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ABSTRACT

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, utilizing either individual calibration (IC) of HR and accelerometry or corresponding mean group calibration (GC) equations. In 12 males (20.6-25.2 $kg \cdot m^{-2}$), IC and GC equations for physical activity intensity (PAI) were derived during treadmill walking and running for both HR (Polar) and hip-acceleration (CSA). HR and CSA were recorded minute-by-minute during 22hrs of whole-body calorimetry and converted into PAI in four different weightings ($P_{1\text{-}4}$) of the HR vs. the CSA ($1\text{-}P_{1\text{-}4}$) relationships: If CSA>X, we used the P_1 weighting if HR>Y, otherwise P_2. Similarly, if CSA≤X, we used P_3 if HR>Z, otherwise P_4. PAEE was calculated for a 12.5hr non-sleeping period as the time-integral of PAI. *A priori*, we assumed $P_1=1$, $P_2=P_3=0.5$, $P_4=0$, X=5counts$\cdot$min^{-1}, Y=walking/running transition HR, and Z=flex HR. These parameters were also estimated *post hoc*. Mean$\pm$SD estimation errors of *a priori* models were -4.4$\pm$29% and 3.5$\pm$20% for IC and GC, respectively. Corresponding *post hoc* model errors were -1.5$\pm$13% and 0.1$\pm$9.8%. All branched models had lower errors ($p \leq 0.035$) than single-measure estimates of CSA ($\leq$-45%) and HR ($\geq$+39%), as well as their non-branched combination ($\geq$+25.7%). In conclusion, combining HR and CSA by branched modeling improves estimates of PAEE. Individual calibration may be less crucial with this modeling technique.

KEY WORDS: Validity, intensity, epidemiology, calorimetry, movement sensor, activity monitor, energy expenditure, individual calibration

Title character count: 158

Running head character count: 50

Abstract word count: 257 (1733 characters)

INTRODUCTION

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. Since 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 heart rate monitoring and accelerometry has been assessed, have used multiple regression techniques, which produce weighted averages. These depend upon 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 heart rate to estimate the model coefficients. The selective use of data derived from either heart rate or accelerometry, depending on the characteristics of the activity assessed, may improve the generalizability of PAEE and PAI 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 combining the two data sources. Combining the methods in this way may provide more robust estimates of intensity and energy expenditure in the intensity region around the flexHR, a HR used to discriminate between activity and non-activity. Definition of flexHR is critical, as the majority of time is spend in this intensity region (28). Although Rennie et al demonstrated the utility of a single piece combined monitor (28), this device is not commercially available. Other studies involved equipping subjects with a Polar heart rate monitor and two Computer Science & Applications (CSA) accelerometers model 7164 (now also known as MTI Actigraphs; Manufacturing Technology Inc., Fort Walton Beach, FL, USA), 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, 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 using 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 thus currently being used in larger cohorts. Additionally, the precision of any objective assessment method, especially energy expenditure estimated from HR, is that it is dependent upon 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 $kJ \cdot kg^{-1} \cdot min^{-1}$) from the combination of a hip mounted CSA accelerometer and a Polar HR monitor against whole-body calorimetry PAEE (in $kJ \cdot kg^{-1}$). This was done by using both accelerometry and HR data in a quantitative manner, and with and without individual calibration.

RESEARCH DESIGN AND METHODS

Subjects

Twelve male subjects (22.7-30.0 years, 63.9-91.2 kg, 169-199 cm, 20.6-25.2 $kg \cdot m^{-2}$) performed individual calibration on a treadmill, following which they spent 22 hrs 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 VO_2 (fitness) of 61.5 $ml \cdot min^{-1} \cdot kg^{-1}$ (range: 51.0-71.5 $ml \cdot min^{-1} \cdot kg^{-1}$). 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 **Figure 1**. The sum of the two time integrals of the sensible and the evaporative power represents the overall energy production for the time interval. Due to 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 comprised of three main components. These are resting energy expenditure (REE), diet-induced thermogenesis (DIT), and physical activity energy expenditure (PAEE). In order 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 (kJ) per kg body weight. The data were analyzed in two epochs: a night-time period from 0:00-07:00hrs and a day-time period from 07:30-20:00hrs.

HR and movement measurement: During both sleeping and waking hours, subjects wore a Polar Vantage NV heart rate monitor (Polar Electro, Kempele, Finland), set to measure HR (in beats per minute, bpm) every 15 seconds and two CSA accelerometers on each hip, sampling at 15 and 60 second 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, as differences between CSA monitors and sites of placement on the hip have been reported (4; 39). We defined resting HR (RHR) as the tenth 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 two hours immediately preceding their arrival at the laboratory at 21:30hrs and to refrain eating and drinking (other than water) from 20:30hrs onwards. Height and body weight were assessed by standard anthropometric methods. Body composition was assessed by the impedance technique (TBF-300, Tanita Europe GmbH, Germany), using an average between the ‘Standard’ and the ‘Athlete’ settings on the impedance scale. Subjects entered the calorimeter at 22:00hrs and left the calorimeter 22hrs later. **Figure 1** shows the overall activity protocol for the 22hrs 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 12.5hrs when subjects were awake, they spent 13.1% on regular physical activity, which comprised of 4.7% cycling, 4% walking, 2.4% stepping, and 2% jogging. The subjects went to bed at 23:00hrs and were woken at 07:30hrs. Breakfast was served at 08:15hrs, lunch at 13:30hrs, and snacks (fruit or chocolate) at 10:15hrs, 15:45hrs, and 17:30hrs. *Ad libitum* quantities and compositions of breakfast and lunch were selected by the subject from a limited menu.

Diet-induced thermogenesis: All consumed foods were registered and analyzed by a national food database (DanKost 2000, Dansk Catering Service A/S, DK) 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).

Resting energy expenditure: A heat source yielding exactly 6 $kJ \cdot min^{-1}$ was introduced from 02:00-05:00hrs, 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 0:00-02:00hrs (SMR_1) and 05:00-07:00hrs (SMR_3) and then averaged (SMR_{1+3}). This was compared to the calculated SMR from 02:00-05:00hrs (SMR_2), which ideally should be 6 $kJ \cdot min^{-1}$ higher if the calorimeter was 100 % accurate, assuming that SMR_{1+3} did indeed approximate SMR during the heat supplementation. The total heat supplement was 1080 kJ, so the SMR for the whole night was calculated as SMR = ($TEE_{0:00\text{-}07:00hrs}$ - 1080kJ) / 7hr. 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 below). Resting energy expenditure (REE) during time awake was obtained by integrating

RMR over 12.5 hrs. 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 four months 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 5min intervals (continuous) at the following treadmill velocities: 3 and 6 $km \cdot h^{-1}$ of walking and 8, 9, 10, 12, 14, 16, 18, and 20 $km \cdot h^{-1}$ of running until volitional exhaustion. On both these treadmill tests, oxygen consumption was measured by an automated system (EO Sprint, Erich Jaeger GmbH, Germany). Aerobic fitness (peak VO_2) was determined as the maximal observed value in either of the two treadmill tests. For each velocity, steady state VO_2 and HR were calculated as the mean of minutes 3.5–5 following change of speed and CSA output was expressed as the mean of 4min, i.e., four epochs not overlapping different speeds. Body mass specific PAI was calculated as VO_2 minus measured RMR from the calorimeter and expressed in $kJ \cdot kg^{-1} \cdot min^{-1}$ by assuming an energetic value of 1 L 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 using predicted RMR. All HR values are expressed as absolute values minus resting heart rate (RHR).

The calibration equations for PAI (calculated both using 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^{-1} range of CSA output (two walking and two running speeds). This relationship was extrapolated to a CSA flex point, defined as 50% of the mean CSA output at 3 km·h^{-1}. Between this flex point and the origin (0 counts·min^{-1}, 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^{-1} interval. Therefore, prediction equations for the HR-PAI relationship were produced using only data in the 3-16 km·h^{-1} intervals by quadratic regression (8). This regression was forced through the origin (0 bpm, 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 the 10 bpm + the average of RHR and the mean HR at 3 km·h^{-1}). 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 and colleagues (32).

Non-branched CSA+HR to PAI conversion (MLR): Multiple linear regression on the treadmill data in the 3-9 km·h^{-1} range was used to produce a non-branched 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 **Figure 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^{-1} is moderately exceeded in cycling activity, so to ensure that cycling was not quantified by Box 4 in **Figure 2**, we set X = 5 counts·min^{-1}.

Conversion of calorimeter CSA and HR into PAEE

The day-time period in the calorimeter lasted 750min, and for each minute we converted the CSA and HR into PAI ($kJ \cdot kg^{-1} \cdot min^{-1}$), 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 $kJ \cdot kg^{-1}$) 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 (**Figure 2**), we also estimated the parameters X, $Y_{1\text{-}2}$, $Z_{1\text{-}2}$, and $P_{1\text{-}4}$, using both the individually calibrated conversion equations and the group mean calibration equations. This estimation was done by minimizing the standard error of 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, $Y_{1\text{-}2}$, $Z_{1\text{-}2}$, and $P_{1\text{-}4}$, are considered and their time integral (PAEE) of the resulting minute-by minute PAI compared to the measured PAEE. Indeed, this procedure would be preferred if the criterion measure was 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 $counts \cdot min^{-1}$, Y range 24 – 105 bpm, Z range 5.5 – 34 bpm (both obtained with the Y_1 and Z_1 range $\pm$5.0, and the Y_2 and Z_2 range $\pm$250 bpm), 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 SEE minimization procedure was re-run disregarding the maximum and the minimum error, resulting in a different set of parameters with a ‘trimmed’ SEE. The relative contribution from HR and CSA was calculated as the fraction of observations being quantified by boxes 1-4 in **Figure 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 day-time 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. Firstly, differences were calculated and tested with Student's paired t-tests. Differences are expressed as percentages of the measured PAEE and TEE values. Secondly, heteroscedasticity was explored by inspection of modified Bland-Altman plots (errors plotted against measured PAEE) and quantified with Pearson correlation (1; 3). Thirdly, precision of the models was assessed by the standard error of the estimates (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 correlation was used to test whether estimation errors could be explained by weight changes, aerobic fitness, body composition, RMR, or energy intake. 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 Corp. TX, USA), except the parameter estimation for the *post hoc* models, which using a macro (available on request), programmed in JAVA *version 1.4.1* (Sun Microsystems Inc, USA).

RESULTS

Internal validation of the calorimeter

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

Calibration equations

CSA flex was 497 $counts \cdot min^{-1}$ at group level (range: 432-563 counts·min-[1]). The group calibration equations for the prediction of PAI were $PAI = 0.053 \cdot CSA + 47.88$ for CSA values above CSA flex and $PAI = 0.15 \cdot CSA$ for CSA values below. The PAI-HR relationship was: $PAI = 0.011 \cdot HR^2 + 5.82 \cdot HR$, and the non-branched CSA+HR model was $PAI = 0.028 \cdot CSA + 4.04 \cdot HR - 38.3$ with all HR values expressed as bpm above RHR. There was no difference between the two treadmill tests for any of these relationships ($p \geq .80$).

Summary of collected variables during awake

Mean (SD) percentage body fat was 9.8 (2.1) %. Mean (SD) values of REE, PAEE, and EI were 52.4 (7.4) $kJ \cdot kg^{-1}$, 33.6 (7.0) $kJ \cdot kg^{-1}$, and 153.5 (17.8) $kJ \cdot kg^{-1}$, respectively for the 12.5hrs when subjects were awake. Mean predicted REE was not significantly different from mean measured REE ($p=.538$) but there was a negative trend ($r=-.73$, $p=.007$) in the Bland-Altman plot (not shown). Energy expenditure from physical activity accounted for an average (SD) of 33 (5.8) % of TEE. DIT accounted for 12 (1.3) %, and REE for the remaining 55 (5.2) %. Mean (SD) RHR was 43.6 (6.3) bpm. Average day-time HR ranged from 14.9 to 27.9 bpm above RHR, with a mean (SD) of 21.5 (3.8) bpm above RHR. All observed CSA values were in the range 0 – 14,636 $counts \cdot min^{-1}$, with a third of the daytime observations being 0 or 1 $count \cdot min^{-1}$ and 1% above 7,500 $counts \cdot min^{-1}$. Average daytime CSA output had a group mean (SD) of 290.2 (64.3) $counts \cdot min^{-1}$, whereas means for each subject ranged from 173.6 to 397.3 $counts \cdot min^{-1}$.

PAEE estimated from CSA, flexHR, 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^{-1}), HR_{day} (R^2=0.35, p=0.044, SEE=5.95 kJ·kg^{-1}), and their combination (R^2=0.78, p=0.001, SEE=3.67 kJ·kg^{-1}).

Using 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 (SD, p 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 flexHR, 29.9 % (71.8 %, p=0.176) and 25.7 % (25.6 %, p=0.004) for the non-branched 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 (**Figure 3.A+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 (**Figure 3.C+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 non-branched CSA+HR (*MLR*) models (**Figure 3.E+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 (**Figure 3.G+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≥0.40), weight change during the calorimeter test (p≥0.07), fitness (p≥0.17), body composition (p≥0.10), RMR (p≥0.10), or energy intake (p≥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 non-branched CSA+HR models (p=.035 and p=.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 non-branched CSA+HR model at the same level of calibration (p=.048). Only the non-branched 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 about 0.18±4.6% of TEE. The branched *post hoc* models were also more precise than their non-branched counterparts (p=.026 and p=.007 for the models using individual and group calibration, respectively). The Bland-Altman plots (**Figure 3.I+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 ($p \geq 0.51$), 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 energy intake ($p \geq 0.24$).

DISCUSSION

The calorimeter used in this study has been previously shown to measure energy expenditure with a precision of $\pm 2\%$ (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 the macro-nutrient intake (19; 23; 27; 29; 40). With the exception of macro-nutrient intake, our sample was relatively homogeneous, with regard to these modifying 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 $0.1 \cdot TEE$ (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 resting HR 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 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 using treadmill derived calibration equations in a branched model. This is mainly because estimates of PAEE derived 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, as 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 towards 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 flexHR method, although the SEE tended to increase (non-significant). For all other models, the group mean estimate and the SEE tended to decrease (only significant for the CSA and CSA+HR (*MLR*) models). Although HR is expressed in beats above resting, which reduces a considerable amount of the inter-individual variance in the HR-PAI relationships, this was not anticipated. Even though genetic and other non-variable components of the inter-individual 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 inter-individual 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 more than 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 and colleagues (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 upon the experimenter and participants. Although in the interests of precision, a representative calibration procedure should perhaps involve 24hr 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*, when expressed in the same way (i.e., relative to TEE) (28). The levels of energy expenditure were also similar in our study and theirs (7.6 $kJ \cdot kg^{-1} \cdot hr^{-1}$ vs. 8.0 $kJ \cdot kg^{-1} \cdot hr^{-1}$, 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 paper, was more precise than the method reported by Rennie, although this may be attributable to our more homogeneous sample. Irrespective of 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 $\pm$14%, corresponding to about 0.18$\pm$4.6% of TEE. Interestingly, the partial contributions of HR and CSA were virtually reversed in the branched models, as compared to 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 where high intensity exercise is uncommon. However, there was some variation in the estimated parameters as compared to 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 is 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-responses relationships between physical activity and disease, and secondly 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, 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 standard errors of the estimates. 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 total energy expenditure 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 to either method used alone or when the traditional non-branched 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.

Acknowledgements

The authors should like to thank the subjects for their time and effort. Mads Rasmussen is acknowledged for technical assistance in handling the calorimeter and Brit Thobo-Carlsen for help with data collection. Dr. Shing-Hing Man developed the Java macro, used for the *post hoc* analyses, and Dr. Jian'An Luan provided other statistical assistance. The study was supported by the Danish Medical Research Council. MYW was supported by a Wellcome Trust grant during her sabbatical leave at the Institute of Public Health, University of Cambridge, UK.

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TABLE 1

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

		Estimated PAEE, using individual calibration					*Estimated PAEE, using group calibration*				
		Non-branched			Branched		Non-branched			Branched	
Id	PAEE	CSA	HR	MLR CSA+HR	*A priori* CSA+HR	*Post hoc* CSA+HR	CSA	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 (p)	1 -	.37 (.037)	.20 (.143)	.23 (.116)	.27 (.086)	.61 (.003)	.61 (.003)	.59 (.003)	.53 (.004)	.61 (.003)	.78 (.000)

Data are in $kJ \cdot kg^{-1}$, except R^2 (p); strength of association between measured and estimated PAEE. SEE is the standard error of the estimate using measured RMR in the calibration, SEE_{pred} is the corresponding SEE when using predicted RMR in the calibration. ♣Significantly different from corresponding model using group calibration (p<.05). †Significantly different from non-branched CSA+HR (*MLR*) model on the same calibration level (p<.05). ‡Significantly different from branched CSA+HR (*a priori*) model on the same calibration level (p<.05). *Significantly different from corresponding model using predicted instead of measured RMR values in the calibration (p<.05).

TABLE 2

Estimated parameters in the branched CSA+HR *post hoc* models, with the utilization of individual and group calibration, respectively. The equation structure of the branched models is shown in Figure 2.

	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	.61 (.64)	1.00 (1.00)
P_2	.32 (.27)	.21 (.21)
P_3	.18 (.26)	.21 (.21)
P_4	0.0 (0.0)	.10 (.10)
Utilization (1 / 2 / 3 / 4)	282 / 4260 / 768 / 3690 (408 / 4134 / 389 / 4069)	80 / 2869 / 2922 / 3129 (230 / 4022 / 1468 / 3280)
HR / CSA contribution	22% / 78% (16% / 84%)	18% / 82% (19% / 81%)

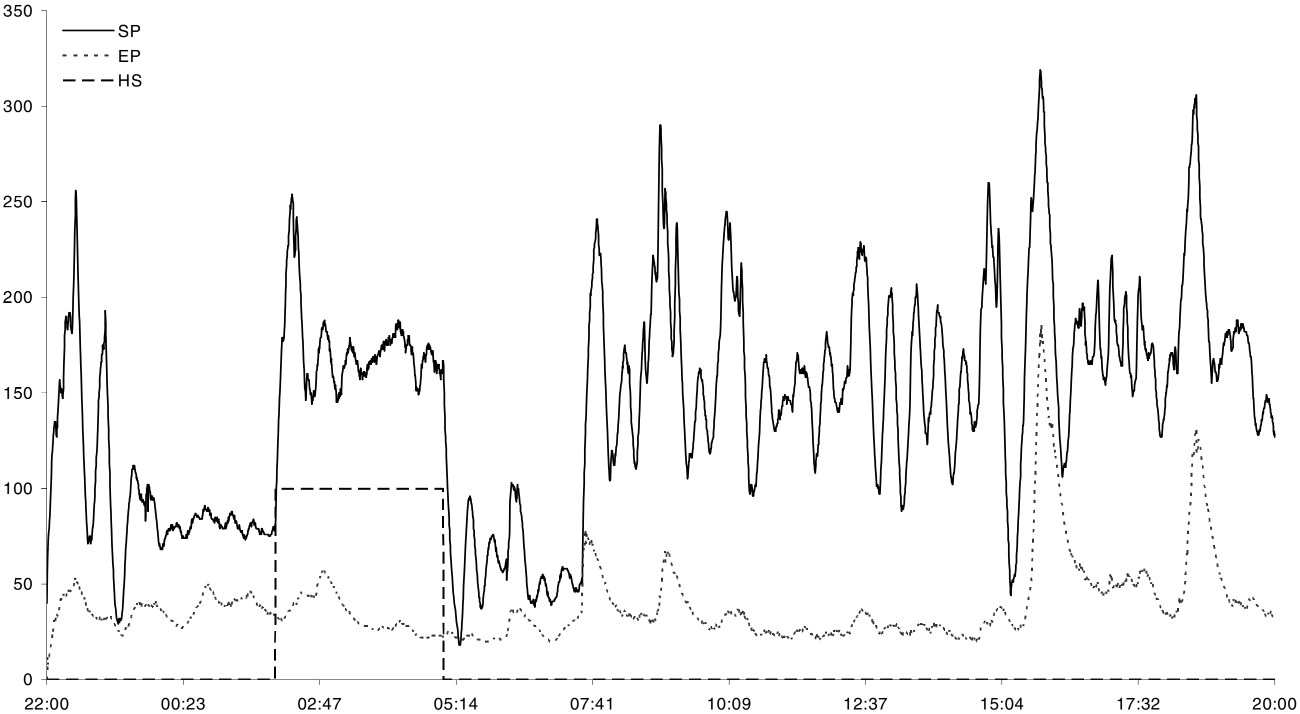
Parameters are obtained by minimizing the SEE or the 'trimmed' SEE (in parentheses). Utilization is the number of observations that end up being quantified by boxes 1, 2, 3, and 4 in the equation structure. HR/CSA contribution is the sum of the fraction of observations being quantified by boxes 1-4 (Figure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

Figure legends:

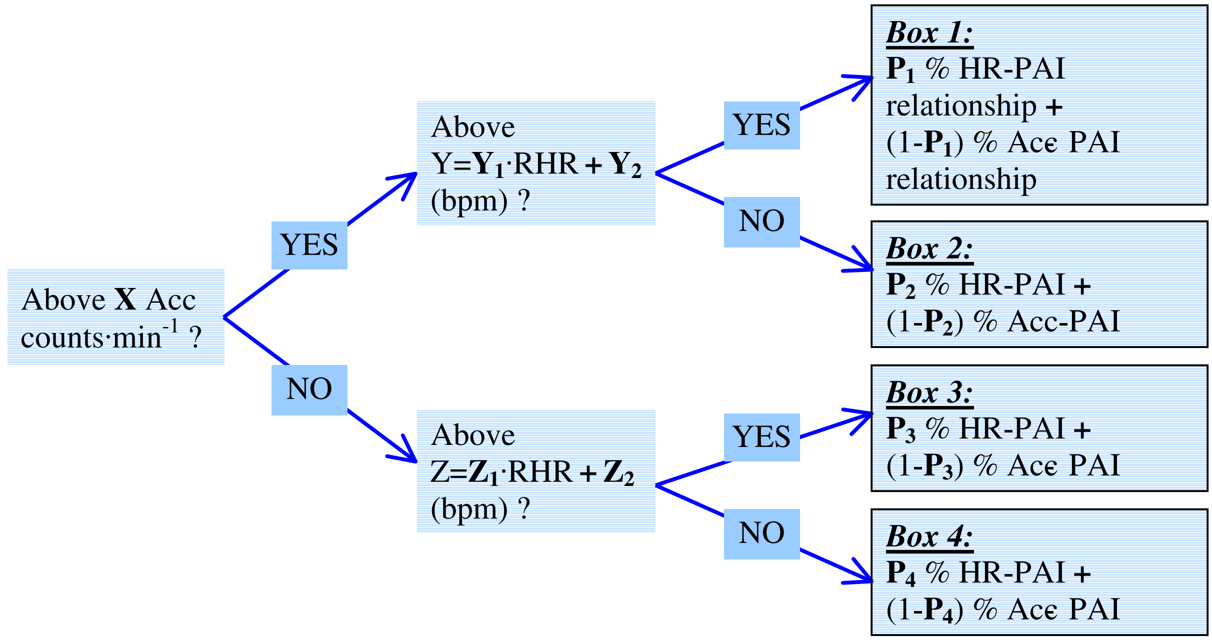
FIGURE 1. Protocol for the calorimeter study with example of calorimeter data output. SP=Sensible Power, EP=Evaporative Power, HS=Heat Source.

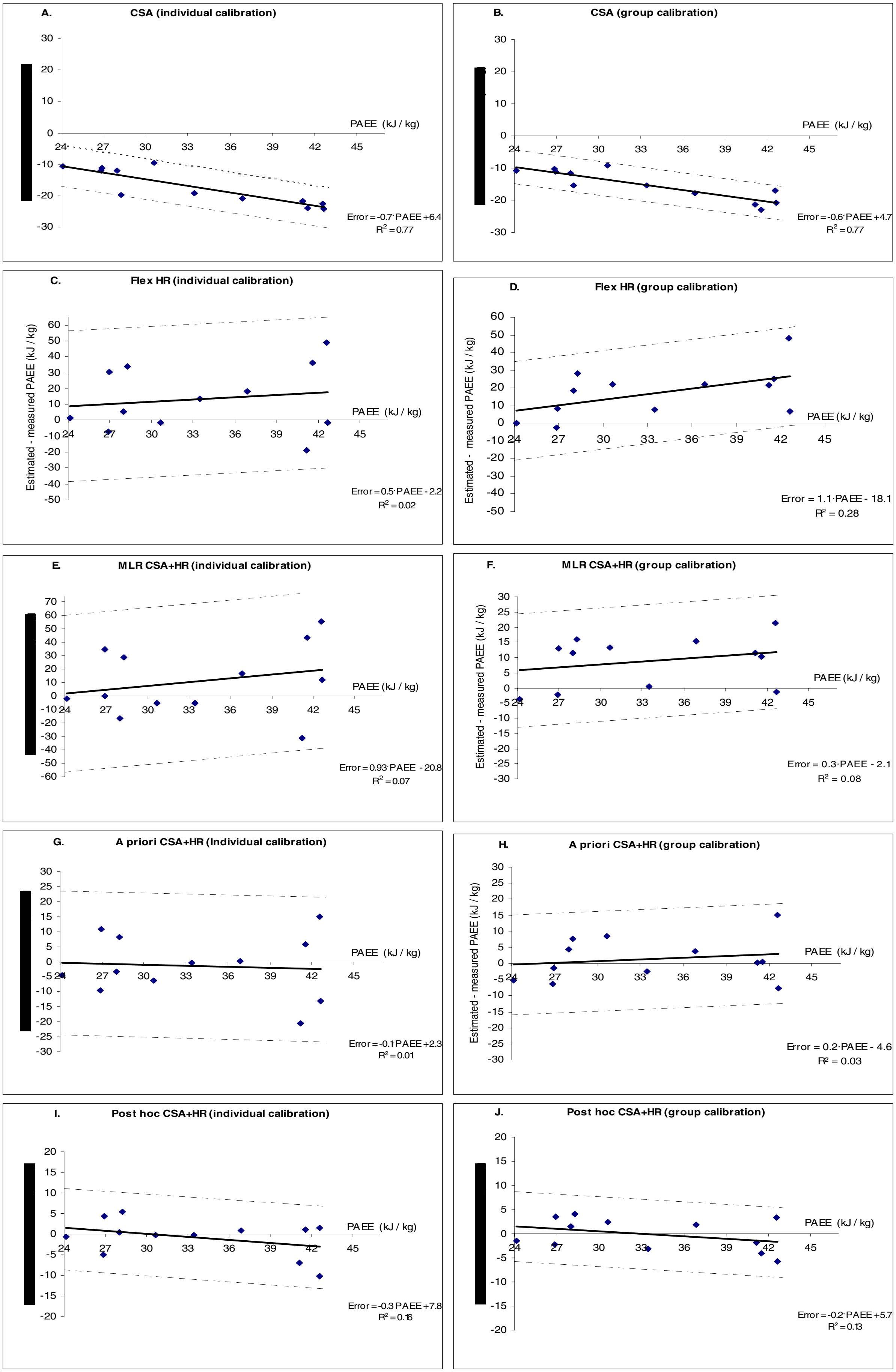
FIGURE 2. Equation structure for the combination of accelerometry and HR. All HR values are absolute HR minus RHR. All "PAI relationships" is determined by calibration. Therefore, this study has two equation complexes, depending on whether individual or group calibration is used. The equation complexes translate minute-by minute data into PAI as follows: If the 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 below or equal to X, we use Box 3 (with P_3) if the HR value is above Z, otherwise we use Box 4 (with P_4). PAEE is obtained by integrating PAI with respect to time. The parameters $\mathbf{X}$, $\mathbf{Y_{1\text{-}2}}$, $\mathbf{Z_{1\text{-}2}}$, and $\mathbf{P_{1\text{-}4}}$ are either assumed *a priori* or can be estimated *post hoc* by simulation of all possible models, whilst minimizing the SEE between predicted and measured PAEE.

FIGURE 3. Bland-Altman plots of differences between measured and estimated PAEE. Panels A+B are CSA estimates, C+D are flexHR estimates, E+F are CSA+HR (*MLR*) estimates, G+H are branched CSA+HR (*a priori*) estimates, and I+J are branched CSA+HR (*post hoc*) estimates. All left panels are results of models using individual calibration, right panels are models using group calibration. Lines are regression of the errors against measured PAEE with 95% error bands (broken lines).



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 $1W\cdot kg^{-1}$ 60 rpm	10 min walk	3 min step test (90 $step\cdot min^{-1}$)	10 min walk	10 min walk	15 min jog	5x3 min step test (75-135 $step\cdot min^{-1}$)	20 min cycling $1W\cdot kg^{-1}$ 60 rpm	Exit


Above X Acc counts·min-1 ?
YES
NO
Above Y=Y1·RHR + Y2 (bpm) ?
Above Z=Z1·RHR + Z2 (bpm) ?
YES
NO
YES
NO
Box 1:
P1 % HR-PAI relationship + (1-P1) % Acc PAI relationship
Box 2:
P2 % HR-PAI + (1-P2) % Acc-PAI
Box 3:
P3 % HR-PAI + (1-P3) % Acc PAI
Box 4:
P4 % HR-PAI + (1-P4) % Acc PAI


A.
CSA (individual calibration)
[redacted]
PAEE (kJ / kg)
Error = -0.7·PAEE + 6.4
R^2 = 0.77
B.
CSA (group calibration)
[redacted]
PAEE (kJ / kg)
Error = -0.6·PAEE + 4.7
R^2 = 0.77
C.
Flex HR (individual calibration)
Estimated - measured PAEE (kJ / kg)
PAEE (kJ / kg)
Error = 0.5·PAEE - 2.2
R^2 = 0.02
D.
Flex HR (group calibration)
Estimated - measured PAEE (kJ / kg)
PAEE (kJ / kg)
Error = 1.1·PAEE - 18.1
R^2 = 0.28
E.
MLR CSA+HR (individual calibration)
[redacted]
PAEE (kJ / kg)
Error = 0.93·PAEE - 20.8
R^2 = 0.07
F.
MLR CSA+HR (group calibration)
Estimated - measured PAEE (kJ / kg)
PAEE (kJ / kg)
Error = 0.3·PAEE - 2.1
R^2 = 0.08
G.
A priori CSA+HR (Individual calibration)
[redacted]
PAEE (kJ / kg)
Error = -0.1·PAEE + 2.3
R^2 = 0.01
H.
A priori CSA+HR (group calibration)
Estimated - measured PAEE (kJ / kg)
PAEE (kJ / kg)
Error = 0.2·PAEE - 4.6
R^2 = 0.03
I.
Post hoc CSA+HR (individual calibration)
[redacted]
PAEE (kJ / kg)
Error = -0.3·PAEE + 7.8
R^2 = 0.16
J.
Post hoc CSA+HR (group calibration)
[redacted]
PAEE (kJ / kg)
Error = -0.2·PAEE + 5.7
R^2 = 0.13