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EXERCISE

Accuracy and validity of a combined heart rate and motion sensor for the measurement of free-living physical activity energy expenditure in adults in Cameroon

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Background The increasing burden of non-communicable diseases in sub-Saharan Africa (SSA) warrants rigorous studies of contributing lifestyle factors. Combined heart rate (HR) and movement monitoring make it possible to objectively measure physical activity in free-living individuals. We examined the validity of a combined HR and motion sensor in estimating physical activity energy expenditure (PAEE) in free-living adults in rural and urban Cameroon compared with doubly-labelled water (DLW) as criterion.

Methods PAEE was measured in 33 free-living rural and urban dwellers by DLW over 7 consecutive days. Simultaneously, the combined sensor recorded HR and uni-axial acceleration. Individual HR vs PAEE calibration was done by a step test. Branched equation modelling was used to estimate PAEE from HR and acceleration. Validity and accuracy of prediction were expressed as mean bias and root mean square error (RMSE). Agreement was analysed using Bland and Altman limits of agreement (LOA).

Results There was no significant mean bias between PAEE estimated from the combined sensor or measured by DLW [mean bias (standard error): −5.4 (5.1) kJ/kg/day; $P = 0.3$; RMSE = 29.3 kJ/kg/day]. The bias doubled for group compared with individual calibration of HR [−9.1 (5.0) kJ/kg/day, $P = 0.08$]. PAEE prediction was more accurate in urban compared with rural volunteers. The 95% LOAs between predicted and measured PAEE were ~50–60 kJ/kg/day above or below perfect agreement.

Conclusions Combined HR and movement sensing is a valid method for estimating free-living PAEE on group level in adults in SSA.

Keywords Physical activity, energy expenditure, doubly labelled water, heart rate monitoring, accelerometry, sub-Saharan Africa, validity, accuracy

Introduction

Physical activity is beneficial for maintaining a healthy life and reducing premature morbidity and mortality.[1–8] However, a full understanding of the dose–response relationships between physical activity and health outcomes is still elusive. Objective and accurate measurement of physical activity is essential in elaborating these relationships.[9] Nevertheless, the accurate measurement of physical activity in epidemiological studies still poses major challenges in terms of both feasibility and validity of the methods proposed.

Physical activity is a complex attribute that can be characterized in terms of volume, domains, type, duration, frequency and intensity. Many objective and subjective methods of measuring physical activity are available.[10] However, the different dimensions of physical activity are not always adequately measured by a single method, producing conflicting results between objective and subjective measures in situations where both have been used to assess population levels of physical activity.[11–13] Self-report methods may accurately rank individuals and can capture the specific domains of physical activity. However, their validity for estimating physical activity energy expenditure (PAEE) and time spent in different intensity levels of activity is usually poor.[14,15]

Objective methods of measuring physical activity offer better prospects for accurately quantifying the total volume of physical activity or PAEE, and for most methods, its sub-components. Doubly-labelled water (DLW) is accepted as the gold standard method of measuring total energy expenditure (TEE) in free-living individuals, but its substantial cost has restricted its use to small validation or exploratory studies, almost exclusively carried out in Western industrialized countries.[16,17] Accelerometers and heart rate (HR) monitors have been proposed separately[18–21] and in combination[22,23] as more feasible and pragmatic alternatives in measuring PAEE in free-living individuals. This combined sensing method has been validated in both laboratories as well as in free-living individuals. Laboratory studies use structured controlled activities, but may not really represent free-living patterns of activity, particularly in a different population.

Validation and implementation of accurate and pragmatic objective methods of measuring free-living physical activity in developing countries such as in sub-Saharan Africa (SSA) would provide opportunity to clearly understand the determinants and effects of physical activity on the current epidemiological transition in this region.[24,25] We have previously developed and validated accelerometer-based regression equations that could be used to estimate free-living PAEE in SSA.[26] However, accelerometry does not fully capture the inter-individual differences in PAEE, especially at high intensities.[19,27] The incorporation of HR data with individual calibration of the HR response to physical activity would remove inter-individual variability in true PAEE due to differences in physiological parameters such as aerobic fitness.[28]

The objective of this study was to examine the validity of a combined HR and motion sensor in estimating PAEE in free-living individuals in Cameroon compared with DLW as criterion.

Methods

Participants

The participants were 35 adult volunteers recruited from an urban and a rural area of Cameroon, to account for potential differences in physical activity due to urbanization.[29] Data on age and occupational history were collected by self-report.

Ethical approval was obtained from the Cameroon National Ethics Committee and all participants provided signed informed consent. One volunteer who withdrew from the study and another who had a very rapid turnover of the DLW isotopes resulting in unrealistic data were excluded from these analyses.

Resting energy expenditure

Resting energy expenditure (REE) was measured using the MedGem® handheld indirect calorimeter (HealtheTech Inc., Golden, CO, USA), previously validated in adults in field settings.[30,31] The device measures oxygen consumption through breath-by-breath sampling over a duration of ~10 min. REE was calculated using the Weir equation[32] assuming a respiratory quotient of 0.85. All measurements were performed under thermo-neutral conditions while the volunteers were sitting in a quiet room after an overnight fast and having refrained from caffeine, nicotine or exercise for at least 4 h. REE was measured using breath-by-breath data collected for each volunteer over 8–10 min.

Free-living energy expenditure by DLW method

The DLW method was used as criterion measure of TEE for 7 continuous days. Details of the procedure in this study have been previously reported.[26] Each volunteer drank a weight-appropriate dose of DLW. Urine samples were collected ~24 h before and after the administration of the DLW dose, and then daily for the next 6 days. The samples were analysed at the Medical Research Council Collaborative Centre for Human Nutrition Research, Cambridge, UK.

Isotopic enrichment of all samples was analysed using procedures described in detail elsewhere.[33] Briefly, for $^2H/^1H$ ratios, a 0.4-ml sample was equilibrated with 3 ml H_2 gas at 1 bar and 22°C for 6 h in the presence of a Pt catalyst. The equilibrated gas samples were then measured relative to an arbitrary hydrogen reference gas using dual inlet isotope ratio mass spectrometry (Sira 10, Micromass, Wythenshaw, UK) and then enrichment values calculated on the international water reference standards (SMOW/SLAP) scale using laboratory references traceable to international standards. For ^{18}O, 0.5-ml samples were equilibrated with 10 ml 5% CO_2 in N_2 at 1 bar at room temperature, overnight. Ratio measurements were made using an AP2003 continuous flow isotope ratio mass spectrometer (Analytical Precision Ltd, Northwich, UK) and enrichment values calculated on the SMOW/SLAP scale as described for the ^2H data.

Rate constants for isotope disappearance were estimated using data from all the samples collected over the 7-day period, after baseline correction using the pre-dose samples. If the rate of ^{18}O disappearance exceeded three half lives in this time, only samples taken up to three half lives were used in the calculation of TEE to maintain an equivalence in precision.[34] Isotope dilution spaces were calculated from the zero-time intercepts of the isotope disappearance curves.

TEE was calculated by means of standard equations[35,36] using Schoeller's estimation of CO_2 production, which normalizes $^2H/^{18}O$ space ratios to $1.04/1.01 = 1.03$. TEE was then calculated from CO_2 production assuming a respiratory quotient of 0.85.[37] Average daily PAEE (kJ/day/kg) was calculated as average 24-h TEE minus awake resting (REE) and sleeping energy expenditure ($= 0.9 \times$ REE) assuming an average daily sleep duration of 8 h, minus 10% of TEE to account for the thermic effect of food.

Free-living PAEE by combined HR and movement monitoring

Free-living PAEE was measured using a combined HR and movement sensor (Actiheart, Cambridge Neurotechnology Ltd, Cambridge, UK). Initially, participants underwent an 8-min step test[38,39] at a step height of 20 cm to provide individual calibration of HR to physical activity intensity. Subsequently, free-living HR and acceleration were measured in 1-min epochs using the combined sensor over 7 continuous days, concurrently with the DLW measurement. The participants were requested to carry on with their habitual lifestyle, carry the monitor at all times, when awake or asleep. The monitors were to be taken off only for showering, bathing or activities like swimming.

Actiheart data processing and calculations

Data from the Actiheart monitors were downloaded into a database using the Actiheart commercial software. The same software was used to clean and recover or interpolate noisy and missing HR data using the manufacturer's algorithm (http://www.camntech.com). HR data were converted to energy expenditure using the individual calibration derived from the step test (HR_{STEP}), whereas the accelerometer data were converted to energy expenditure using group calibrated accelerometry equations corresponding to level walking or running acceleration (ACC).[39] A group calibration HR equation (HR_{GROUP}), modified from the equation published by Brage *et al*.[39], was used to assess the additional benefit of using individual calibration compared with group calibration. The coefficients of the regression parameters were modified using estimates from valid step tests in a different population-based sample ($N = 546$) of the same target population. Physical activity intensity (PAI, J/kg/min) equation for HR_{GROUP}:

$$\begin{aligned} PAI_{HR-GROUP} = {} & 5.9 \cdot \text{HR above sleep} \\ & + 0.5 \cdot \text{HR above sleep} \\ & \times \text{gender} + 5.8 \times \text{gender} - 68.7 \end{aligned}$$

Minute-by-minute HR and movement derived PAI were combined in a branched equation model[40] to calculate daily free-living PAEE. Separate acceleration and flex HR models (ACC or HR_{FLEX}) were also used to estimate PAEE. Flex HR was estimated using a published sleeping HR-based regression equation.[38] For all minutes above flex HR, PAEE was estimated using the individual HR to PAEE slope derived during the step-test calibration. Below flex HR, energy expenditure was assumed to equal REE. Basal metabolic rate ($\approx$ REE) was estimated from Schofield equations[41] and TEE was calculated by adding REE and a component for the thermic effect of food (10% of TEE) to the derived PAEE. The distribution of intensity of activity was expressed as average daily time spent below 1.5 metabolic equivalents (METs) corresponding to time spent asleep or sedentary, between 1.5 and 3 METs as time spent in light intensity physical activity (LPA), above 3 METs as time spent in moderate-to-vigorous intensity physical activity (MVPA). Individual separate daily estimates were then collapsed to obtain individual mean estimates using a probability weighting inversely proportional to the daily fraction of lost and recovered data.

Statistical analyses

Analyses were carried out using STATA® version 10.1 (StataCorp, College Station, TX, USA).

Descriptive characteristics of the study sample are presented as means with standard deviations and stratified by rural/urban residential area. Student's *t*-test was used to assess differences in the descriptive variables between the rural and urban volunteers. Unadjusted Pearson correlations were used to examine the association between PAEE derived from separate or combined HR and movement models, mean acceleration, mean HR above sleeping HR (HRaS) and time spent at different activity intensity levels with mean daily PAEE measured by DLW.

Criterion validity of the combined monitoring protocol against DLW measured PAEE was analysed using Bland and Altman agreement method.[42] The mean bias and the root mean square error (RMSE) between PAEE measured by DLW and estimated by the combined sensor were calculated. Sensitivity analyses were carried out to test the effect of outliers on the observed agreement.

Results

Table 1 presents some descriptive characteristics of the study sample. Rural–urban stratification was according to our a priori objective. The frequency of physically demanding jobs was higher among the rural compared with urban volunteers (76 and 25%, respectively). Conversely, 61% of urban volunteers were engaged in mainly sedentary occupations. PAEE was ~31% higher in rural volunteers compared with their urban counterparts. A similar difference was observed when physical activity was expressed as physical activity level (PAL) (=TEE/REE).

Table 2 presents correlations between PAEE derived from DLW with variables from combined HR and motion monitoring. There was a comparable positive correlation between PAEE measured by DLW and estimated from the combined sensor with either individual or group calibration. This correlation was stronger in urban compared with rural volunteers, and was accounted for mainly by the correlation with movement variability (mean acceleration) than HR variability (mean HRaS). PAEE predicted from the branched equation model ($ACC + HR_{STEP}$) accounted for 16% of the total variance in DLW-measured PAEE. Meanwhile, the separate HR_{FLEX} and ACC models accounted for 10 and 29% of the total variance, respectively.

There was no mean bias between mean PAEE estimated from combined HR and motion monitoring or measured by DLW (Table 3 and Figure 1). Furthermore, the mean bias between DLW-measured PAEE and that estimated from combined HR and motion monitoring was almost halved following individual step-test calibration compared with group calibration, even though the RMSE was largely unchanged. The accuracy of predicting PAEE from combined HR and motion monitoring was always greater in the urban volunteers compared with their rural counterparts, with the RMSE being almost two times greater in rural compared with urban volunteers. The LOA between predicted and measured PAEE were wide, being ~50–60 kJ/kg/day above or below the measured value. Similar to the RMSE, the LOAs were two times wider in the rural compared with the urban volunteers. Compared with the combined models, the separate ACC or HR_{FLEX} models were less accurate in predicting DLW-measured PAEE (RMSE of 37.5 and 35.2 kJ/kg/day, respectively). Moreover, the ACC model underestimated DLW-measured PAEE ($P < 0.001$). These results did not change when we re-analysed the data omitting the two subjects who had large residuals (Figure 1).

Table 1 Descriptive characteristics of study participants, Actiheart free-living validation in SSA study, Cameroon, 2006

	All	Rural	Urban	P
Sex (M/F)	16/17	8/9	8/8	
Age (years)	34.2 (7.3)	35.4 (6.8)	33.0 (7.8)	0.3
BMI (kg/m^2)	27.1 (4.6)	27.8 (4.7)	26.25 (4.6)	0.3
TEE from DLW (MJ/day)	12.44 (3.53)	13.13 (4.16)	11.71 (2.64)	0.3
PAEE from DLW (kJ/kg/day)	58.2 (31.0)	65.7 (36.5)	50.2 (22.1)	0.2
PAL from DLW	1.79 (0.37)	1.89 (0.45)	1.68 (0.23)	0.1
PAEE from Actiheart[a] (kJ/kg/day)				
$ACC7 + HR_{STEP}$	52.8 (19.4)	56.6 (20.8)	48.7 (17.5)	0.2
$ACC + HR_{GROUP}$	49.1 (17.3)	50.1 (18.8)	48.0 (16.1)	0.7
HR_{FLEX}	59.4 (30.3)	63.4 (33.4)	55.2 (27.1)	0.4
ACC	31.6 (10.0)	33.3 (9.4)	29.8 (10.6)	0.3
Mean Acceleration (m/s^2)	0.112 (0.049)	0.117 (0.049)	0.107 (0.05)	0.6
Mean HRaS (beats/min)	16.2 (4.1)	17.0 (3.6)	15.4 (4.5)	0.3
Sedentary time (min/day)	988 (136)	954 (143)	1024 (122)	0.1
LPA (min/day)	319 (100)	334 (96)	303 (104)	0.4
MVPA (min/day)	133 (58)	152 (64)	113 (45)	0.05

BMI, body mass index. Data are means standard deviation (SD). *P*-value for difference between rural and urban groups.
[a]Models of PAEE prediction from Actiheart: ACC = group acceleration equation; HR_{STEP} = individual step test calibration of heart rate; HR_{GROUP} = group heart rate calibration; HR_{FLEX} = individual step test calibration with PAEE prediction based only on flex HR method.

Table 2 Correlations between PAEE (kJ/kg/day) measured by DLW and parameters derived from heart rate and movement monitoring in free-living healthy adults, Actiheart free-living validation in SSA study, Cameroon, 2006

	PAEE from DLW (kJ/kg/day)					
	All ($n=33$)		Rural ($n=17$)		Urban ($n=16$)	
	R	*P*	*r*	*P*	*r*	*P*
PAEE from Actiheart[a] (kJ/kg/day)						
ACC + HR_{STEP}	0.40	0.02	0.29	0.3	0.55	0.03
ACC + HR_{GROUP}	0.39	0.02	0.34	0.2	0.51	0.04
HR_{FLEX}	0.32	0.07	0.25	0.3	0.40	0.1
ACC	0.54	0.001	0.45	0.07	0.70	0.002
Mean acceleration	0.54	0.001	0.48	0.05	0.66	0.01
Mean HRaS (beats/min)	0.23	0.2	0.31	0.2	0.05	0.8
Sedentary time (min/day)	−0.43	0.01	−0.33	0.2	−0.54	0.03
LPA (min/day)	0.37	0.03	0.28	0.3	0.49	0.05
MVPA (min/day)	0.37	0.03	0.31	0.2	0.34	0.2

[a]Models of PAEE prediction from Actiheart: ACC = group acceleration equation; HR_{STEP} = individual step test calibration of heart rate; HR_{GROUP} = group heart rate calibration; HR_{FLEX} = individual step test calibration with PAEE prediction based only on flex HR method

Table 3 Criterion validity of PAEE derived from combined heart rate and movement monitoring and measured by DLW in free-living healthy adults, Actiheart free-living validation in SSA study, Cameroon, 2006

Model	PAEE	Bias[a]	*P* for bias	RMSE	95% LOA
Criterion method					
DLW	58.2 (31.0)				
Heart rate and movement models[b]					
ACC + HR_{STEP}	52.8 (19.4)	−5.4 (5.1)	0.3	29.3	−62.7, 51.9
Rural	56.6 (20.8)	−9.1 (8.9)	0.32	36.5	−80.6, 62.4
Urban	48.7 (17.5)	−1.4 (4.8)	0.77	18.7	−39.3, 36.4
ACC + HR_{GROUP}	49.1 (17.3)	−9.1 (5.0)	0.08	29.9	−65.8, 47.6
Rural	50.1 (18.8)	−15.6 (8.5)	0.08	37.3	−84.1, 52.9
Urban	48.0 (16.1)	−2.2 (4.9)	0.66	19.2	−40.8, 36.3
HR_{FLEX}	59.4 (30.3)	1.2 (6.2)	0.85	35.2	−68.9, 71.3
Rural	63.4 (33.4)	−2.4 (10.4)	0.82	41.4	−86.3, 81.5
Urban	55.2 (27.1)	5.0 (8.8)	0.47	26.9	−48.4, 58.5
ACC	31.6 (10.0)	−26.6 (4.7)	<0.001	37.5	−79.3, 26.1
Rural	33.3 (9.4)	−32.5 (8.1)	0.003	45.9	−97.9, 33.0
Urban	29.8 (10.6)	−20.4 (4.1)	0.001	25.9	−52.7, 12.0

Units of all data are (kJ/kg/day). Values of PAEE are mean (SD), bias are means standard error (SE).
[a]Mean bias = predicted − criterion.
[b]Models of PAEE prediction from Actiheart: ACC = group acceleration equation; HR_{STEP} = individual step test calibration of heart rate; HR_{GROUP} = group heart rate calibration; HR_{FLEX} = individual step test calibration with PAEE prediction based only on flex HR method.

We also assessed the influence of outliers by calculating Cook's D[43] and leaving out three subjects whose values were greater than the conventional cut-off point of $4/n$ or 0.12. The results remained largely unchanged, though the RMSE and the range of the LOAs were reduced by ~30% (data not shown).

Discussion

In this study, we have shown that PAEE derived from free-living HR (with individual or group calibration) and movement monitoring using a branched equation modelling approach[40] was positively correlated with

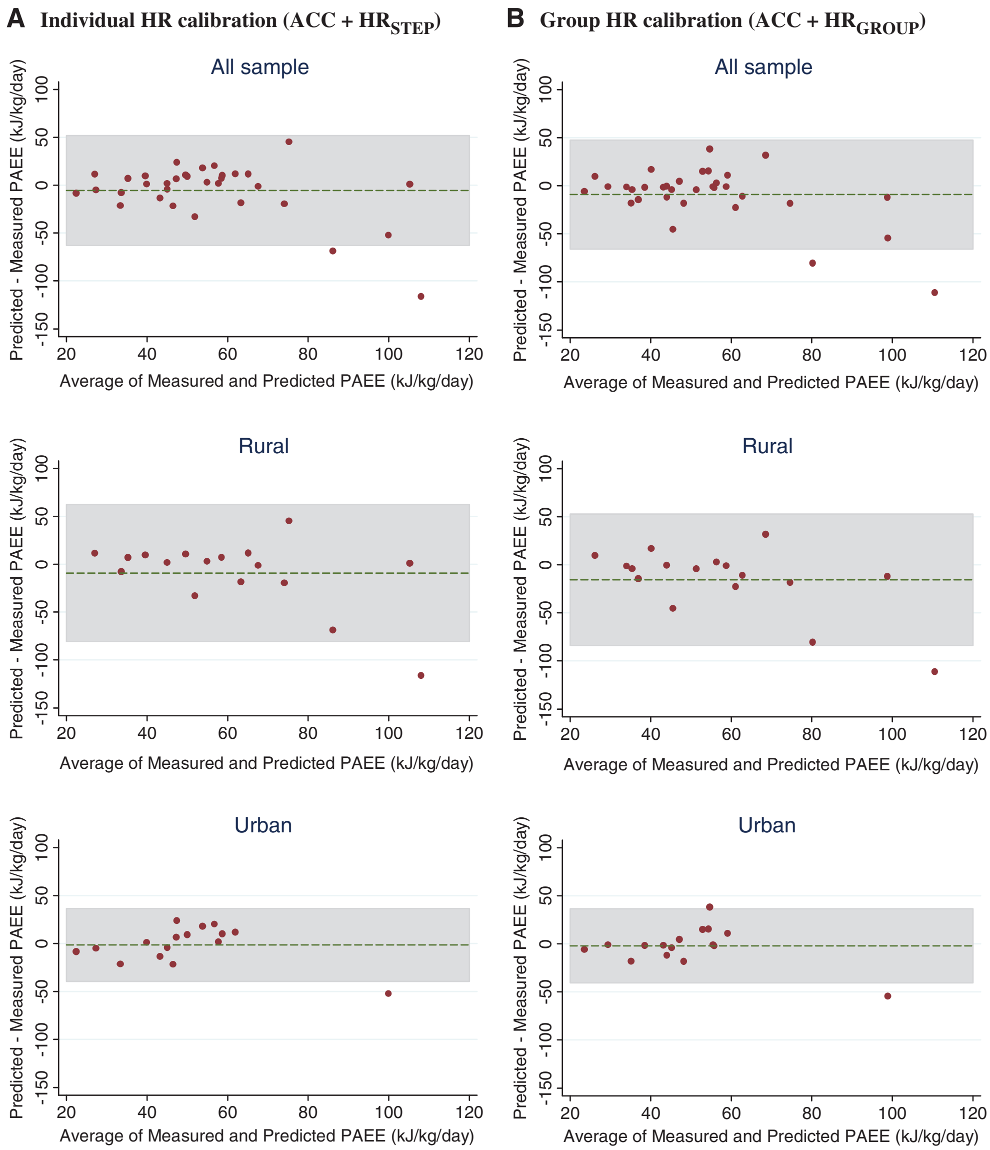

Figure 1 Bland and Altman plots of the difference vs the mean of PAEE measured by DLW and derived from combined heart rate and movement monitoring in healthy adults using individual HR calibration (**A**) or using group HR calibration (**B**) Actiheart free-living validation in SSA Study, Cameroon, 2006

DLW-measured PAEE. There was no mean bias between PAEE estimated by the combined sensor compared with DLW in both rural and urban dwellers. The accuracy of predicting PAEE from the combined sensor in urban dwellers was slightly better than in their rural counterparts. However, these minor rural–urban differences did not affect the overall significance or interpretation of our results. These results suggest that the combined HR and movement sensor could be used in both rural and urban populations in SSA for measuring free-living activity in adults.

We have previously developed and evaluated PAEE prediction equations using accelerometer (Actigraph) counts in this population.[26] Similar to our previous study,[26] movement sensing captured the inter-individual variance in PAEE more strongly in urban than rural dwellers. This may reflect differences in types and patterns of activities between rural and urban regions in SSA. A higher prevalence of labour-intensive occupational activity (subsistence agriculture) in the rural population would explain the negative rural–urban gradient in physical activity reported in studies using self-report of activity,[29,44] and which is evident even in this small validation study using DLW. However, activities performed in rural areas involve much digging, lifting and load carrying, which may not be fully captured by uni-axial accelerometers.[45–47] Television viewing, reading, needlework and leisure walking are among the most frequently reported leisure activities in urban dwellers as opposed to light farming, animal rearing and leisure walking in rural dwellers in Cameroon.[29]

Previous studies have validated free-living HR monitoring using the Flex HR methods against DLW for estimating PAEE.[18,48] Combining HR data with accelerometry has been proposed[22,23,40] to improve the estimation of PAEE by accounting for some of the inter-individual variance in the energy cost of MVPA. These differences, which may be due to individual traits such as age, sex or aerobic fitness, are not fully reflected in accelerometers counts. Similarly, the estimation of the energy cost of non-acceleration dependent activities, which are frequent among rural dwellers, would be improved by incorporating HR data with acceleration. In our study, the association between mean HRaS and PAEE measured by DLW was about six times stronger among rural compared with urban subjects, suggesting that combining HR data with accelerometry should improve the estimation of PAEE, particularly in the rural population.

Our results in rural and urban SSA are comparable with a previous validation study in Europe.[49] In a sample of 51 British adults (mean age of 34 years) using a step-test calibration, Brage[49] reported that the combined sensor had an accuracy (RMSE) of 25 kJ/kg/day and explained 34% of the variance in DLW-measured PAEE. This European population would be more comparable with our urban sample (RMSE of 19 kJ/kg/day and explained variance of 30%) in terms of types and pattern of activity. However, in contrast to our study, which found no mean bias, the European study reported a positive mean bias.[49] The European environment is much more urbanized and mechanized than the urban areas of SSA, which may favour more acceleration-dependent activities that are easily picked up by the accelerometer of the combined sensor.

Other validation studies in adults of this combined HR and movement sensor have been carried out against indirect calorimetry during treadmill walking and running,[50] laboratory- or field-based activities,[51,52] or a 6-h ‘free-living’ activity.[53] The use of indirect calorimetry for free-living monitoring may cause behaviour change or constraint and the activities undertaken would not truly reflect real life. Also, the carefully controlled activities usually employed when evaluating the validity of any activity monitor in the laboratory are not a true reflection of the lifestyle and patterns of activities in free-living individuals. However, these studies all demonstrate the improved accuracy of the combined sensor in estimating the energy expenditure of activities and the potential for use in epidemiological studies.

A challenge to the use of HR monitoring in free-living individuals is the issue of missing or noisy data. HR monitors pick up and register the electrical signals generated by the electrical system of the heart during each heart beat. These monitors are susceptible to interferences from electrical appliances or other sources of static current. Furthermore, the Actiheart unit clips on the chest using standard ECG electrodes that need good skin contact for optimal signal detection. These electrodes may become loose, resulting in noisy or loss of signal detection. This was a problem in our study since the tropical climate is usually warm and humid, and so the electrodes lose contact easily due to profuse sweating during habitual daily activities. The problem of noisy or missing HR data is resolved, in part, by the use of a cleaning and recovery or interpolation algorithm (http://www.camntech.com). Additionally, the use of a branched equation modelling approach[40] enables the prediction of PAEE to be based mainly on acceleration when the HR data cannot be recovered.

The small sample size of this validation study is another potential limitation in terms of power to make valid inferences. This was principally due to the high cost of DLW measurements. However, the high accuracy and precision of the DLW methods compensates for the small sample.

SSA is undergoing a rapid epidemiological transition characterized by increasing prevalence of obesity, diabetes and cardiovascular disease.[54–57] Urbanization resulting in lifestyle modification, with the adoption of more sedentary behaviour and less physical activity, has been suggested as part of the behavioural risk factors driving this transition. It is therefore important to objectively quantify this exposure in order to more appropriately inform and guide policy or interventions. The results from this study suggest that combined HR and movement sensing is a feasible and valid method, which can be used in epidemiological studies to accurately assess free-living physical activity in this region.

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Conflict of interest: None declared.

KEY MESSAGES

- The increasing burden of non-communicable diseases in SSA warrants rigorous studies of contributing lifestyle factors. However, the validity of objective measures of free-living physical activity in this region is scarce.
- This study showed that combined HR and movement sensing was a valid and accurate method of objectively measuring PAEE in free-living adult populations in rural and urban areas.
- PAEE estimated from combined HR and movement sensing was more accurate and valid compared with either HR or accelerometry alone.
- Individual calibration of HR response to exercise improved the validity of PAEE estimated by the combined sensor compared with the use of group equations.

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