

Prediction of Activity Energy Expenditure Using Accelerometers in Children

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ABSTRACT

PUYAU, M. R., A. L. ADOLPH, F. A. VOHRA, I. ZAKERI, and N. F. BUTTE. Prediction of Activity Energy Expenditure Using Accelerometers in Children. *Med. Sci. Sports Exerc.*, Vol. 36, No. 9, pp. 1625–1631, 2004. **Purpose:** To validate two accelerometer-based activity monitors as measures of children's physical activity using energy expenditure as the criterion measure. **Methods:** Actiwatch (AW) and Actical (AC) activity monitors were validated against continuous 4-h measurements of energy expenditure (EE) in a respiratory room calorimeter and 1-h measurements in an exercise laboratory using a portable calorimeter and treadmill in 32 children, ages 7–18 yr. The children performed structured activities including basal metabolic rate (BMR), playing Nintendo, using a computer, cleaning, aerobic exercise, ball toss, treadmill walking, and running. Equations were developed to predict activity energy expenditure (AEE = EE – BMR), and physical activity ratio (PAR = EE/BMR) from a power function of AW or AC, and age, sex, weight, and height. Thresholds were determined to categorize sedentary, light, moderate, and vigorous levels of physical activity. **Results:** Activity counts accounted for the majority of the variability in AEE and PAR, with small contributions of age, sex, weight, and height. Overall, AW equations accounted for 76–79% and AC equations accounted for 81% of the variability in AEE and PAR. Relatively wide 95% prediction intervals suggest the accelerometers are best applied to groups rather than individuals. Sensitivities were higher for the vigorous threshold (97%) than the other thresholds (86–92%). Specificities were on the order of 66–73%. The positive predictive values for sedentary, light, moderate, and vigorous categories were 80, 66, 69, and 74% for AW, respectively, and 81, 68, 72, 74% for AC, respectively. **Conclusion:** Both accelerometer-based activity monitors provided valid measures of children's AEE and PAR, and can be used to discriminate sedentary, light, moderate, and vigorous levels of physical activity but require further development to accurately predict AEE and PAR of individuals. **Key Words:** MOTION SENSORS, ACTIWATCH, ACTICAL, CALORIMETRY, EXERCISE, THRESHOLDS

Physical activity is integral to the normal health and development of children and adolescents, whereas physical inactivity is associated with a number of risk factors for hyperlipidemia, hypertension, cardiovascular disease and Type 2 diabetes. Nonintrusive, valid, and precise methods are needed to understand how intensity, frequency, and duration of physical activity influence the health of children (9). Assessment of physical activity encompasses monitoring compliance with physical activity guidelines, understanding dose-response relationships between activity and health outcomes, and testing effectiveness of intervention programs (17). Direct observation, questionnaires, heart rate monitoring, pedometry, and accelerometry are approaches applicable to children. Because of the intrusiveness of direct observation, unreliability of self-report measures, and the complexity of heart rate analysis, accelerometry has gained in popularity. With technological

advances in integrated circuitry and memory capacity, accelerometers can measure continuously the intensity, frequency, and duration of body movement for extended periods of time.

Accelerometers can be used to predict energy expenditure (EE) and to classify levels of physical activity; however, these devices must be validated and calibrated in the population of interest. Laboratory and field validation studies using the accelerometers—Caltrac, Tritrac, Computer Science and Applications Actigraph (CSA), Mini Mitter 2000, and Actiwatch (AW)—in children yielded moderate-to-high correlations between activity counts and EE (2,4,5,7,8,14,15,19,20). Several studies were performed in children using EE during treadmill walking/running (2,5,15,20). There is now appreciation that all types of body movement need to be captured for the prediction equations to be valid and applicable under free-living conditions. In addition to treadmill walking/running, room respiration calorimeters have been used to stage typical activities in which children engage to validate CSA and AW accelerometers (14).

Prediction equations for EE of children have been published for the Caltrac, CSA, and AW accelerometers (14,15,20). Eisenmann et al. (3) recently evaluated the equations for Caltrac and CSA using a portable gas analyzer. Although moderate to strong correlations were found between measured and predicted EE, both equations underestimated EE. Prediction equations for EE and activity energy

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TABLE 1. Subject characteristics.

	<i>N</i>	Age (yr)	Height (cm)	Weight (kg)	BMI (kg·m ⁻²)	BMI (Percentile)
Boys	14	12.3 ± 3.2 (7–18)	149 ± 19 (116–173)	55 ± 20 (20–85)	24.3 ± 6.6 (14.4–35.7)	0.75 ± 0.34 (0.08–0.99)
Girls	18	13.3 ± 3.3 (7–18)	148 ± 13 (118–165)	50 ± 16 (24–74)	22.0 ± 5.2 (13.7–31.3)	0.66 ± 0.34 (0.03–0.98)

* Mean ± SD (range); BMI, body mass index.

expenditure (AEE) using CSA and AW were acceptable for groups of children, but not for individual children (14), indicating a need to improve accelerometry prediction equations.

The purpose of this study was to validate two accelerometer-based monitors, AW and Actical (AC), as measures of children's physical activity using measured EE as the criterion and to determine thresholds of the AW and AC outputs for sedentary, light, moderate, and vigorous levels of physical activity. Activity monitors were validated against measurements of AEE (EE-BMR) or physical activity ratio (PAR = EE/BMR). Prediction equations for AEE and PAR were developed accounting for the effects of age, sex, weight, and height.

MATERIALS AND METHODS

Study design. The activity monitors were tested in 32 children under controlled laboratory settings. Inclusion criteria required the children to be healthy and free from any medical condition that would limit participation in physical activity or exercise. The activity monitors were validated and calibrated against continuous 4-h measurements of EE in one of four respiratory room calorimeters and 1-h measurements in an exercise laboratory using a portable calorimeter and treadmill. The Institutional Review Board for Human Subject Research for Baylor College of Medicine and Affiliated Hospitals approved the protocol. All subjects and their parents gave written informed consent.

Subjects. The characteristics of the 32 boys and girls who took part in the study are presented in Table 1. The children were equally distributed across the age range of 7–18 yr. Twelve of the children were classified as overweight (≥ 95 th BMI percentile) by the Center for Disease Control and Prevention (CDC) growth charts (10).

Physical activity monitors. AW and AC (Mini Mitter Co., Inc., Bend, OR) monitors were evaluated. The monitors were affixed side by side above the iliac crest of the right hip with an elastic belt and adjustable buckle. Both monitors contain an omnidirectional accelerometer built from a cantilevered rectangular piezo-electric bimorph plate and seismic mass, which is sensitive to movement in all directions. The piezo-electric sensor was reoriented in the AC such that maximum sensitivity is obtained when the center of body mass is moved against gravity. When positioned on the hip, the device is most sensitive to vertical movements of the torso. AW is designed to detect a wide range of limb movements related to sleep/wake behavior, whereas AC is designed for measurement of whole body physical activity. AW is sensitive to movements in the 0.5- to 7-Hz frequency range, whereas AC is sensitive to movements in the 0.5- to 3-Hz range. AC's sensitivity allows for detection of seden-

tary movements as well as high-energy movements. AC's reduced frequency range also minimizes the effect of undesirable noise impulses, which tend to skew EE results. AW firmware detects the peak value of 32 samples in a 1-s window and adds this to the accumulated value for that epoch. In contrast, AC sums all 32 values in a 1-s window, divides the sum by four, then adds this result to the accumulated value for the epoch. In this study, sixty 1-s values were summed together to generate one resultant raw activity datum for each 1-min epoch.

Room respiration calorimetry. Oxygen consumption ($\dot{V}O_2$) and carbon dioxide production ($\dot{V}CO_2$) were measured continuously in an 18- or 30-m³ room calorimeter for 4 h and in the exercise laboratory for 1 h using a metabolic cart (model 2900, SensorMedics, Inc., Yorba Linda, CA). The performance of the respiration calorimeters has been described in detail previously (13). EE was computed using the de Weir equation (21). Heart rate was recorded by telemetry in the room calorimeter (DS-3000, Fukuda Den-shi, Tokyo, Japan) and heart rate monitor in the exercise laboratory (Polar Electro Co., Woodbury, NY). $\dot{V}O_2$, $\dot{V}CO_2$, EE, and heart rate were averaged at 1-min intervals. PAR was calculated in terms of the child's measured BMR where PAR = EE/BMR.

All children completed the following calibration protocol of supervised physical activities. Specific measurements obtained during the 4 h in the room calorimeter included:

BMR. Under thermoneutral conditions upon awakening after a 12-h fast, the children were asked to remain still, but awake, for 30 min. The children were monitored both visually and by the motion sensor to confirm that they were lying still (< 50 activity counts per minute) for the entire measurement.

Nintendo. Children played Nintendo for 20 min in a sitting position.

Computer. Children worked at the computer for 20 min sitting in a chair.

Cleaning. Children continuously dusted all contents in the room calorimeter for 10 min.

Aerobics. Children performed aerobic exercises, as demonstrated on a videotape, for 12 min.

Ball toss. Children practiced free throws from a set distance in a standing position for 10 min.

In the exercise laboratory, three levels of walking/running on a treadmill (model 5500, Quinton) were performed. Treadmill speed was age-adjusted for the capability and safety of the children.

Walk 1. Children walked on the treadmill at 2.0 mph for 7 min.

Walk 2. Treadmill speed was set at 3.5 to 4 mph for 7 min.

Jogging/running. Treadmill speed was set at 4.5 mph to 7 mph for 7 min.

Except for the BMR measurement, all activities were performed in the fed state. The children were given breakfast at 8:30 am and lunch at 12:00 noon. The morning activities began at 9:30 am. The treadmill testing was done 2–3 h after lunch.

Statistical analysis. Data are summarized as means \pm SD. The sample size of 32 children was based on detecting a statistically significant correlation of 0.6 between activity counts and EE with a power of 0.80 at significance level of $P = 0.05$. Descriptive statistics, Pearson correlations and multiple regression analyses were performed using SPSS (release 11.50, SPSS Inc., Chicago, IL). The concordance correlation coefficient was computed which consists of a precision component, the Pearson correlation coefficient, which measures how closely observations lie on the line fit to the data, and an accuracy component, which measures how closely the fitted line deviates from the 45° line through the origin (11,12).

Minute-to-minute EE and activity counts from the AW and AC monitors were compiled from the 4 h of room calorimetry and 1-h treadmill protocol. To determine the best prediction equation, the minute-to-minute data were analyzed using Table Curve Fitting Software (version 4.0, Jandel Scientific, San Rafael, CA). This program processes X-Y data through linear and nonlinear power and exponential functions, and ranks valid equations by goodness of fit criteria according to r^2 coefficients and SEE. Linear regression was then used to develop equations predicting AEE or PAR from the power function of AW or AC, and age, gender, height, and weight.

Optimal thresholds for classifying counts into sedentary, light, moderate and vigorous levels of physical activity were determined by regression and receiver operating characteristic (ROC) analysis. Minute-to-minute data were categorized into sedentary, light, moderate, or vigorous levels according to the following definitions. Sedentary level was defined as $AEE < 0.01 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ or $PAR < 1.5$, encompassing physical activities of minimal body movements in the sitting or reclined position. Light level was set at $0.01 \leq AEE < 0.04 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ or $1.5 \leq PAR < 3.0$, reflective of a low level of exertion in the standing position. Moderate level was set at $0.04 \leq AEE < 0.10 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ or $3.0 \leq PAR < 6.0$, and involved medium exertion in the standing position. Vigorous level was set $AEE \geq 0.10 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ or $PAR > 6.0$, reflective of activities at a high level of exertion in the standing position. Next, AW and AC counts corresponding to the AEE and PAR cutoffs were calculated from our final prediction equations. The sensitivity (true positives/(true positives + false negatives)) and specificity (true negatives/(true negatives + false positives)) of the thresholds for AW and AC were then calculated. ROC analysis was conducted to evaluate and compare the performance of AC and AW at all possible cut-points. ROC analysis is the standard approach to evaluate the sensitivity and specificity of test results. ROC analysis for two classes, such as sedentary and light activities, is based on plotting false positive rates on the x-axis and true positive rates on the y-axis, by varying the decision

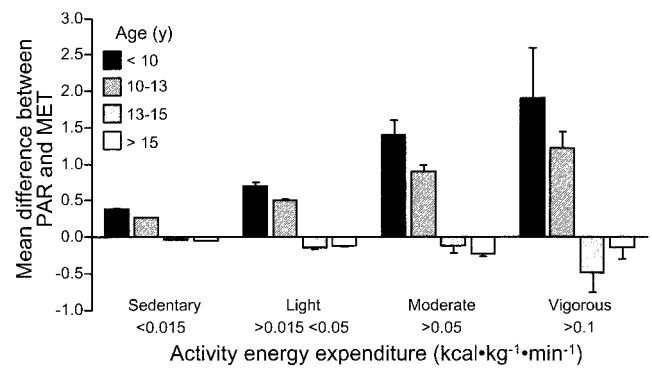


FIGURE 1—Mean difference between physical activity ratio (PAR) and metabolic equivalent (MET) as a function of children's age and physical activity level.

threshold for the two classes. Each threshold value corresponds to a point on the ROC curve. Lastly, the positive predictive values (true positives/(true positives + false positives)) for the sedentary, light, moderate, and vigorous categories were calculated applying the final threshold values for AW and AC.

RESULTS

Because the utility of the activity monitors is to detect body movement, the EE above BMR, which is by definition reflective of no movement, was computed as AEE ($EE - BMR$) and PAR (EE/BMR), and used in further analysis. AEE and PAR were computed using the child's measured BMR. During childhood, BMR decreases with age, as seen in this study ($r = -0.53$; $P = 0.001$). In terms of $\dot{V}O_2$, the children's BMR values averaged 3.9 ± 1.1 (range 2.3 to 7.1) $\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$. If the adult reference value of 3.5 $\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ had been used, AEE and PAR would have been biased with significant overestimation at younger ages. The difference between observed PAR and calculated MET using the adult reference value of 3.5 $\text{mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ was inversely correlated with age ($r = -0.41$; $P = 0.001$). The mean difference was greater at younger ages and at higher EE levels, as demonstrated in Figure 1.

Mean EE, AEE, PAR, heart rate, and AW and AC counts observed for the discrete physical activities are summarized in Table 2 and displayed in Figure 2. The discrete activities covered an eightfold range in EE relative to BMR, with mean heart rates ranging from 92 to 178 bpm. The dynamic range of the AW (mean range for specific activities from 5 to 3574 counts) was more contracted than AC (mean range from 12 to 10,061 counts). AW and AC counts were significantly correlated ($P = 0.001$) with one another ($r = 0.93$), and with EE ($r = 0.79, 0.83$), AEE ($r = 0.82, 0.85$), PAR ($r = 0.85, 0.87$), and heart rate ($r = 0.63, 0.60$).

Graphical examination of EE versus AW or AC counts data revealed clear nonlinearity. The minute-to-minute AEE (absolute and normalized by kilograms body mass) and PAR versus AW and AC data were processed using Table Curve Fitting Software to select the best fitting equations. Power equations ($Y = b_0 + b_1 \cdot X^{b_2}$) were ranked the highest

TABLE 2. Energy expenditure, heart rate, and activity counts during physical activities.

Activity	N	Energy Expenditure (kcal·min ⁻¹)	Energy Expenditure (kcal·kg ⁻¹ ·min ⁻¹)	Activity Energy Expenditure (kcal·min ⁻¹)	Activity Energy Expenditure (kcal·kg ⁻¹ ·min ⁻¹)	PAR	HR (bpm)	AW (counts)	AC (counts)
Basal metabolic rate	32	1.00 ± 0.20*	0.021 ± 0.005				79.2 ± 14.4	5 ± 5	12 ± 12
Computer	32	1.23 ± 0.28	0.025 ± 0.006	0.23 ± 0.15	0.005 ± 0.003	1.23 ± 0.16	92.4 ± 11.4	18 ± 23	27 ± 25
Nintendo	32	1.30 ± 0.15	0.027 ± 0.006	0.30 ± 0.15	0.006 ± 0.003	1.30 ± 0.16	92.1 ± 12.1	24 ± 29	55 ± 52
Cleaning	32	2.36 ± 0.63	0.048 ± 0.009	1.36 ± 0.47	0.027 ± 0.006	2.36 ± 0.34	113.9 ± 13.1	292 ± 124	551 ± 229
Walk 1	32	3.01 ± 0.73	0.062 ± 0.015	2.01 ± 0.58	0.041 ± 0.011	3.02 ± 0.39	109.6 ± 11.6	779 ± 227	1641 ± 410
Aerobics	32	3.73 ± 1.39	0.074 ± 0.017	2.73 ± 1.26	0.054 ± 0.016	3.72 ± 1.06	130.3 ± 17.2	1054 ± 435	2768 ± 1160
Ball toss	32	3.78 ± 1.39	0.076 ± 0.016	2.78 ± 0.84	0.055 ± 0.012	3.73 ± 0.50	129.8 ± 13.3	756 ± 308	1477 ± 456
Walk 2	31	5.63 ± 1.46	0.114 ± 0.028	4.62 ± 1.29	0.094 ± 0.023	5.59 ± 0.75	145.4 ± 15.3	2040 ± 645	4664 ± 709
Jogging/running	23	8.87 ± 2.68	0.171 ± 0.033	7.83 ± 2.52	0.151 ± 0.030	8.57 ± 1.41	177.5 ± 13.8	3574 ± 936	10061 ± 2034

* Mean ± SD; PAR, physical activity ratio; HR, heart rate; AW, Actiwatch; AC, Actical.

for AW and AC. Linear regression was then used to develop equations predicting AEE or PAR from the power function (b₂) of AW or AC, and age, sex (male = 1, female = 2), weight, and height according to the following general equation:

$$Y = b_0 + b_1 \cdot X^{b_2} + b_3 \cdot \text{Age} + b_4 \cdot \text{Sex} + b_5 \cdot \text{Weight} + b_6 \cdot \text{Height} \quad [1]$$

The coefficients, r², and SEE for prediction equations of AEE and PAR are summarized in Table 3, with the independent variables ordered as entered into stepwise regression. The r² and SEE indicated slightly better predictability with AC compared with AW. Activity counts accounted for the majority of the variability in EE, with small incremental contributions of age, sex, weight, and height. Weight made a perceptible change in r² and SEE, indicating a benefit of correcting for weight directly (AEE, kcal·kg⁻¹·min⁻¹), or

indirectly (PAR) by dividing by BMR, which is a function of weight. Although the contributions of age, sex, and height were statistically significant for AEE and height in the case of PAR, their contributions were negligible. For practical purposes, the prediction equations for AEE per kilogram and PAR were simplified to:

$$\text{AEE (kcal·kg}^{-1}\text{·min}^{-1}) = 0.00441 + 0.00032 \cdot \text{AW}^{0.724} \quad [2]$$

$$\text{PAR} = 1.221 + 0.0186 \cdot \text{AW}^{0.703} \quad [3]$$

$$\text{AEE (kcal·kg}^{-1}\text{·min}^{-1}) = 0.00423 + 0.00031 \cdot \text{AC}^{0.653} \quad [4]$$

$$\text{PAR} = 1.215 + 0.0153 \cdot \text{AC}^{0.654} \quad [5]$$

Overall, the AW prediction equations (Eq. 2 and 3) accounted for 76–79%, and the AC prediction equations (Eq. 4 and 5) account for 81% of the variability in AEE and PAR. The predicted PAR and AEE values are displayed against the observed values for AW (Fig. 3) and AC (Fig. 4). Regression residuals were normally distributed. The relatively wide 95% prediction intervals show considerable variability around the mean for the individual observations.

The concordance correlation coefficients between measured and predicted PAR (AEE) also were computed for AC and AW. The mean concordance correlation coefficient of 0.90 and 95% confidence interval (0.89 to 0.90) for AC indicated high similarity between measured and predicted values. The mean concordance correlation coefficient for AW was 0.87 and 95% confidence interval was 0.86 to 0.89.

The thresholds corresponding to AEE values of 0.01, 0.04 and 0.10 kcal·kg⁻¹·min⁻¹ or PAR values of 1.5, 3.0, and 6.0 and associated sensitivity and specificity determined by binary classification, that is, sedentary-light, light-moderate, and moderate-vigorous thresholds of physical activity, are presented in Table 4. The resulting ROC curve characterized the performance of a binary classification by describing the trade-off between sensitivity and specificity over an entire range of possible thresholds. The areas under the empirical ROC curves were highly significant, indicating the ability of AC and AW to correctly classify the levels of physical activity. On a scale of 0 to 1, the areas under the curves for sedentary-light, light-moderate, and moderate-vigorous thresholds were 0.85, 0.92, and 0.97 for AW, and 0.85, 0.93, and 0.95 for AC. Sensitivities were higher for the vigorous threshold (97%) than the other thresholds (86–92%). Specificities for the three thresholds were on the order of 66–73%. The positive predictive values for sedentary, light, moderate and vigorous categories were 80, 66, 69, and 74%

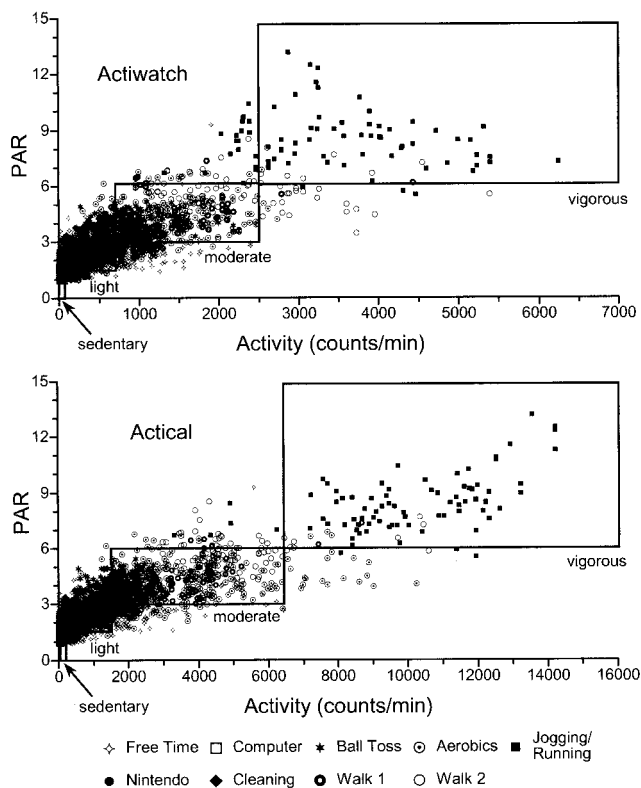


FIGURE 2—Physical activity ratio (PAR) vs Actiwatch and Actical activity counts for structured activities performed in the calorimeter and treadmill walking/running in the exercise laboratory.

TABLE 3. Prediction of activity energy expenditure (AEE) and physical activity ratio (PAR) from stepwise linear regression.

AEE (kcal·min ⁻¹)			AEE (kcal ⁻¹ ·kg ⁻¹ ·min)			PAR		
Model	r ²	SEE	Model	r ²	SEE	Model	r ²	SEE
Actical								
AC ^{0.685}	0.763	0.663	AC ^{0.653}	0.806	0.0111	AC ^{0.654}	0.809	0.560
AC ^{0.685} + WT	0.788	0.628	AC ^{0.653} + Age	0.811	0.0110	AC ^{0.654} + HT	0.810	0.558
AC ^{0.685} + WT + Sex	0.788	0.627	AC ^{0.653} + Age + Sex	0.811	0.0110	AC ^{0.654} + HT + Age	NS	
AC ^{0.685} + WT + Sex + HT	0.789	0.626	AC ^{0.653} + Age + Sex + HT	NS		AC ^{0.654} + HT + Age + Sex	NS	
AC ^{0.685} + WT + Sex + HT + Age	0.789	0.626						
Actiwatch								
AW ^{0.712}	0.694	0.760	AW ^{0.724}	0.792	0.0117	AW ^{0.703}	0.759	0.632
AW ^{0.712} + WT	0.735	0.708	AW ^{0.724} + Age	0.793	0.0117	AW ^{0.703} + HT	0.764	0.624
AW ^{0.712} + WT + HT	0.736	0.706	AW ^{0.724} + Age + HT	0.794	0.0117	AW ^{0.703} + HT + Sex	NS	
AW ^{0.712} + WT + HT + Sex	0.737	0.704	AW ^{0.724} + Age + HT + Sex	NS		AW ^{0.703} + HT + Sex + Age	NS	
AW ^{0.712} + WT + HT + Sex + Age	0.738	0.704						

AEE, activity energy expenditure; PAR, physical activity ratio; AC, Actical; WT, weight; HT, height; AW, Actiwatch. r² and SEE are given for the entire regression model.

for AW, respectively, and 81, 68, 72, and 74% for AC, respectively, based on the entire data set.

DISCUSSION

The purpose of this study was to validate two accelerometer-based activity monitors, AW and AC, as measures of children's physical activity using EE as the criterion measure. Our data revealed that AW and AC activity counts were highly correlated with EE, with minor additional contributions of age, sex, weight, and height. Prediction equations for AEE and PAR, and thresholds to partition counts into sedentary, light, moderate, and vigorous levels of physical activity were developed for children.

As technology advances in integrated circuitry and memory capacity, accelerometer-based activity monitors have become smaller, more sensitive, and capable of monitoring activity for extended periods. Newly designed devices require validation and calibration in specific subject populations. Several accelerometers (Caltrac, Tritrac, CSA, Mini Mitter 2000, AW) have been validated for assessing physical activity in children under laboratory and field conditions (2,4,5,7,8,14,15,19,20). It is now recognized that the validation protocol needs to simulate the range of activities in which children typically engage. Although treadmill walking/running has the advantage of being precisely controlled and reproducible, it does not reflect all torsional accelerations associated with free-living activities. In our study, a series of lifestyle activities were performed in a room respiration calorimeter, in addition to treadmill walk-

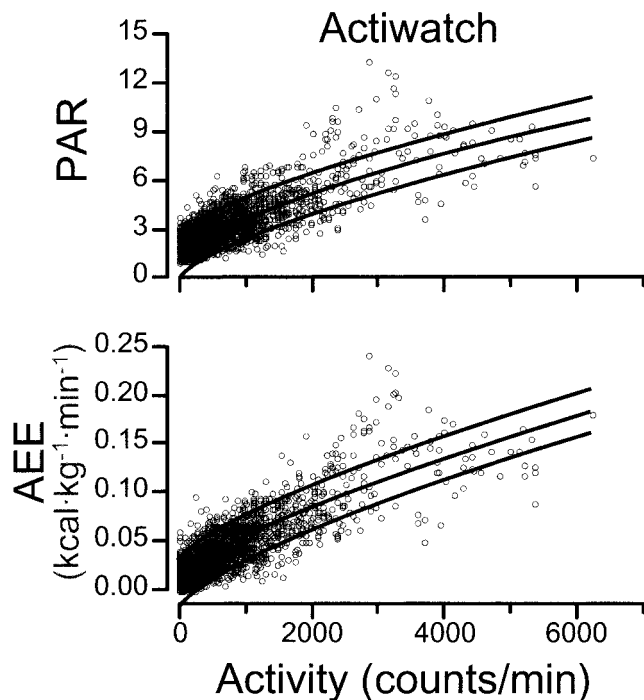


FIGURE 3—The predicted physical activity ratio (PAR) and activity energy expenditure (AEE) values are displayed against the observed values for Actiwatch (AW) with corresponding 95% prediction intervals.

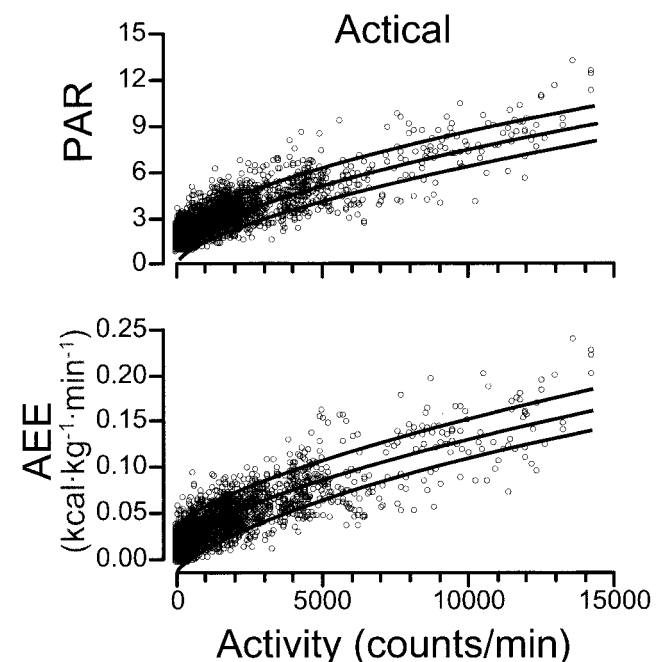


FIGURE 4—The predicted physical activity ratio (PAR) and activity energy expenditure (AEE) values are displayed against the observed values for Actical (AC) with corresponding 95% prediction intervals.

TABLE 4. Threshold counts for activity monitors for sedentary, light, moderate, and vigorous levels of physical activity.

Physical Activity Level	AEE (kcal·kg ⁻¹ ·min ⁻¹)	PAR	AW (counts)	AC (counts)	Sensitivity (%) [*]		Specificity (%) [*]	
					AW	AC	AW	AC
Sedentary	<0.01	<1.5						
Light	0.01	1.5	50	100	86	86	71	72
Moderate	0.04	3	700	1500	92	92	68	73
Vigorous	0.1	6	2500	6500	97	95	66	70

AEE, activity energy expenditure; PAR, physical activity ratio; AW, Actiwatch; AC, Actical.

^{*} Sensitivity and specificity determined by binary classification, i.e., sedentary-light, light-moderate, and moderate-vigorous levels of physical activity.

ing/running. The activities reflected a broad range of gross and fine motor movements as well as the spontaneous, sporadic movements characteristic of children.

In the present study, we evaluated two omnidirectional accelerometer-based monitors that may capture total body movement better than uniaxial devices. In a comparison of uniaxial and triaxial accelerometers in adults, the sum of all three axes best predicted sedentary and light standing activities, but the anteroposterior plane was the most accurate predictor of the EE during treadmill walking, despite the fact that the major acceleration was in the vertical direction (1). For each activity, movement recorded in the anteroposterior and mediolateral planes also was associated with movement detected in the vertical plane. Despite these findings, differences in performance between uniaxial and triaxial accelerometers have not been striking when tested in children. Evaluation of the three-dimensional Tritrac-R3D against uniaxial accelerometers during laboratory exercise and free play showed only slightly higher correlations with EE or heart rate for Tritrac-R3D (5,22). The uniaxial and triaxial accelerometers were highly correlated with one another, indicating that both provide useful information about children's activity. In our comparison of AW and AC, we observed an improvement in the responsiveness of AC compared with AW at higher levels of exertion. Design modifications may have improved the performance of AC. The piezoelectric sensor was reoriented in AC to increase sensitivity to vertical movements of the torso, the frequency range was optimized to detect sedentary movements as well as high-energy movements, and the firmware was modified to record total activity movement for a given epoch rather than peak movement. Underestimation of activity at high levels of exertion by AW may be problematic in assessing children engaged in vigorous exercise or sports. Nevertheless, a reasonably valid estimate of total daily physical activity can be estimated, because most children spend a small fraction of time at vigorous levels of activity. Despite engineering advances, there remain limitations inherent to all accelerometers. Static work and movement against external forces such as pushing or lifting objects, stair climbing, cycling, rowing, or resistance training result in an increase in EE without a proportional increase in body movement and are not accurately captured by accelerometers. Also, there are times when the decline in EE lags behind the cessation of body movement, such as in post-exercise periods, resulting in an underestimation of EE using the accelerometers.

As seen with other accelerometers, AW and AC counts were linearly correlated with EE, but we found that a power function best described the relationships between counts and EE, AEE, or PAR. Prediction equations for AEE and PAR

were then developed using the power function of AW and AC counts. Activity counts explained the majority of the variability in EE, with small incremental contributions of age, sex, weight, and height. The final equations accounted for 76–79% of the variability in AEE and PAR using AW, and 81% of the variability in AEE and PAR using AC. The relatively wide 95% prediction intervals for AEE and PAR suggest that the accelerometers are best applied to groups rather than individuals.

Prediction equations for EE of children have been published for Caltrac, CSA, and AW accelerometers (14,15,20). Two of these equations based on Caltrac and CSA were recently evaluated against portable indirect calorimetry (3). Although moderate to strong correlations were found between measured and predicted EE, both equations underestimated EE. These treadmill-derived equations of Trost et al. (20) and Sallis et al. (15) may not have been applicable to the lifestyle activities of sweeping, bowling, and basketball performed by the children in the validation. Equations also were developed to predict total energy expenditure (TEE) from CSA counts based on doubly labeled water in children (4). In 26 9-yr-old children, total CSA counts were significantly correlated with TEE ($r = 0.39$; $P = 0.05$), AEE ($r = 0.54$; $P = 0.01$), and TEE/BMR ($r = 0.58$; $P = 0.01$). The best prediction equation based on gender, activity counts, and weight explained 60% of the variation in TEE. Gender and activity counts explained 45% of the variation in AEE. Due to large SEE and wide limits of agreement, the prediction equations may be limited to the assessment of TEE on a group level.

In some applications, categorizing levels of physical activity of children is of interest. Several approaches can be taken to define thresholds to partition counts into different levels of physical activity. Thresholds may be based on discrete activities, or specific levels of EE, AEE, MET, or PAR. Because of the variability between children in performing any discrete activity, we chose to define the thresholds based on specific PAR and AEE values. For adults, the American College of Sports Medicine categories for physical activity have been used to define accelerometer thresholds (light < 3 METs; moderate: 3–6 METs; vigorous > 6 METs) (6). The accuracy of five published CSA accelerometer cut-points for predicting time spent in physical activity was evaluated in adults (18). Substantially different estimates of the time spent in different intensity categories were found. The types of activities performed, the placement of the monitors, and the setting under which measurements are made affect the development of prediction equations and thresholds for different activity levels. Adult-

derived accelerometer-thresholds for physical activity are not applicable to children. Interpreting rates of oxygen consumption during activity in terms of the adult resting metabolic equivalent or MET, defined as $3.5 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$, is incorrect in children, because their resting metabolic rate (RMR) is not constant but declines with age (16). The use of the adult MET value to define thresholds in children whose RMR range from 6 to $3.4 \text{ mL}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$ would create an erroneous age-dependent bias in the prediction equations.

Standard categories for defining physical activity levels have not been defined for children. In our previous publication, we defined physical activity levels based on AEE ($\text{kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) to reduce the age-dependence of the accelerometer thresholds. In the present study, we defined physical activity levels in terms of AEE (0.01, 0.04, and $0.10 \text{ kcal}\cdot\text{kg}^{-1}\cdot\text{min}^{-1}$) and PAR (1.5, 3.0, and 6.0). The sedentary level represented activities with minimal body movements in the sitting or reclined position such as playing Nintendo. Light level reflected activities of low exertion in the standing position such as cleaning. Moderate level reflected activities of medium exertion in the standing position such as aerobics and walking. Vigorous level was reflective of activities at a high level of exertion in the standing position such as running. Because considerable variability among children was seen in the AEE or PAR for any given structured activity, it was critical to base the categorization on objective measures of energy expenditure rather than observation. Also, anchoring the thresholds on

levels of PAR or AEE permit other investigators to duplicate our results with AW and AC, or compare AW/AC results with other accelerometers. Sensitivities and specificities for AW and AC were comparable. The positive predictive values for both monitors indicate acceptable performance for categorizing minute-to-minute AW and AC counts into the four levels of physical activity. The positive predictive values are somewhat lower for the light and moderate levels, reflective of the inevitable overlap of counts in these areas. Our prediction equations and thresholds for categorizing activity levels of children will require validation with an independent data set.

In conclusion, both accelerometer-based activity monitors provided valid measures of children's AEE and PAR, and can be used to discriminate sedentary, light, moderate, and vigorous levels of physical activity but require further development to accurately predict AEE and PAR of individuals.

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