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Predicting Energy Expenditure from Accelerometry Counts in Adolescent Girls

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Abstract

Purpose—Calibration of accelerometer counts against oxygen consumption to predict energy expenditure has not been conducted in middle school girls. We concurrently assessed energy expenditure and accelerometer counts during physical activities on adolescent girls to develop an equation to predict energy expenditure.

Methods—Seventy-four girls aged 13–14 yr performed 10 activities while wearing an Actigraph accelerometer and a portable metabolic measurement unit (Cosmed K4b2). The activities were resting, watching television, playing a computer game, sweeping, walking 2.5 and 3.5 mph, performing step aerobics, shooting a basketball, climbing stairs, and running 5 mph. Height and weight were also assessed. Mixed-model regression was used to develop an equation to predict energy expenditure (EE) ($Kj \cdot min^{-1}$) from accelerometer counts.

Results—Age (mean [SD] = 14 yr [0.34]) and body-weight–adjusted correlations of accelerometer counts with EE ($kJ \cdot min^{-1}$) for individual activities ranged from −0.14 to 0.59. Higher intensity activities with vertical motion were best correlated. A regression model that explained 85% of the variance of EE was developed: [EE ($kJ \cdot min^{-1}$) = 7.6628 + 0.1462 [(Actigraph counts per minute − 3000)/100] + 0.2371 (body weight in kilograms) − 0.00216 [(Actigraph counts per minute − 3000)/100]^2 + 0.004077 [((Actigraph counts per minute − 3000)/100) × (body weight in kilograms)]. The MCCC = 0.85, with a standard error of estimate = 5.61 $kJ \cdot min^{-1}$.

Conclusions—We developed a prediction equation for kilojoules per minute of energy expenditure from Actigraph accelerometer counts. This equation may be most useful for predicting energy expenditure in groups of adolescent girls over a period of time that will include activities of broad-ranging intensity, and may be useful to intervention researchers interested in objective measures of physical activity.

Keywords

EXERCISE; ADOLESCENCE; MEASUREMENT; SCHOOL

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Regular physical activity has a variety of well-established health benefits (18) and is recommended in national objectives for all age groups of the general population (19). Unfortunately, data from the Youth Risk Behavior Survey indicate that youths become less physically active between puberty and age 18 (2). There are ongoing interventions to find ways to assist youths in increasing physical activity and maintaining a healthy level of daily energy expenditure, including the Trial of Activity in Adolescent Girls (TAAG). TAAG is a multicenter intervention trial, funded by NIH, with a goal of developing an intervention to prevent the decline in physical activity that typically occurs in girls as they move through the pubertal transition. One challenge of TAAG and other similar intervention studies is accurate, reliable measurement of daily energy expenditure. Though valid and reliable self-report measures for physical activity have been developed, there are limits to self-report. For example, when self-reported measures are used, bias in intervention studies may be introduced if participants in the exercise treatment group overreport physical activity to please the study investigators; this is a well-established form of information bias (7). By the same token, those in the control group may under-report physical activity or overreport to a lesser extent (7). This type of bias is the very reason it is preferable to blind participants to treatment status, a type of blinding not possible in a behavioral intervention.

Furthermore, it may be more difficult to remember the amount of time or intensity of walking done as part of daily activities (walking to the bus, between classes, in the grocery store, etc.) than to remember the amount of time spent doing a scheduled, structured activity intended specifically for exercise (e.g., soccer practice, a session of jogging, or a tennis match). An objective measurement approach may assist in avoiding these important limitations of self-report. For example, an accelerometer will count movement from walking between classes and to or from the bus stop in the same objective manner as taking a walk for the purpose of exercise. There are other domains of physical activity for which it may be difficult to recall time and intensity as well, including household chores, personal care, and transportation activities. An accelerometer will detect movement in all of these activities with no differential ability to record the movement according to whether the movement is done for the purpose of exercise or to accomplish activities of daily living.

Because it will not bias observations according to treatment status, nor record movement activity differentially according to whether the movement was done specifically for the purpose of exercise, accelerometry may offer an alternative or a supplement to self-report in evaluating interventions designed to assist youth in achieving and maintaining a health daily energy expenditure level, including adequate moderate to vigorous physical activity.

One challenge in using accelerometry data for evaluation of physical activity interventions is that raw data from accelerometers (counts representing acceleration in the vertical plane of movement, summed over a user-specified time interval) are difficult to interpret. Therefore, conversion of accelerometer counts into energy expenditure would assist in interpreting results of intervention studies.

There have been studies that have calibrated accelerometer counts against oxygen consumption in adults (4) and children (14), but not in middle school aged children, nor toward the goal of predicting daily energy expenditure in middle school aged children. A measurement substudy of the Trial of Activity in Adolescent Girls (TAAG) was undertaken to calibrate accelerometer counts against oxygen consumption during a variety of commonly performed activities. Presented elsewhere are analyses for determining the threshold of accelerometer counts for light, moderate, and vigorous-intensity activity from this TAAG substudy (15). The purpose of this paper is to present analyses to develop an equation for predicting energy expenditure from accelerometer counts using data collected during common physical activities of varying intensities in adolescent girls. It is hoped that this equation will be useful to investigators interested in evaluating interventions to increase daily energy expenditure or moderate to vigorous energy expenditure in adolescent girls. A secondary purpose of this paper is to present the correlations of EE and accelerometer counts for each activity performed.

METHODS

Subjects and Recruitment

Participants—In spring 2001, 74 healthy eighth-grade girls, age 13–14 yr, were recruited to participate in this study from three TAAG field sites, specifically from urban areas of Baltimore, MD, Minneapolis/St. Paul, MN, and Columbia, SC. Recruitment approaches varied across field centers, and included having TAAG staff visit the schools to tell groups of girls about the study, as well as postcards mailed to the homes of eighth-grade girls who attended participating schools to assess interest and willingness to participate. Girls were recruited to produce a sample that was diverse in terms of height, weight, ethnicity, and history of sport participation. None of the girls had physical limitations. Each participating institution's human subjects review board approved the protocol. Written informed consent to participate was obtained from one parent, and written assent was obtained from each girl.

Instrumentation—Age and ethnicity were obtained from the girl by a self-report questionnaire. Weight and height were measured in duplicate with the child wearing lightweight clothing, without shoes, using a SECA 880 scale (SECA, Hamburg, Germany) and the Schorr portable height board (Schorr Productions, Olney, MD), respectively. The scale was calibrated with a known weight before each measurement visit.

Oxygen uptake ($\dot{V}O_2$), carbon dioxide production ($\dot{V}CO_2$), and heart rate were measured using a portable, breath-by-breath, metabolic unit available from Cosmed (Model K4b2, Rome, Italy). The K4b2 is a lightweight (925 g) system worn on the back. It includes a patented oxygen analyzer, an infrared nondispersive theromostated CO_2 analyzer, a bidirectional digital turbine and opto-electric reader for monitoring airflow, and proprietary software to allow all of these systems to report to the user real-time $\dot{V}O_2$, $\dot{V}CO_2$, and $\dot{V}_E$. The unit also includes a POLAR Pacer heart rate transmitter (Port Washington, NY). This instrument was used to measure resting $\dot{V}O_2$ as well as $\dot{V}O_2$ during performance of 10 selected activities. The Cosmed system was calibrated before each visit, and recalibrated for biking outside; calibration followed standard procedures across all sites. The Cosmed metabolic measurement unit has been compared to the Douglas bag method during resting and cycle ergometry at 50–250 W (9). The results of this validation study indicated that the kilojoules-per-minute values would have differed by 2% during exercise as measured by the COSMED versus the criterion Douglas bag method (9). For the present study, $\dot{V}O_2$ and $\dot{V}CO_2$ values were converted to EE using the formula developed by Weir et al. (21).

The accelerometer used in this study was the MTI Actigraph (Manufacturing Technologies, Inc., Model 7164, Shalimar, FL). This uniaxial electromechanical device records vertical plane acceleration and deceleration at a frequency of $10\times s^{-1}$, and at a threshold of $0.033 \times g$. Additional engineering specifications for this device are available (17). All Actigraph® accelerometers were checked for similarity of basic functional condition using a standard laboratory shaker before use. Each monitor was put on a shaker and run at a slow speed (similar to walking) and a fast speed (similar to running) for 15 min each. The results were compared between units and monitors with more than a 10% difference. The other monitors were retested and, if again found unreliable, were returned to the manufacturer for replacement. Each girl wore two accelerometers, one over each hip. All accelerometer values used for the analysis were the mean of right- and left-hip accelerometer counts. The results of the analysis did not differ when only the left-or right-hip monitor data were used. The monitors were attached to a belt worn around the waist. These belts were standardized across sites and provided by the study. For each visit, the monitors were initialized before the first activity, and data were uploaded from the monitor to a laptop computer after performance of all activities was complete. Activity counts were stored in 30-s time intervals, which were summed over the time of the activities and divided by the time each activity was performed to give counts per minute for each activity.

Study design—Participants attended two visits to obtain accelerometer and V O_2 data for 10 activities (Table 1). The selected activities were chosen because they varied in intensity from sedentary to vigorous. Each girl completed both 2- to 3-h visits within a 3-wk time frame, with at least 24 h between visits. Girls were required to fast for 3 h before each visit in an attempt to limit additional variability in energy expenditure due to the thermic effect of food. Participants were provided with *ad libitum* access to water during the measurement session. No other foods or drinks were provided, except for a snack at the end of each measurement visit. Data were collected in a laboratory setting and/or in a large, indoor, air-conditioned setting such as a gymnasium; the exception to this was bicycling, which took place outside or in a field house. All sites provided a climate-controlled, comfortable, quiet space for the resting energy expenditure measurement, and enough open space to accommodate performance of vigorous physical activities in a manner that is normal among free-living girls.

At the first visit, participants were given an overview of the physical activity assessments, and height and weight were measured. Girls were then fitted with two Actigraph monitors and the Cosmed system, and given an opportunity to become familiar with breathing through the mask. Each activity was performed for 7 min, during which accelerometer counts were recorded in 30-s intervals (summed to give minute-by-minute values) and heart rate, VCO_2, and $\dot{V}O_2$ were recorded on a breath-by-breath basis (averaged to give minute-by-minute values). Rest periods between activities were allowed as necessary to ensure that each girl's heart rate was below 100 bpm before beginning the next activity. Five activities were completed during the first visit, and five during the second visit.

Activities—Table 1 provides a brief description of the activities assessed. Resting $\dot{V}O_2$ (REE) was collected for 15 min in a dark, quiet room. The girl was in a reclined position and awake. Several (3–5) minutes of rest were allowed before metabolic measurement occurred. Data from minutes 3 through 15 were averaged for analyses. For all activities other than rest, metabolic measurements, heart rate, and accelerometer counts were collected for 7 min, with the average of the last 4 of the 7 min used for data analysis. The order of activities was always from lowest to highest intensity in a given measurement visit.

To ensure uniform implementation of the study protocol across field centers, the girls were provided with specific guidelines for performing each activity as they occurred, and an external monitor checked compliance. Television (movie) watching and playing computer games were both performed in a seated position; all other activities (except biking) were performed in an upright standing position, and were set at specific paces. To standardize the activity (pace and movement) whenever possible, a staff member completed these activities along with the girl. For biking outside, girls used a speedometer on the bicycle to monitor their pace. For sweeping, girls were self-paced, but the same material was swept up, and the same broom was used with all girls within the site. For running 5 mph, girls were paced with a stopwatch between marked distances with verbal guidance to speed up or slow down as needed. For stair climbing, music with a tempo of 80 bpm was used to keep girls on pace. Data collection was monitored continuously throughout all activities by trained staff. The staff recorded the exact time of the measurements and marked the event button on the Cosmed unit.

Statistical analysis—Statistical analysis was conducted using SAS version 8.0 (SAS Institute, Cary, NC). Differences between sites for anthropometric and demographic data were assessed using chi-square and *F* tests.

Prediction of energy expenditure in kilojoules per minute from accelerometer counts was accomplished with a regression analysis based on the general linear mixed model (5). For these models, Actigraph counts were centered on the value of 3000, so that the intercept and main effects of variables, which interact in the model with Actigraph counts, could be interpreted at the value Actigraph = 3000 rather than at Actigraph = 0. The value of 3000 was chosen for this centering because it was approximately at the middle of the distribution of Actigraph counts per minute in all activities performed. But more importantly, centering of Actigraph counts improves the stability of the estimation by making the linear and quadratic effects approximately independent. Finally, printed estimates of the quadratic and other interactive effects of Actigraph counts lack significant digits when Actigraph ranges greatly (0–16,000). This issue can be resolved by this centering procedure, which results in a return of two additional significant digits when the Actigraph counts are divided by 100. For example, instead of $0.00009*(\text{Actigraph counts per minute} - 3000)^2$, the coefficient is reported as $0.00854*A^2$, where $A = (\text{Actigraph} - 3000)/100$.

Quality of fit of the regression models was assessed using the model concordance correlation coefficient (MCCC), a statistic similar to R^2 in a linear model, but appropriate for nonindependent responses. This MCCC indicates how well the observed and predicted values would fit a line with an intercept of zero and a slope of one (20). A variety of models were tested to find the model with the best fit, including ones with log and square-root transformations of predictor and outcome variables. The site was included in all models as a random effect. Effects that remained the same within the girls regardless of activity, but that varied between girls, included age and body weight. Effects that varied both between and within girls included Actigraph counts for the following activities: computer time, sweeping, walking 2.5 mph and 3.5 mph, shooting hoops, running, climbing stairs, and step aerobics. An *a priori* decision was made not to include bicycling in the model, because it does not involve vertical motion, and thus was expected to distort the true relationship between accelerometer counts and energy expenditure. Television viewing was no different than computer time in intensity and type of activity. Furthermore, by including a quadratic term for Actigraph counts, we assessed whether the slope in kilojoules per minute changed between different levels of intensity of the performed activity. We also assessed whether the slope of EE was modified by fitness level (assessed by a bicycle test, which is described elsewhere (15)), race (white vs black), or body weight. There was no change in the slope according to fitness level or race (results not shown). However, there was a significant interaction term for body weight with Actigraph counts that improved the model fit, as evidenced by an increase in the MCCC. Addition of race, height, or resting energy expenditure did not alter the findings reported here (results not shown). The final model was fit with the variance components' covariance structure, which assumes independence of variance components (23).

To investigate possible nonlinearity in the relationship between energy expenditure and body weight, body weight was modeled as a continuous variable in some models, and as tertiles in other models. Because the results were similar, only models with continuous weight were included in the results here. Furthermore, we considered whether to adjust for weight as an independent variable, or to correct for weight in the dependent variable of our models. We chose to adjust for weight as an independent variable to allow for prediction of EE ($\text{kJ}\cdot\text{min}^{-1}$) because this would not preclude determining EE in kilojoules per kilogram per minute thereafter.

Correlation coefficients for EE (kJ·min^{-1}) with Actigraph counts for each measured activity were calculated after adjusting for age and body weight.

RESULTS

Table 2 shows the anthropometric and demographic characteristics of participants. The oldest girls were seen at the Minnesota site. Differences by race that were seen across sites were marginally statistically significant. The between-site age and race differences led us to consider site as a random effect in models predicting energy expenditure from multiple activities.

Table 3 presents the Pearson's correlation coefficients between EE (kJ·min^{-1}) and Actigraph counts for each activity included in this study. Correlations for specific activities were highest for sweeping the floor, step aerobics, bicycling, shooting hoops, and jogging 5.0 mph, and were lowest for stair climbing and a variety of low-intensity activities (television viewing, playing a computer game, walking 2.5 mph and 3.5 mph).

Table 4 shows the mean, standard deviation, and range for Actigraph counts per minute and EE (kJ·min^{-1}) for each activity performed, including rest. Sample sizes for each activity are provided, because not all girls completed all activities successfully, and there were instances of equipment failure. More specifically, there were four girls with one activity for which we could not use the Actigraph data, and seven girls with one activity for which we could not use the Cosmed metabolic measurement data. This was out of a total of 814 activities (11 activities per girl, 74 girls), for an equipment failure rate of less than 1% for the Actigraph and the Cosmed. The Actigraph counts increased strongly with activity intensity, and the standard deviation of these counts increased less, resulting in a decreasing coefficient of variability, with increasing intensity for activities involving vertical motion. The coefficient of variability for EE (kJ·min^{-1}) ranged from 20 to 27% for all activities except playing a computer game and biking, which had coefficients of variability of 39 and 34%, respectively.

The model with the best fit to predict EE (kJ·min^{-1}) across a variety of activity intensities from Actigraph counts is presented below:

[EE (kJ·min^{-1}) = 7.6628 + 0.1462 [(Actigraph counts per minute − 3000)/100] + 0.2371 (body weight in kilograms) − 0.00216 [(Actigraph counts per minute − 3000)/100]^2 + 0.004077 [((Actigraph counts per minute − 3000)/100) × (body weight in kilograms)]. The MCCC = 0.85, with a standard error of estimate = 5.61 kJ·min^{-1}].

DISCUSSION

Prediction of energy expenditure from an objective measurement tool that requires no collection of respiratory gases will be useful for physical activity researchers. We present such an equation, specifically for middle school girls. The primary intended use of this equation is for prediction of energy expenditure over a period of time during which a broad variety of activity intensities are likely to occur, such as for daily energy expenditure. Our analyses detected a significant attenuation of the slope of energy expenditure per accelerometer counts as activity intensity increased. This finding is consistent with early reports that accelerometers underestimated energy expenditure at lower intensity, but overestimated energy expenditure at higher intensities (8,11). We accounted for the attenuation by modeling both a linear and quadratic term for accelerometer counts in the final model presented herein.

We observed an energy expenditure increase of 0.24 kJ·min^{-1} with every kilogram increase in body weight. Furthermore, the impact of body weight on slope of EE (kJ·min^{-1}) is also positive in our data, as indicated by the positive interaction term for body weight times EE (beta = 0.0041). Those with higher body weights increase in energy expenditure, with a steeper slope for any given increase in accelerometer counts. This finding is consistent with prior observations that overestimation of energy expenditure by accelerometers is likely to occur at a lower intensity in obese compared with nonobese individuals (13).

A review of the modest correlations of accelerometer counts with energy expenditure from indirect calorimetry for individual field activities reported herein and elsewhere (6,22) might lead some to challenge the assertion that accelerometer counts can accurately and reliably estimate energy expenditure. However, within any specific activity, the range of Actigraph counts between subjects is considerably restricted, as are the corresponding energy expenditures. Furthermore, each subject contributes only one point per activity, so the association between energy and count is based on purely cross-sectional (between-subject) differences. From the aspects both of (a) the restricted range in the predictor, and (b) the use of differences between girls (in contrast to changes within girls), it is not surprising that the relationship between energy and count is modest if attention is restricted to a single activity. By taking advantage of 11 activities measures within each girl to examine the relationship between change in energy associated with change in counts over a wide range of activity levels, we were able to establish a much stronger relationship between energy expenditure and accelerometer counts. The resulting equation explains 85% of the variance in energy expenditure measured by indirect calorimetry.

We chose, *a priori*, to exclude bicycling from the model, because bicycling does not involve much vertical motion, and thus was expected to distort the true relationship between accelerometer counts and energy expenditure. The data in Table 4 show that the accelerometer counts per minute during bicycling is discordant when compared with other activities of similar energy expenditure, such as step aerobics or shooting hoops. This observation provides some validation that our *a priori* choice was appropriate. However, it also underscores a major limitation of a uniaxial accelerometer; there are many activities the accelerometer will not assess well, including bicycling, swimming, and weight lifting with the upper body.

The majority of studies that have developed prediction equations for oxygen uptake, METs, or energy expenditure from accelerometer counts have been conducted in adults (10,22,6,4,1, 12); only a few such studies have been conducted in children (3,14,16). Furthermore, only three of the studies in adults included field activities outside of the laboratory (10,22,6). The R^2 values for these prediction equations have ranged from 0.35 (6) for lifestyle (field) activities to a high of 0.98 in a study of adults that also included field activities (10). In children, Eston et al. (3) reported R^2 values for the equation to predict oxygen uptake from accelerometer counts of 0.61 in children aged 8–10 yr. Puyau et al. (14) had children aged 7–16 spend 6 h in a room calorimeter while wearing an Actigraph accelerometer, as well as an evaluation of free-living activities without assessing oxygen consumption. The correlation of $\dot{V}O_2$ and accelerometer counts over 6 h was 0.66, with the final model to predict $\dot{V}O_2$ from accelerometer counts with an R^2 of 0.75. Finally, Trost et al. developed an equation to predict EE ($kcal \cdot min^{-1}$) from Actigraph accelerometer counts from data collected while children walked on a treadmill at three different speeds that had an R^2 of 0.83 (16). Our equation has several key advantages for the specific population of middle school girls, because (a) none of these prior studies in children included the broad range and widely varying intensity and types of activities; (b) we employed statistical methods that enabled us to take full advantage of the range of intensity of activities performed as well as the number of participants; (c) we accounted for nonlinearity of the slope of energy expenditure predicted by accelerometer counts; and (d) we modified the slope relating count and energy expenditure according to body weight.

Users of this model should keep in mind that estimates of energy expenditure from this model may be more useful for group comparisons than for determining absolute values of energy expenditure for a single individual, given a large standard error of estimate of 5.6 $kJ \cdot min^{-1}$.

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Further, it is also important for users of this model to keep in mind that using the equation to predict energy expenditure for a single activity may also produce spurious results, particularly for activities of low intensity, such as computer use, sweeping, or walking 2.5 mph. This is because the SEE of 5.6 $kJ \cdot min^{-1}$ represents a larger proportion of energy expenditure at low than at high intensities.

In this study, participants were asked to perform each of the activities at a set pace. It could be argued that the activities should have been performed at a self-selected pace, as this is how the girls would do the activities in real life. It is likely that the energy expenditure and accelerometer counts for each individual activity, as reported herein, will incorrectly estimate the actual energy expenditure or accelerometer counts of girls doing each of these activities in the real world, as girls do not all walk up and down stairs at 80 bpm, nor do they all walk at 3.5 mph. However, the primary goal of the study was not to provide accurate accelerometer counts and energy expenditure for individual activities, but rather to combine these concurrent measurements in a large group of girls, over a wide range of activity intensities. To be certain that a sample of concurrent accelerometer and energy expenditure data were obtained at a broad variety of activity intensities, the pacing of the activities was set for the girls.

In summary, we have developed an equation to predict energy expenditure in kilojoules per minute from Actigraph accelerometer counts to be used specifically in middle school girls (13–15 yr). This equation will be useful for the main TAAG trial, as well as to others interested in objective measures of energy expenditure in middle school girls. Independent validation of this equation within a separate set of adolescent girls would be of value.

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TABLE 1

Descriptions of Ten Selected Physical Activities.*

	Physical Activity	Activity Description
1	Television viewing	Subject watches a video while sitting on a comfortable chair without getting up at any time.
2	Playing a computer game	Subject plays the Chip's Challenge computer game using the arrow keys while sitting on a chair facing the computer.
3	Household chores—sweeping the floor	Subject uses a broom to sweep confetti spread on a large area of the room.
4	Walking slowly	Subject walks at an average of 2.5 mph on a marked area. She is prompted to keep her pace close to that speed with the guidance of timed distances.
5	Walking briskly	Subject walks at an average of 3.5 mph on a marked area. She is prompted to keep her pace close to that speed with the guidance of timed distances.
6	Step aerobics	Subject follows an aerobics routine prerecorded in a step aerobics videotape with an estimated average MET value of 6.0.
7	Riding a bicycle	Subject rides a bicycle at about 12 mph. The bicycle is a Giant Rincon, ATB 17.5/M frame; a speedometer helps keep pace.
8	Basketball (shooting baskets alone)	Subject shoots basketball at a regulation hoop continuously. She chases the ball if needed and carries on shooting the ball.
9	Climbing up and down stairs	Subject goes up and down a flight of stairs without stopping, but at her own pace.
10	Jogging	Subject jogs at an average of 5.0 mph on a marked area. She is prompted to keep her pace close to that speed, with the guidance of timed distances.

*All activities were performed for 7 min, data from minutes 4 to 7 were averaged for data analysis.

TABLE 2

Description of participants, mean (SD) or percentage.

	Johns Hopkins University, Baltimore, MD	**University of South Carolina, Columbia, SC**	**University of Minnesota, Minneapolis, MN**	**Total**
N	23	26	25	74
Body weight (kg)	60.6 (14.3)	60.4 (15.6)	60.3 (17.2)	60.4 (15.6)
Height (cm)	160.9 (6.1)	159.5 (6.0)	160.9 (7.9)	160.4 (6.7)
BMI ($kg \cdot m^{-2}$)	23.4 (5.4)	23.2 (6.4)	23.7 (5.7)	23.4 (5.8)
Age (yr)*	14.0 (0.2)	14.2 (0.4)	14.3 (0.3)	14.2 (0.3)
Race:				
White	57%	27%	52%	45%
Black	35%	65%	8%	36%
Asian/Pacific Islander	0%	0%	16%	5%
Multiethnic	9%	8%	24%	14%

*Significant difference between field site differences based on chi-square or 2-sided *t*-tests.

TABLE 3

Correlations: Energy expenditure (kJ·min^{-1}) with accelerometer counts.

Activity	Adjusted Correlation Coefficients*	
	ρ	*P*-value
Television viewing	0.01	0.94
Playing a computer game	−0.03	0.82
Sweeping the floor	0.31	0.008
Walking 2.5 mph	−0.18	0.14
Walking 3.5 mph	0.13	0.27
Step aerobics	0.57	<0.001
Bicycling 12.0 mph	0.40	0.001
Shooting hoops	0.49	<0.001
Climbing stairs	0.11	0.36
Jogging 5.0 mph	0.45	<0.001

*Pearson's coefficients were adjusted for age and body weight.

TABLE 4

Average energy expenditure and Actigraph counts for all activities.

Activity	*N*	Actigraph (counts per minute)			Energy expenditure ($kJ \cdot min^{-1}$)		
		Mean	SD	Range	Mean	SD	Range
Rest	64	0.7	1.4	0–7	4.5	1.2	2.1–7.2
Television viewing	67	1.7	3.5	0–15	4.6	1.2	2.3–7.2
Playing a computer game	71	2.2	6.5	0–45	4.9	1.9	2.4–17.6
Sweeping the floor	72	405	346	47–1915	13.1	3.5	7.3–21.2
Walking 2.5 mph	72	2359	560	1257–5209	14.0	3.7	8.8–23.5
Walking 3.5 mph	73	4170	759	2336–5817	19.1	5.2	8.6–36.7
Step aerobics	71	2742	913	1337–5198	25.1	6.3	14.3–42.9
Bicycling 12.0 mph	66	739	593	81–2895	26.5	8.9	3.1–55.9
Shooting hoops	69	4003	1168	1804–7535	29.0	5.7	18.0–47.0
Climbing stairs	72	4277	785	2852–7320	30.0	7.1	17.5–46.3
Jogging 5.0 mph	65	7857	2340	1007–16952	35.5	7.1	22.6–56.5