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Cross-Sectional Time Series and Multivariate Adaptive Regression Splines Models Using Accelerometry and Heart Rate Predict Energy Expenditure of Preschoolers[1–3]

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Abstract

Prediction equations of energy expenditure (EE) using accelerometers and miniaturized heart rate (HR) monitors have been developed in older children and adults but not in preschool-aged children. Because the relationships between accelerometer counts (ACs), HR, and EE are confounded by growth and maturation, age-specific EE prediction equations are required. We used advanced technology (fast-response room calorimetry, Actiheart and Actigraph accelerometers, and miniaturized HR monitors) and sophisticated mathematical modeling [cross-sectional time series (CSTS) and multivariate adaptive regression splines (MARS)] to develop models for the prediction of minute-by-minute EE in 69 preschool-aged children. CSTS and MARS models were developed by using participant characteristics (gender, age, weight, height), Actiheart (HR+AC_*x*) or ActiGraph parameters (AC_*x*, AC_*y*, AC_*z*, steps, posture) [x, *y*, and *z* represent the directional axes of the accelerometers], and their significant 1- and 2-min lag and lead values, and significant interactions. Relative to EE measured by calorimetry, mean percentage errors predicting awake EE (−1.1 ± 8.7%, 0.3 ± 6.9%, and −0.2 ± 6.9%) with CSTS models were slightly higher than with MARS models (−0.7 ± 6.0%, 0.3 ± 4.8%, and −0.6 ± 4.6%) for Actiheart, ActiGraph, and ActiGraph+HR devices, respectively. Predicted awake EE values were within ±10% for 81–87% of individuals for CSTS models and for 91–98% of individuals for MARS models. Concordance correlation coefficients were 0.936, 0.931, and 0.943 for CSTS EE models and 0.946, 0.948, and 0.940 for MARS EE models for Actiheart, ActiGraph, and ActiGraph+HR devices, respectively. CSTS and MARS models should prove useful in capturing the complex dynamics of EE and movement that are characteristic of preschool-aged children. J. Nutr. 143: 114–122, 2013.

Introduction

Prediction equations of energy expenditure (EE)[6] of preschool-aged children are useful for clinical and research applications for quantifying rates of EE when calorimetry measures are not available. Alternative methods to calorimetry have been developed for the prediction of EE using accelerometers and miniaturized heart rate (HR) monitors in older children and adults but not in preschool-aged children (1–8). Because the relationships between accelerometer counts (ACs), HR, and EE are confounded by growth and maturation, age-specific EE prediction equations are required for preschool-aged children.

Preschool-aged children have higher basal metabolic rates, HRs, and metabolic costs of movement than do older children. Depending on the developmental stage of the preschool-aged children, types and patterns of physical activity vary considerably (9). Movement of preschoolers is characterized by short, intermittent bursts of activity (10). Preschoolers lack the attention span and physical and motor development for continuous bouts of high-intensity physical activity. The metabolic cost of movement expressed relative to body mass decreases as children mature. The optimal speed of locomotion or the speed at which the minimum mechanical work occurs increases from 3 to 12 y of age, such that a preschooler may run at the speed an older child walks.

Conventional techniques for the measurement of EE include calorimetry and doubly labeled water. Although highly accurate

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[3] Supplemental Figure 1 is available from the "Online Supporting Material" link in the online posting of the article and from the same link in the online table of contents at http://jn.nutrition.org.
[6] Abbreviations used: AC, accelerometer count; bpm, beats per minute; CCC, concordance correlation coefficient; CSTS, cross-sectional time series; EE, energy expenditure; HR, heart rate; MARS, multivariate adaptive regression spline; $\dot{V}CO_2$, carbon dioxide production; $\dot{V}O_2$, oxygen consumption.
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and precise, these methods can be intrusive, confining, expensive, and not readily applicable to large-scale studies. Cost-effective, nonintrusive, valid, and precise methods for quantitative assessment of EE in preschool-aged children are needed. Alternative methods to calorimetry have been developed for the prediction of EE using accelerometers and miniaturized HR monitors in older children and adults (1–8). In preschool-aged children, direct observation during structured and unstructured activities has been used to calibrate accelerometers (11–14). In a few studies, calorimetry has been used to validate accelerometers and to set thresholds for levels of physical activity but not to predict EE per se (1–4). In addition, the doubly labeled water method for the measurement of total energy expenditure has been applied to validate physical activity levels estimated by accelerometry in preschool-aged children (5–8). The mean physical activity level by the doubly labeled water method was consistent with the time spent in sedentary activities and moderate-vigorous physical activity (7). In contrast, 2 other studies found poor agreement between total energy expenditure by the doubly labeled water method and activity counts in preschool-aged children, indicating further method development was needed (5,8).

The mathematical modeling of the relationships between EE, AC, and HR in preschool-age children has been limited to linear regression models that do not take into account the interdependence of the data and do not exploit all of the available information. Advanced techniques such as cross-sectional time series (CSTS) and multivariate adaptive regression splines (MARS) modeling have proven to be powerful in the prediction of EE in older children (15–17). CSTS analysis provides a body of techniques for analyzing the dynamics of the dependent structure of repeated observations. MARS is a multivariate nonparametric regression approach that approximates a complex nonlinear relationship by a series of spline functions on different intervals of the independent variable.

In this study, we apply advanced technology (fast-response room calorimetry, Actiheart and Actigraph accelerometers, and miniaturized HR monitors) and sophisticated mathematical modeling techniques to develop prediction equations of EE in preschool-aged children. Room respiration calorimetry eliminates the discomfort of a face mask and can be used to measure EE during physical activities typical of this age group. To model EE completely, data are needed while the child is awake as well as asleep, which can be done nonintrusively in a room calorimeter. Our specific aims were to develop CSTS and MARS models for the prediction of minute-by-minute EE in 69 preschool-aged children on the basis of accelerometry and HR by using room respiration calorimetry as the criterion method.

Participants and Methods

Study design. For model development, a cross-sectional study design of simultaneous room respiration calorimetry, the criterion method, accelerometry, and HR monitoring were used. The protocol entailed a 7-h visit to the Children's Nutrition Research Center metabolic research unit. While inside a room respiration calorimeter, the child was instructed to follow a protocol of physical activities designed to characterize EE, AC, and HR relationships typical of this age group. Upon exiting the calorimeter, the participants' body weight and height were measured. The Institutional Review Board for Human Subject Research for Baylor College of Medicine and Affiliated Hospitals approved the protocol. All parents gave written informed consent to participate in this study.

Participants. A total of 69 preschool-aged children, balanced for age and gender, were enrolled. All participants were healthy 3–5-y-old children. Children who were taking prescription drugs or with chronic diseases including metabolic or endocrine disorders, asthma treated with steroids, sleep apnea, and any condition that interfered with physical activity were excluded from the study. Informed consent was obtained from all parents/primary caretakers before enrollment in the study.

Anthropometric measurements. Body weight to the nearest 0.1 kg was measured with a digital balance, and height to the nearest 1 mm was measured with a stadiometer. BMI was calculated as weight/height^2 (kg/m^2). Nonoverweight was defined as <85th percentile for BMI and overweight/obese was defined as ≥85th percentile for BMI according to the CDC growth charts (18).

Accelerometry and HR monitoring: Actiheart. The Actiheart (CamNtech Ltd.) is a small (7-mm thick, 33-mm diameter, 10-g total weight) device equipped with an omnidirectional accelerometer and electrocardiogram signal processor.

Actiheart was attached to the chest by using 2 electrodes (Skintact Premier; Leonhard Lang GmbH). The main sensor was attached left of the sternum and secured with the adhesive tab on the electrode. The lead was attached parallel to the midclavicular line at the level of the third intercostal space (upper position) or just below the left breast (lower position). The electrodes were checked and replaced if there was poor adhesion.

At the conclusion of the study, the data were downloaded into Excel (Microsoft Corporation). HR and AC data acquisition by Actiheart was set at 15-s intervals. Actiheart data were collapsed into 60-s intervals and aligned with the minute-by-minute EE data. HR data were filtered with an upper cutoff of 220 beats/min (bpm) and a lower cutoff of 40 bpm.

Accelerometry: ActiGraph. The GT3X+ activity monitor (ActiGraph), a triaxial accelerometer, was used to measure the amount and frequency of movement of the children. The GT3X+ monitor is compact and lightweight, measuring 4.6 × 3.3 × 1.5 cm with a weight of 19 g. The GT3X+ output includes activity counts (vertical x, horizontal y, and diagonal z axes); vector magnitude, which is equal to the square root [(amplitude $x)^2$ + (amplitude $y)^2$ + (amplitude $z)^2$], and number of steps taken. The GT3X+ has an inclinometer to determine participant position (0 = monitor off or person lying on his/her side, 1 = standing, 2 = lying down, 3 = sitting) and to identify periods when the device has been removed. The GT3X+ records time-varying accelerations ranging in magnitude from ±6 g. The accelerometer output is sampled by using a 12-bit analog to digital convertor, set at 30 Hz for our application. The digital filter band limits the accelerometer to the frequency range of 0.25 to 2.5 Hz, which was carefully chosen to detect normal human motion and to reject changing accelerations outside the pass band. Each sample was summed over a 60-s epoch.

GT3X+ monitors were affixed above the iliac crest of the right hip with an adjustable elastic belt. Data acquisition storage by ActiGraph was set at 15-s intervals. Data were downloaded into Excel and collapsed into 60-s intervals to align with the calorimeter minute-by-minute data.

Room respiration calorimetry. During room respiration calorimetry, continuous measurements of EE were collected while the children completed a series of physical activities and while sleeping. Oxygen consumption (VO_2) and carbon dioxide production ($\dot{V}CO_2$) were measured continuously in a 19-m^3 fast-response room calorimeter whose performance has been described previously (19). EE was computed by using the Weir equation (20). $\dot{V}O_2$, $\dot{V}CO_2$, EE, and HR were averaged at 1-min intervals.

The calorimeters were redecorated as a playroom for the preschool-aged children. While in the calorimeter, all children were asked to perform a series of physical activities in the same order between 0900 and 1600 h under staff supervision. In between the series of scheduled physical activities, the children were given "free time" to engage in light activities of their choice while in the calorimeter. The staff recorded minute-to-minute observations of the child's activities. The children were given lunch at 1130 h outside the calorimeter and snacks at ~0930 and 1430 h inside the calorimeter. The calorimeter protocol included the following discrete physical activities:

Sleep: Children slept on a children's bed in the calorimeter for 45–120 min after lunch.

Stationary, watching television: Children reclined against a pillow and watched a movie on television for 20 min.

Stationary play, coloring: Children sat in a chair at a desk drawing with crayons for 10 min.

Stationary play, video games: Children while sitting played video games for 10 min.

Stationary play, puzzles: Children while sitting on the floor assembled puzzles for 10 min.

Low-active play, kitchen/toys: Children while standing played at a child's kitchen or with other toys (trucks, blocks, etc.) for 15 min.

Moderate-active play, ball toss: Children while standing repeatedly threw balls at targets across the room and walked quickly to retrieve them for 15 min.

Moderate-active play, active video game: Children while standing on a video game mat played a variety of motion games for 10 min.

Moderate-active play, dance: While following an instructor in a video displayed on a television screen, children performed a variety of dances for 15 min.

Moderate-active play, aerobics: While following an instructor in a video displayed on a television screen, children performed a variety of aerobic activities for 15 min.

Very active play, running in place. Children ran in place on a game mat while competing in a video race displayed on a television screen for 6 min.

CSTS model. We considered the following CSTS or mixed-regression model with random intercepts and random slopes to predict the minute-by-minute EE on the basis of HR, AC, and other potential covariates:

$$y_{ij} = x'_{ij}\beta + z'_{ij}b_i + \varepsilon_{ij}, \quad i = 1, \ldots, N \quad j = 1, \ldots, n_i$$

where y_{ij} denotes the minute-by-minute EE measures on the ith individual at consecutive time points j, β is a vector of regression coefficients associated with the covariates x_{ij} (i.e., HR, PA, etc.) and contains population-specific parameters describing average trends, b_i are independent vectors of random effects associated with covariates z_{ij} and contain participant-specific parameters describing how the response of the ith individual deviates from the mean response over time, and ε_{ij} is the random noise for the ith individual at time j. For more details regarding the CSTS model, please see our previous publication (29).

MARS model. The fundamental idea of MARS is to use the combination of the linear truncated basis functions to model the dependence of y_{ij} on x_{ij}, which is capable of representing the complex nonlinear relationship. The basic model that we consider is that the minute-by-minute EE, y_{ij}, of the ith child are generated by an unknown "smooth" function f and additive noise ε_{ij} (13). More specifically, we investigate the following nonparametric regression model:

$$y_{ij} = f(x_{ij}) + \varepsilon_{ij},$$

where the error terms ε_{ij} are mean zero random variables. For more details regarding the MARS model, please refer to our previous publications (15–17).

Model evaluation. Values are presented as means ± SD. Descriptive statistics were performed by using STATA (release 11; StataCorp LP).

Goodness-of-fit methods were used to assess and compare competing models on the basis of their agreement between the observed values and model estimates derived from CSTS or MARS. We analyzed concordance between the observed and predicted EE. Bland and Altman recommend a graphical method to assess concordance or agreement between 2 variables (21). In our application, the observed EE measured by calorimetry was taken as the "true" value and used on the x-axis. Although the Bland-Altman (21) diagnostic plot of the difference versus the mean can provide insight into the measurement differences between 2 methods, it does not provide a single measure of agreement. Krippendorff (22) and Lin (23,24) considered the concordance correlation coefficient (CCC), which is appropriate for measuring agreement when the data are measured on a continuous scale.

Results

Participants. A description of the 69 children who participated in the study is presented in **Table 1**. The sample was equally stratified by age and gender. Twenty percent of the children were classified as overweight or obese.

Observed EE, HR, ACs, and steps. Mean rates of EE, HR, ACs, and steps during calorimetry are presented in **Table 2**. A wide range of EE (0.3–5.1 kcal/min) and HR (71–217 bpm) was attained within the confines of the calorimeter from minimal rates during sleep to near maximum rates while running. A correlation matrix between EE and the potential predictors (HR, Actiheart AC_x, Actigraph AC_x, AC_y, AC_z, and steps) is graphically displayed in **Supplemental Figure 1**. ACs (r = 0.73–0.76, P = 0.001) and HR (r = 0.78, P = 0.001) were all significantly correlated with EE but displayed distinct relationships with EE. Despite the high level of multicollinearity between predictors, they were shown to make independent contributions to EE in our model development.

TABLE 1 Participant characteristics[1]

	Age group			
	3 y	4 y	5 y	Total
n	23	23	23	69
Gender, *M/F*	13/10	9/14	12/11	34/35
Age, *y*	3.6 ± 0.5	4.6 ± 0.5	5.7 ± 0.5	4.6 ± 1.0
Weight, *kg*	15.9 ± 2.3	18.7 ± 4.1	21.3 ± 4.1	18.7 ± 4.2
Height, *cm*	100 ± 5	107 ± 6	114 ± 5	107 ± 8
BMI z-score, *SD units*	0.16 ± 0.93	0.23 ± 1.19	0.39 ± 1.03	0.29 ± 1.09
Ethnicity, *n Hispanic/not Hispanic*	5/18	8/15	6/17	19/50
Race, *n*				
American Indian	1	0	0	1
Asian	0	0	2	2
Black	9	5	6	20
White	11	17	13	41
Mixed race	2	0	1	3
Not reported	0	1	1	2
Overweight/obese children (BMI ≥85th percentile), *%*	13	22	26	20

[1] Values are means ± SD unless otherwise indicated.

TABLE 2 Measured values for total, awake, and sleep periods of preschool-aged children while in the room respiration calorimeter[1]

Activity	n	Duration	Heart rate	Energy expenditure	Actiheart x counts	ActiGraph x counts	ActiGraph y counts	ActiGraph z counts	Steps
		min	*bpm*	*kcal/min*		*cpm*	*cpm*		*steps/min*
Total time	69	261 ± 44	112 ± 8	1.05 ± 0.19	170 ± 88	629 ± 232	654 ± 212	714 ± 252	11 ± 3
Awake	69	222 ± 50	115 ± 7	1.12 ± 0.19	195 ± 87	729 ± 228	758 ± 191	829 ± 240	12 ± 3
Sleep	39	67 ± 20	93 ± 9	0.59 ± 0.07	1 ± 2	2 ± 2	4 ± 5	4 ± 4	0 ± 0

[1] Values are means ± SD. bpm, beats per minute; cpm, counts per minute.

Model development. In the process of model development, we began by evaluating the potential predictors of EE. First, we compared the performance of uniaxial versus triaxial accelerometry for the prediction of EE. Next, we evaluated the inclusion of the vector magnitude, provided in the ActiGraph GT3X+ output. Last, we evaluated step counts and position as potential adjunct measures for the prediction of EE.

Uniaxial versus triaxial accelerometry output from the ActiGraph GT3X+ was compared by using CSTS models without steps or inclinometer values. The CSTS model for EE using the vertical axis (AC_*x*) only was inferior (R^2 = 0.84, P = 0.001) compared with the model using all 3 axes (AC_*x*, AC_*y*, AC_*z*) (R^2 = 0.87, P = 0.001). The root mean square errors were 0.09 and 0.08 for the uniaxial and the triaxial models, respectively.

The use of the 3 axes (AC_*x*, AC_ *y*, AC_ *z*) versus the vector magnitude, which is mathematically derived from the 3 axes, also was evaluated by using CSTS models. The CSTS model for EE was slightly superior using the individual axes (AC_*x*, AC_*y*, AC_*z*) (R^2 = 0.87, P = 0.001) rather than the vector magnitude (R^2 = 0.86, P = 0.001). Because of the high degree of multicollinearity between the 3 axes and the vector magnitude, subsequent models were developed by using the individual axes only.

The ActiGraph inclinometer determines participant position (0 = monitor off or person lying on his/her side, 1 = standing, 2 = lying down, 3 = sitting). By staff observations, the inclinometer correctly detected lying on side or lying down 76% of the time, sitting 44% of the time, and standing 90% of the time.

Implementation of the final CSTS models. CSTS models to predict EE were developed by using participant characteristics [gender coded as M = 0, F = 1, age (y), weight (kg), height (cm)], Actiheart parameters (HR+AC_*x*) or ActiGraph parameters (AC_*x*, AC_*y*, AC_*z*; steps; inclinometer = 1, 2, and 3), and their significant 1- and 2-min lag and lead values, and significant interactions. The application of the final CSTS model to the ActiGraph and HR data for 1 child is shown in **Figure 1***A*, which graphically displays the minute-by-minute EE measured by calorimetry and EE predicted by the ActiGraph+HR model.

In **Table 3**, the coefficients for the 3 CSTS models for the prediction of minute-by-minute EE based on Actiheart, ActiGraph (awake only), and ActiGraph+HR are presented. ActiGraph alone is applicable only during awake time, because zero ACs recorded during sleep are uninformative for the prediction of minute-by-minute EE. However, if ActiGraph is combined with HR, the resultant CSTS model would be useful throughout a 24-h period. Therefore, a third CSTS model (ActiGraph+HR) was formulated for ActiGraph with the addition of HR. These CSTS mixed-regression models can be implemented in standard statistical programs or computational spreadsheet programs such as Excel.

Implementation of the final MARS models. MARS models were developed from participant characteristics, Actiheart parameters (HR+AC_*x*) or ActiGraph parameters (AC_*x*, AC_*y*, AC_*z*, steps, position), 1- and 2-min lag and lead values, and appropriate interaction terms. All of the potential knot locations for each of the predictors or main effects were investigated in the development of the MARS models. On the basis of the generalized cross-validation, the optimal number of basis functions and knot locations was selected. MARS models for EE are based on linear combinations of 30, 50, and 50 basis functions using Actiheart, ActiGraph, and ActiGraph+HR, respectively. The application of the final MARS model to the ActiGraph and HR data for 1 child is demonstrated in Figure 1*B*, which graphically displays the minute-by-minute EE measured by calorimetry and EE predicted by the ActiGraph+HR model.

The linear regression equations for the 3 MARS models based on Actiheart, ActiGraph (awake only), and ActiGraph+HR are presented in **Table 4**. The basis functions (BF1–BF50), which are the predictors in the linear regression equations, are specified in

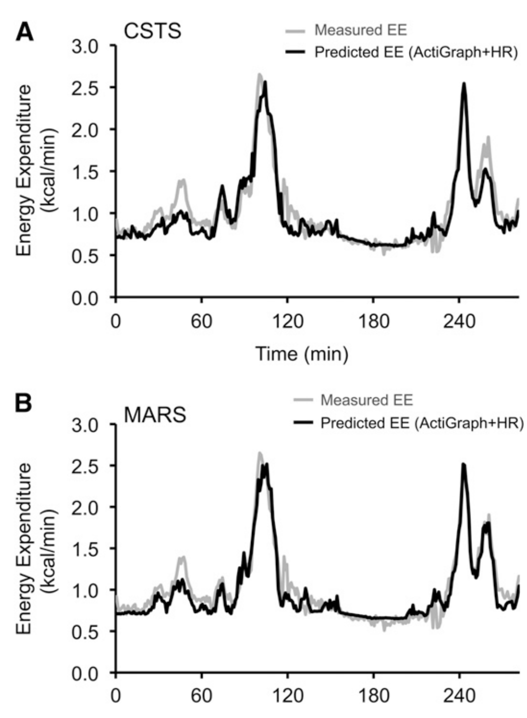

FIGURE 1 Comparison of minute-by-minute energy expenditure measured by calorimetry and predicted by the CSTS (*A*) and MARS (*B*) models based on ActiGraph+HR for 1 child. CSTS, cross-sectional time series; EE, energy expenditure; HR, heart rate; MARS, multivariate adaptive regression spline.

TABLE 3 Actiheart and ActiGraph CSTS model specifications for the prediction of EE from HR and ACs[1]

	Coefficients for CSTS prediction equations of EE (kcal/min)					
	Actiheart model		ActiGraph model (awake only)		ActiGraph+HR model	
Variables	Coefficient	SE	Coefficient	SE	Coefficient	SE
Gender: M = 0, F = 1	1.66e-01	3.10e-02	−4.77e-02	1.76e-02	−5.47e-02	1.90e-02
Age, y	−3.12e-02	2.60e-02	−3.74e-02	1.77e-02	−1.81e-02	1.80e-02
Weight, kg	−3.885e-02	6.60e-03	2.28e-02	3.95e-03	1.95e-02	4.00e-03
Height, cm	7.60e-03	4.30e-03	5.27e-03	2.92e-03	6.00e-03	2.90e-03
AC_*x*, cpm	4.94e-05	2.80e-05	−3.28e-06	4.31e-06	5.74e-06	8.00e-08
AC_*x*-lag1, cpm	1.04e-04	7.30e-06	1.14e-05	3.40e-06	1.25e-05	7.00e-08
AC_*x*-lag2, cpm	6.25e-05	4.70e-06	−9.90e-06	3.18e-06	−6.88e-06	8.80e-07
AC_*x*-lead1, cpm	9.95e-05	8.10e-06	3.68e-07	3.40e-06	8.82e-06	8.70e-07
AC_*x*-lead2, cpm	1.24e-04	7.30e-06	−4.31e-07	3.15e-06		
AC_x^2, cpm^2	−1.46e-07	4.20e-09				
AC_*x* * Weight	1.80e-05	1.40e-06				
HR * Weight	4.62e-04	2.70e-05				
HR * Gender	−1.79e-03	1.40e-04				
Sleep HR, bpm	−1.802e-02	2.30e-03			−1.11e-02	1.60e-03
HR, bpm	−1.47e-02	7.60e-04			−1.20e-02	6.00e-04
HR-lag1, bpm	2.70e-03	2.30e-04			8.82e-04	3.30e-05
HR-lag2, bpm	5.67e-03	1.70e-04			4.17e-03	9.90e-05
HR-lead1, bpm	3.34e-03	2.30e-04			2.52e-03	3.30e-05
HR-lead2, bpm	3.67e-03	2.00e-04			2.46e-03	1.10e-05
HR^2, bpm^2	3.87e-05	2.30e-06			5.72e-05	1.90e-07
AC_*y*, cpm			2.40e-05	4.87e-06	1.66e-05	4.60e-07
AC_*z*, cpm			−2.84e-05	1.18e-05	1.54e-05	2.00e-07
AC_*y*-lag1, cpm			3.21e-05	4.82e-06	3.02e-05	4.20e-07
AC_*y*-lag2, cpm			5.29e-05	4.54e-06	3.57e-05	1.80e-07
AC_*y*-lead1, cpm			2.89e-05	4.80e-06	1.97e-05	3.90e-07
AC_*y*-lead2, cpm			1.75e-05	4.49e-06	9.35e-06	1.00e-07
AC_*z*-lag1, cpm			3.13e-05	4.59e-06	1.33e-05	1.80e-07
AC_*z*-lag2, cpm			5.16e-05	4.33e-06	1.97e-05	9.60e-07
AC_*z*-lead1, cpm			2.93e-05	4.56e-06	1.05e-05	1.20e-07
AC_*z*-lead2, cpm			3.04e-05	4.28e-06	1.41e-05	6.50e-07
Steps, steps/ min			8.46e-04	8.09e-04	4.40e-04	8.20e-05
Steps-lag1, steps/min			−3.03e-03	6.33e-04	8.82e-04	7.90e-05
Steps-lag2, steps/min			3.86e-03	1.62e-04	1.96e-03	5.70e-05
Steps-lead1, steps/min			−1.55e-03	6.35e-04	1.23e-03	7.40e-05
Steps-lead2, steps/min			2.24e-03	1.61e-04	2.10e-03	3.00e-05
Age * AC_*z*			1.37e-05	2.24e-06		
Age * Steps			3.21e-04	1.60e-04		
Age * Steps-lag1			1.05e-03	1.22e-04		
Age * Steps-lead1			8.41e-04	1.23e-04		
Gender * Steps			−1.07e-03	3.27e-04		
Gender * Steps-lag1			−6.98e-04	2.11e-04		
Gender * Steps-lead1			−5.14e-04	2.11e-04		
Gender * AC_*x*			2.01e-05	5.55e-06		
Gender * AC_*z*			−2.01e-05	5.32e-06		
Constants for position						
Position = 1			6.66e-02	6.13e-03	4.93e-02	5.70e-03
Position = 2			−9.88e-03	5.79e-03	−3.10e-04	5.30e-03
Position = 3			7.01e-02	5.92e-03	4.14e-02	5.40e-03
Constant	1.019	0.395	−0.131	0.208	0.352	0.267

[1] Values are coefficients and SE for the implementation of the CSTS models. AC, accelerometer count; bpm, beats per minute; cpm, counts per minute; CSTS, cross-sectional time series; EE, energy expenditure; HR, heart rate.

Table 5. The MARS regression equation starts with the constant basis function in the model. Then successively, a pair of basis functions (BF1 and BF2, BF3 and BF4, etc.) is added to the model. For each basis function, the maximum value is chosen from a set of values that is equal to 0 or the computed value. These MARS regression models can be implemented in standard statistical programs or computational spreadsheet programs such as Excel.

Prediction errors of the CSTS and MARS models. CSTS and MARS models were evaluated separately for all data, awake

TABLE 4 Actiheart and ActiGraph MARS model equations for the prediction of EE from HR and accelerometer counts[1]

Model	MARS equations for prediction of EE (kcal/min)
Actiheart	EE_ AH = 1.801 + 8.99e-006 * BF1 − 6.48e-005 * BF2 + 0.0127 * BF3 − 0.000726 * BF4 + 0.0601 * BF5 + 0.00723 * BF7 − 0.00265 * BF8 − 0.0176 * BF9 + 0.0113 * BF10 − 0.00120 * BF11 − 0.00127 * BF12 − 0.00474 * BF14 + 0.000138 * BF15 − 0.00757 * BF16 − 2.26e-009 * BF17 + 2.22e-007 * BF18 − 0.0345 * BF19 − 0.0299 * BF20 + 0.244 * BF21 + 0.00311 * BF22 + 0.000813 * BF23 − 0.000347 * BF24 + 0.00291 * BF25 + 0.0355 * BF26 + 1.14e-005 * BF27 − 0.000423 * BF28 + 3.81e-008 * BF29 − 1.31e-006 * BF30
ActiGraph (awake only)	EE _AG = 2.239 + 0.00309 * BF1 − 0.00629 * BF2 + 7.60e-005 * BF3 − 6.27e-005 * BF4 + 0.0110 * BF5 − 0.0782 * BF6 + 0.00202 * BF7 − 0.0139 * BF8 − 0.000530 * BF9 + 0.000538 * BF10 + 0.00737 * BF11 − 0.00954 * BF12 + 8.806e-005 * BF13 − 4.52e-005 * BF14 + 0.000680 * BF15 + 0.000668 * BF16 − 0.143 * BF17 + 0.000103 * BF19 − 0.00179 * BF20 + 0.000675 * BF21 − 0.00309 * BF22 + 73.3 * BF23 + 0.0374 * BF24 − 0.211 * BF25 − 0.00445 * BF26 + 5.75e-007 * BF27 − 5.14e-006 * BF28 − 0.00108 * BF29 − 0.000649 * BF30 − 1.02e-005 * BF31 + 1.87e-006 * BF32 − 0.00166 * BF33 − 0.00169 * BF34 − 0.0455 * BF35 − 0.000185 * BF36 − 4.63e-007 * BF37 − 7.52e-006 * BF38 − 0.00347 * BF39 − 0.00255 * BF40 + 3.96e-005 * BF41 − 0.000951 * BF42 + 0.00188 * BF43 + 0.000442 * BF44 + 2.20e-005 * BF45 + 5.55e-005 * BF46 + 1.96 * BF47 + 2.92e-005 * BF49 − 5.11e-006 * BF50
ActiGraph + HR	EE_AG_HR = 1.519 + 0.00250 * BF1 − 0.00850 * BF2 + 0.00692 * BF3 − 0.00104 * BF4 + 0.0727 * BF5 + 0.00759 * BF6 + 4.84e-005 * BF7 − 0.00222 * BF8 − 0.00117 * BF9 − 0.000679 * BF10 + 0.00172 * BF11 − 0.0113 * BF12 − 0.0162 * BF13 + 0.0932 * BF14 + 0.00702 * BF15 − 0.00181 * BF16 + 0.0710 * BF17 − 0.0422 * BF18 + 3.72e-005 * BF19 − 0.00110 * BF20 − 7.57e-005 * BF21 + 0.000189 * BF22 − 0.00332 * BF23 + 0.000407 * BF26 + 0.000262 * BF27 − 0.00257 * BF28 − 0.00449 * BF29 − 0.00103 * BF30 + 0.000349 * BF31 − 3.48e-005 * BF32 + 0.00329 * BF33 − 0.000462 * BF34 + 3.60e-005 * BF35 − 0.00138 * BF36 + 2.37e-005 * BF37 − 6.88e-006 * BF38 + 0.000363 * BF39 − 0.00364 * BF40 + 0.00179 * BF41 − 0.0286 * BF42 + 2.21e-005 * BF43 − 5.45e-007 * BF44 − 0.0183 * BF46 − 4.91e-005 * BF48 + 2.27e-005 * BF49 + 9.21e-005 * BF50

[1] BF, basis function; EE, energy expenditure; EE_AG, energy expenditure ActiGraph; EE_AG_HR, energy expenditure ActiGraph plus heart rate; EE_AH, energy expenditure Actiheart; HR, heart rate; MARS, multivariate adaptive regression spline.

data, and sleep data collected during calorimetry. Mean absolute error, mean percentage error, and root mean square errors for all EE, awake EE, and sleep EE are presented in **Table 6**. The mean percentage errors predicting awake EE (−1.1 ± 8.7%, 0.3 ± 6.9%, and −0.2 ± 6.9%) with the CSTS models were slightly higher than with the MARS models (−0.7 ± 6.0%, 0.3 ± 4.8%, and −0.6 ± 4.6%) for Actiheart, ActiGraph and ActiGraph +HR devices, respectively.

Bland-Altman plots show the lack of bias and extent of agreement between the observed values and model estimates. The Bland-Altman plots for the prediction of awake EE are shown for the CSTS (**Fig. 2**) and MARS (**Fig. 3**) models using ActiGraph and Actiheart. The 95% limits of agreement were slightly wider for the CSTS models than for the MARS model. Predicted awake EE values were within ±10% for 81, 87, and 87% of the individuals for the CSTS models and within ±10% for 91, 96, and 98% of individuals for the MARS models using Actiheart, ActiGraph, and ActiGraph+HR devices, respectively. The CCCs, indicating the degree of agreement between the observed and predicted values, were 0.94, 0.93 and 0.94 for the CSTS EE models and 0.95, 0.95, and 0.94 for the MARS EE models using Actiheart, ActiGraph, and ActiGraph+HR, respectively.

Discussion

Advanced technology (fast-response room calorimetry, accelerometers, and miniaturized HR monitors) and sophisticated CSTS and MARS modeling techniques were used to successfully develop prediction equations of EE in preschool-aged children. The CSTS and MARS models for the prediction of EE were based on measurements across a wide range of body sizes and physical activities typical of this age group and therefore should be robust for preschool-aged children.

By using room respiration calorimetry, we assembled an unprecedented database on the EE of preschool-aged children during sleep and during stationary, low-active, moderate-active, and very active play. Minimum EE and HR values during sleep and near maximum values while running were attained within the calorimeter. As a result, the EE and HR values represent the physiologic ranges that can be expected of this age group, which differ from those of older children (15–17).

The minute-to-minute data generated by the calorimeter provided a high density of data for model development. To begin, we tested several potential predictors of EE in preschool-aged children. New advances in accelerometer design provide not only triaxial output but also position and steps. HR is available with the Actiheart device and can be added to the ActiGraph. Although these predictors are highly correlated with one another, our modeling effort demonstrated significant contributions of each. We found that the triaxial configuration was slightly superior to uniaxial accelerometer in the prediction of EE, which is in agreement with other reports in children (25) and preschoolers (3). The error analysis of the ActiGraph+HR model did not indicate improvement in prediction errors, but nevertheless HR was shown to be a significant contributor in the CSTS and MARS equations. The number of steps taken by the preschool-aged children was underestimated, especially during light activities, and position was often misclassified, especially while sitting. Nevertheless, steps and position also were shown to be significant contributors in the ActiGraph models, despite their inherent limitations.

The final CSTS and MARS models for EE included participant characteristics of gender, age, weight, and height. Both CSTS and MARS models provide interpretable coefficients and can be implemented easily by using standard software such as Excel. For 24-h applications, the Actiheart and ActiGraph+HR EE models are recommended. For awake periods only, the Actiheart or ActiGraph EE models can be used.

Our models are acceptable, not only for groups but also for individual children based on the error analysis, lack of bias, and limits of agreement relative to calorimetry shown in the Bland-Altman plots. The EE of individual children was predicted within ±10% for 81–87% of children with the CSTS models and for 91–98% of children with the MARS models. The MARS models performed slightly better than did the CSTS models. For instance, the mean percentage error for awake EE was 6.0%

TABLE 5 Actiheart and ActiGraph MARS model BFs for the prediction of EE from HR and ACs[1]

	Actiheart model	ActiGraph model (awake only)	ActiGraph+HR model
BF1	max(0, AC * Weight - 5394)	max(0, Steps_lag1 − 34)	max(0, Steps_lag1–31)
BF2	max(0, 5394 − AC * Weight)	max(0, 34 − Steps_lag1)	max(0, 31 − Steps_lag1)
BF3	max(0, HR_lag1 − 118)	max(0, AC_*y*_lead1 − 1329)	max(0, HR_lead1 − 121)
BF4	max(0, 118 − HR_lag1)	max(0, 1329 − AC_*y*_lead1)	max(0, 121 − HR_lead1)
BF5	max(0, Height − 120.5)	max(0, Weight − 21.8)	max(0, Height − 120.5)
BF6		max(0, 21.8 − Weight)	max(0, 120.5 − Height)
BF7	max(0, HR_lead2 − 127)	max(0, Steps_lag2 − 38)	max(0, AC_*y*_lag2 − 24)
BF8	max(0, 127 - HR_lead2)	max(0, 38 − Steps_lag2)	max(0, 24 − AC_*y*_lag2)
BF9	max(0, HR_Sleep − 75.8)	max(0, Steps_lag1 − 32) * BF6	max(0, Weight − 23.1) * BF3
BF10	max(0, 75.8 − HR_Sleep)	max(0, 32 − Steps_lag1) * BF6	max(0, 23.1 − Weight) * BF3
BF11	max(0, Weight − 21.8) * BF3	max(0, Steps_lead2 − 31)	max(0, Steps_lead2 − 30)
BF12	max(0, 21.8 − Weight) * BF3	max(0, 31 − Steps_lead2)	max(0, 30 − Steps_lead2)
BF13		max(0, AC_*z* − 1978)	max(0, HR_Sleep − 75.8)
BF14	max(0, 173 − HR_lag2)	max(0, 1978 − AC_*z*)	max(0, 75.8 − HR_Sleep)
BF15	max(0, AC_lead1 − 12)	max(0, Weight − 24.2) * BF12	max(0, HR_lag2 − 124)
BF16	max(0, 12 - AC_lead1)	max(0, 24.2 − Weight) * BF12	max(0, 124 − HR_lag2)
BF17	max(0, AC^2 − 50625) * BF9	[Gender in (1)]	max(0, Weight − 17.4)
BF18	max(0, 50625 − AC^2) * BF9	[Gender in (0)]	max(0, 17.4 − Weight)
BF19	max(0, Weight − 18)	max(0, AC_*y*_lag2 − 26)	max(0, AC_*z* − 31)
BF20	max(0, 18 − Weight)	max(0, 26 − AC_*y*_lag2)	max(0, 31 − AC_*z*)
BF21	max(0, HR_Sleep − 97.39) * BF19	max(0, Steps_lead1 – 40) * BF18	max(0, Steps_lag1 − 24) * BF6
BF22	max(0, 97.39 − HR_Sleep) * BF19	max(0, 40 − Steps_lead1) * BF18	max(0, 24 − Steps_lag1) * BF6
BF23	max(0, HR_lead2 − 118) * BF19	max(0, Age − 5.98) * BF5	[Gender in (1)] * BF15
BF24	max(0, 118 - HR_lead2) * BF19	max(0, 5.98 − Age) * BF5	
BF25	max(0, Age − 4.92) * BF19	max(0, Height − 119.9) * BF5	
BF26	max(0, 4.92 − Age) * BF19	max(0, 119.9 − Height) * BF5	max(0, 28.8 − Weight) * BF12
BF27	max(0, AC_lag2 − 380)	max(0, Steps_lead1 − 30) * BF3	max(0, HR_Sleep − 76) * BF12
BF28	max(0, 380 − AC_lag2)	max(0, 30 − Steps_lead1) * BF3	max(0, 76 − HR_Sleep) * BF12
BF29	max(0, HR − 129) * BF1	max(0, Weight − 24.9) * BF11	max(0, Weight − 22.6) * BF6
BF30	max(0, 129 − HR) * BF1	max(0, 24.9 − Weight) * BF11	max(0, 22.6 − Weight) * BF6
BF31		max(0, AC_*y*_lag2 − 2429) * BF8	max(0, HR_lead2 − 160) * BF6
BF32		max(0, 2429 − AC_*y*_lag2) * BF8	max(0, 160 − HR_lead2) * BF6
BF33		max(0, Age − 4.7) * BF11	max(0, HR_lead2 − 191) * BF17
BF34		max(0, 4.7 − Age) * BF11	max(0, 191 − HR_lead2) * BF17
BF35		max(0, Height − 115.3) * BF6	max(0, AC_*y*_lead1 − 31)
BF36		max(0, 115.3 − Height) * BF6	max(0, 31 − AC_*y*_lead1)
BF37		max(0, Steps − 30) * BF13	max(0, HR^2 − 16129)
BF38		max(0, 30 − Steps) * BF13	max(0, 16129 − HR^2)
BF39		max(0, Steps − 149)	max(0, Steps_lag2 − 43)
BF40		max(0, 149 − Steps)	max(0, 43 − Steps_lag2)
BF41		max(0, AC_*z*_lag1 − 33)	max(0, HR_Sleep − 78.77) * BF18
BF42		max(0, 33 − AC_*z*_lag1)	max(0, 78.77 − HR_Sleep) * BF18
BF43		max(0, Weight − 28.8) * BF8	max(0, Height − 120.5) * BF37
BF44		max(0, 28.8 − Weight) * BF8	max(0, 120.5 -−Height) * BF37
BF45		max(0, AC_*x*_lag1 − 774)	
BF46		max(0, 774 − AC_*x*_lag1)	max(0, 106.6 − Height) * BF17
BF47		max(0, Age − 5.92) * BF5	
BF48			max(0, 15.1−- Weight) * BF7
BF49		max(0, AC_*z*_lead2 − 2092) * BF5	max(0, AC_*x*_lead1 − 224)
BF50		max(0, 2092 − AC_*z*_lead2) * BF5	max(0, 224 − AC_*x*_lead1)

[1] ACs in counts/min; age in y; EE in kcal/min; gender, M = 0, F = 1; HR in beats/min; height in cm; steps in steps/min; weight in kg. AC, accelerometer count; BF, basis function; EE, energy expenditure; HR, heart rate; MARS, multivariate adaptive regression spline.

versus 8.7% for Actiheart and 4.8% versus 6.9% for ActiGraph using MARS or CSTS, respectively. The addition of HR to the ActiGraph device did not improve the errors for the CSTS model and made only a slight improvement in the mean percentage error for the MARS model (4.8–4.6%). The high concordance between the predicted and measured EE (CCC = 0.93–0.95) affirms the validity of the models for preschool-aged children.

Although theoretically different, both CSTS and MARS models were shown to be strong prediction models for EE of preschool-aged children. CSTS is a parametric approach to model a collection of correlated data, taking into account within-individual changes

TABLE 6 Prediction errors of the CSTS and MARS models for the prediction of EE[1]

	CSTS model			MARS model		
	Actiheart	ActiGraph	ActiGraph+HR	Actiheart	ActiGraph	ActiGraph+HR
Mean absolute error, *kcal/min*						
All data	−0.006 ± 0.092		−0.001 ± 0.070	0.000 ± 0.062		0.002 ± 0.049
Awake	−0.015 ± 0.100	0.000 ± 0.075	−0.005 ± 0.077	−0.010 ± 0.067	0.000 ± 0.049	−0.008 ± 0.051
Sleep	0.038 ± 0.085		0.019 ± 0.068	0.049 ± 0.063		0.041 ± 0.045
Mean percentage error, %						
All data	−0.3 ± 8.6		0.0 ± 6.8	0.2 ± 6.0		0.4 ± 4.7
Awake	−1.1 ± 8.7	0.3 ± 6.9	−0.2 ± 6.9	−0.7 ± 6.0	0.3 ± 4.8	−0.6 ± 4.6
Sleep	6.3 ± 14.2		2.8 ± 11.7	8.3 ± 10.6		7.0 ± 8.0
RMSE, *kcal/min*						
All data	0.092		0.069	0.062		0.049
Awake	0.100	0.074	0.077	0.067	0.049	0.051
Sleep	0.092		0.070	0.079		0.060
r^2	0.873	0.867	0.898			

[1] Values are means ± SD unless otherwise indicated. CSTS, cross-sectional time series; MARS, multivariate adaptive regression spline; RMSE, root mean square error.

and between-individual heterogeneity (26,27). The key idea of the CSTS application is that by pooling information from a large number of time series we can obtain more accurate estimates of the parameters, instead of evaluating a single time series. CSTS models explicitly distinguish between-participant and within-participant sources of variability and allow for participant-specific description of the mean response profile. However, in CSTS model development the search and inclusion of variables and interaction terms has to be done individually, which may not be very efficient. Also, model specification and identification of heterogeneity may be time consuming and difficult.

MARS is a multivariate nonparametric regression that approximates a complex relationship (nonlinear) by a series of spline functions on different intervals of the independent variable (28). MARS is a local regression method and well suited to model nonlinearity, complex interactions, and large number of predictors. Therefore, MARS is more flexible and can successfully discover nonlinear relationships and complex interactions. For model development, CSTS is available in popular software packages, but this is not the case for MARS. Although the development of these models required sophisticated statistical software, the resultant models can be easily implemented with the regression equations presented in Tables 3 and 4 and with the basis functions in Table 5 by using standard statistical programs or computational spreadsheets such as Excel. In some respects, the difference between the CSTS and MARS models is similar to the difference between global and local regression models. MARS is a simpler automated way to develop nonlinear regression models and is especially useful in settings in which complex interactions exist among variables. We recently validated CSTS and MARS models for the prediction of EE from HR and ACs in school-aged children and adolescents (15–17).

The CSTS and MARS models represent a significant advancement in the prediction of EE of preschool-aged children. Importantly, these population-specific models predict minute-by-minute EE from accelerometry or accelerometry+HR monitoring and do not require individual calibration in a laboratory. Predictions errors were found to be acceptable at the level of the individual. A few studies have used calorimetry to validate accelerometers and have set thresholds for levels of physical activity but not to predict EE per se (1–4). Pate et al. (1) developed a linear equation to establish ActiGraph cutoff points for moderate and vigorous physical activity on the basis of $\dot{V}O_2$ measurements in 29 preschool children. Although these cutoffs are useful and have been confirmed for group-level estimates of moderate and vigorous physical activity (14), the calibration protocol was limited and did not include sedentary or light activities or very vigorous activities >6400 cpm.

On the basis of unique EE measurements previously unavailable in preschool-aged children, accurate and precise CSTS and MARS models have been developed for the quantitative assessment of EE in this age group. CSTS and MARS models should prove useful in capturing the complex dynamics of EE and movement that are characteristic of preschool-aged children.

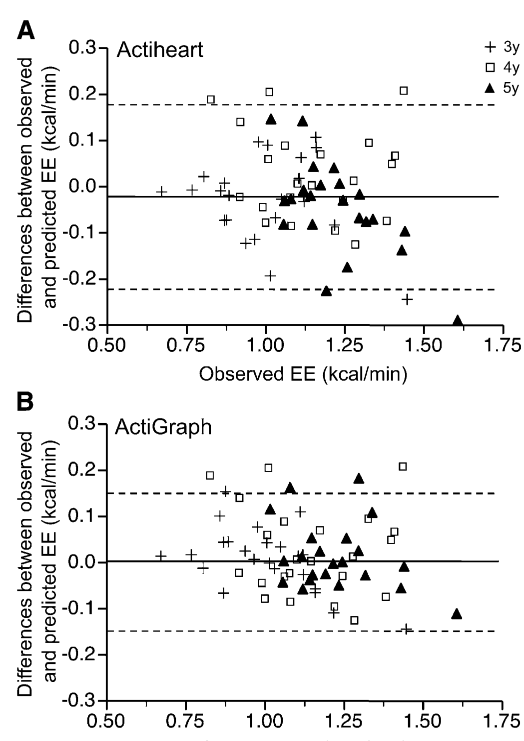

FIGURE 2 Bland-Altman plots for the prediction of EE during awake periods are shown for the cross-sectional time series models using Actiheart (*A*) and ActiGraph (*B*). The mean difference between observed and predicted EE is shown by a solid line and the 95% limits of agreement are shown by dash lines. EE, energy expenditure.

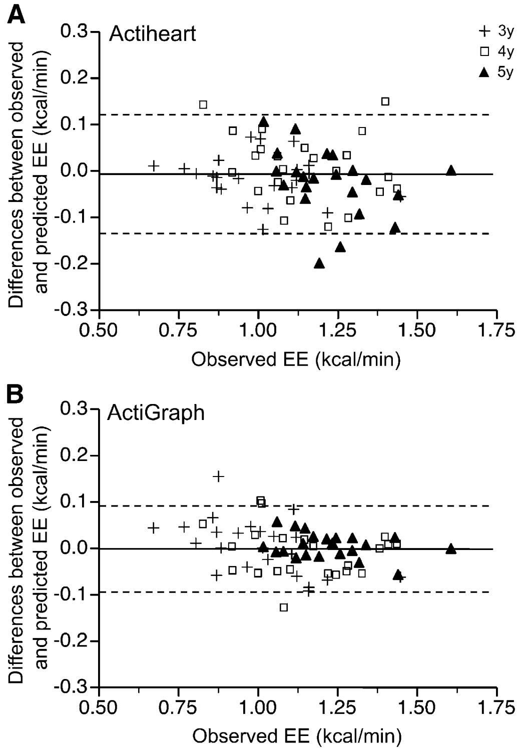

FIGURE 3 Bland-Altman plots for the prediction of EE during awake periods are shown for the multivariate adaptive regression splines models using Actiheart (*A*) and ActiGraph (*B*). The mean difference between observed and predicted EE is shown by a solid line and the 95% limits of agreement are shown by dash lines. EE, energy expenditure.

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