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Predicting Activity Energy Expenditure Using the Actical® Activity Monitor

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This study developed algorithms for predicting activity energy expenditure (AEE) in children (n = 24) *and adults* (n = 24) *from the Actical® activity monitor. Each participant performed 10 activities (supine resting, three sitting, three house cleaning, and three locomotion) while wearing monitors on the ankle, hip, and wrist; AEE was computed from oxygen consumption. Regression analysis, used to create AEE prediction equations based on Actical® output, varied considerably for both children* ($R^2 = .45–.75$; $p < .001$) *and adults* ($R^2 = .14–.85$; $p < .008$). *Most of the resulting algorithms accurately predicted accumulated AEE and time within light, moderate, and vigorous intensity categories* ($p > .05$). *The Actical® monitor may be useful for predicting AEE and time variables at the ankle, hip, or wrist locations.*

Key words: exercise, locomotion, physical activity

Accurately estimating free-living energy expenditure (EE) using electronic monitoring devices is of interest to researchers and clinicians. Research validating the use of electronic monitoring devices has primarily focused on accelerometers, pedometers, and heart rate monitors. Using accelerometers (hereafter referred to as activity monitors), however, appears to be the most promising because of their small size, long-term data storage capabilities, and potential to assess the intensity, frequency, and duration domains of physical activities. For assessing whole-body EE, activity monitors placed at the hip along the belt line have provided valid estimates of EE in adults (Freedson, Melanson, & Sirard, 1998; Hendelman, Miller, Baggett, Debold, & Freedson, 2000; Swartz et al., 2000) and children (Janz 1994; Janz, Cassady, Barr, & Kelly, 1995; Puyau, Adolph, Vohra, & Butte, 2002; Trost et al., 1998). It has been suggested, however, that activity monitors placed at the hip cannot accurately detect the EE associated with upper body movements (Swartz et al., 2000). This capacity may be especially important for populations whose primary physical activity results from household and garden activities, occupational tasks (e.g., laborer versus office worker), or those with limited mobility (e.g., activity limited to wheelchairs). Despite the potential advantage for predicting EE from wrist-based monitors, few have attempted to validate alternatives to hip-placed monitors (Heil 2002; Leenders, Nelson, Sherman, 2003; Melanson & Freedson, 1995; Puyau et al., 2002; Swartz et al., 2000). Despite the lack of research, it seems reasonable to suggest that wrist and ankle accelerometer locations can provide some valuable information about time-based (e.g., time accumulated in moderate-to-vigorous intensity activity) or EE-based (e.g., daily activity energy expenditure) variables.

Complicating the issue of monitor placement is the technology underlying the use of activity monitors to measure and process acceleration. The motion-sensing mechanism for the most common commercially available monitors can be described as uniaxial (sensing motion in a single plane) or triaxial (sensing motion in all three planes), while a single company describes their monitor as omnidirectional (sensing motion primarily in a single plane and less sensitively in the other planes). The ability to sense motion in more than one plane should be an advantage for measuring complex human

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movements; thus, the triaxial or omnidirectional measurement mechanisms may be more appropriate for evaluating alternatives to hip-placed activity monitors.

Last, many of the published equations for predicting EE from activity monitor output in adults have been reported exclusively in units of metabolic equivalents (METs). The MET unit can be useful for direct comparisons with published compilations of MET intensities for physical activities (Ainsworth et al., 2000). These MET equations, however, have the practical limitation of forcing those interested in EE to convert METs into units of caloric expenditure (e.g., kcal•kg•min^{-1}). While the conversion of METs to EE is a simple transformation, the MET unit also assumes adult population averages of 0.9 and 1.0 for basal and resting metabolic rates (BMR and RMR, respectively). This assumption is certainly problematic for clinicians doing physical activity interventions in which BMR may change over the course of the program. In addition, researchers and clinicians may prefer predicting AEE instead of gross EE in children, because BMR and RMR can vary with age, maturation, body mass, and level of physical activity. Thus, a more practical unit of output for predicting EE from activity monitor output may be activity energy expenditure (AEE), in which AEE is defined as the relative EE (kcal•kg•min^{-1}) to perform a task above resting metabolism.

The primary purpose of this study was to develop equations for predicting AEE in children and adults using the Actical® activity monitor (Mini Mitter Co., Inc., Bend, OR) when worn at the ankle, hip, or wrist locations. The resulting AEE prediction equations were then used to create algorithms (i.e., defined computational procedures) for converting the raw activity monitor data into time and AEE based activity variables of interest. Analysis of the resulting algorithms was then used to evaluate the potential usefulness of the monitors for field evaluations of AEE in children and adults.

Method

Participants and Procedures

Volunteers from the surrounding community gave written informed consent in accordance with procedures approved by the Montana State University (MSU) Internal Review Board. Testing for each participant occurred during a single 1.5-hr visit to the Movement Science/Human Performance Lab (constant 21–21 °C, 35–40% relative humidity) on the MSU campus (Bozeman, MT). All participants (and the children's parents) received standardized instructions prior to the lab visit (e.g., minimize physical activity for 6 hr prior; avoid caffeinated food and beverages at least 2–3 hr prior; last meal at least 2–3 hr prior). After measuring body height and weight to the nearest 0.1 cm and kg (Health-o-Meter beam scale, Continental Scale Corp., Bridgeview, IL), respectively, participants were fit with three activity monitors and a small backpack that carried a portable metabolic measurement system. Participants wore one activity monitor secured with a VELCRO® strap on the dorsal side of the nondominant wrist (dominance was defined as the participant's preferred hand for writing). Participants wore the second activity monitor on the ankle (just proximal to the lateral malleolus and secured with a VELCRO® strap) on the same side of the body as the wrist monitor, while they wore the third monitor on a belt around the hips (just posterior to the right iliac crest). Data collection for the activity monitors and metabolic system reported data over 1-min sample intervals and was synchronized relative to an external time piece.

Participants performed a series of 10 activities within the lab (see Table 1) that included supine resting (10 min), three sitting activities, three simulated house cleaning activities, and walking and jogging (55–60 min total). The treadmill walking (67 m•min^{-1} and 80.4 m•min^{-1}, respectively) and jogging speeds (120.6 m•min^{-1}) were based on pilot testing and chosen as speeds both children and adults could walk and jog. Measurements during supine resting were used to determine supine resting metabolic rate. The sitting activities were designed to emphasize use of the upper limbs, while cleaning activities emphasized use of both upper and lower limbs. Verbal and visual instructions were provided from a script to standardize the pacing and performance of each task, and corrective feedback was given to maintain consistency among participants. With the exception of the walking and jogging activities, tasks were separated by 1 min of quiet sitting or standing. Pilot testing with 2 children and 2 adults indicated this measurement strategy was adequate to achieve steady-state oxygen uptake values across all activities (unpublished observations). The one exception was for video game playing in which the children required several minutes for the activity monitor output to stabilize. Due to a treadmill malfunction partway through data collection, some participants (16 of 24 children) performed two speeds (self-selected as "slow" and "fast") of overground walking at an indoor track (within the same building as the lab) in place of treadmill walking. For these participants, self-paced overground jogging was not performed because of problems with consistent pacing. The testing order for activity groups (i.e., supine resting and sitting, cleaning, and locomotion activities) was the same across participants, but the testing order within each group (e.g., sweeping, vacuuming, and dusting within the cleaning activity) was counterbalanced across participants. In addition, using the same procedures described above, 11 participants (6 adults, 5 children) were retested in the same test order within 2 weeks of their first test to assess test-retest reliability.

Instrumentation

A portable metabolic measurement system (VmaxST™, SensorMedics Corporation, Yorba Linda, CA) worn in a small backpack during all activities was used to determine energy expenditure from oxygen uptake (VO_2) and carbon dioxide production (VCO_2) during all activities. The VmaxST™ system has demonstrated similar validity as other portable metabolic measurement systems (Prieur, Castells, & Denis, 2003). The oxygen and carbon dioxide analyzers of the metabolic system were calibrated using certified gases of known concentration, while a calibrated 3-l syringe (Model D, SensorMedics Corporation, Yorba Linda, CA) was used to calibrate the system's pneumotach for ventilation measurement. Within 10 min of completing the calibration, the metabolic system was attached to the participant using a face mask, and metabolic measurements began with supine resting. Metabolic measures were recorded continuously across all activities for each participant without recalibration.

The Actical® activity monitors used for this study are water resistant, lightweight (17 g), small (2.8 x 2.7 x 1.0 cm^3), and have a data storage capacity of 64,800 data points that will saturate after 44 days of continuous measurement using 1-min recording epochs. The monitors are initialized and downloaded using a serial port computer interface, with the resulting data exportable as text files. According to the manufacturer, the Actical® uses a single internal "omnidirectional" accelerometer that senses motion in all directions but is most sensitive within a single plane. A blue arrow on the outside of the monitor points in the direction of the most sensitive axis. The accelerometer detects low frequency (0.5–3.2 Hz) G-forces (0.05–2.0 Hz) common to human movement

Table 1. Description of activities performed by children and adults, as well as the duration of each activity (time, minutes) while measuring oxygen consumption and activity monitor output at the ankle, hip, and wrist simultaneously

Activity type	Name of activity	Time	Description of activity
Resting	Supine resting	10	Participants rested in a supine position while lying on a bed, arms at their side, with instructions to minimize all bodily movements.
Sitting activities[a]	Typing	3	(Adults only) While sitting in a chair at a desk, participants used a computer keyboard to type a standardized script (self paced).
	Hand writing	3	While sitting in a chair at a desk, participants used a ball point pen and a pad of paper to transcribe a standardized script (self paced).
	Card sorting	3	Participants were instructed to "quickly" alphabetize a stack of 100 note cards, each of which was labeled with a single unique word.
	Video game playing	5	(Children only) Participants used a handheld joystick to control the action of an animated figure on a TV screen using a commercially available video game.
Cleaning activities[b]	Floor sweeping	3	Using a standard upright sweeping broom, participants swept a 3.6- x 3.6-m section of lab floor covered with a thin layer of sand. Once the floor section was swept, participants used a dust pan and the broom to collect the sand and return it to a nearby bucket. This procedure was repeated until 3 min ended.
	Carpet vacuuming	3	Participants used an upright power vacuum cleaner to clean a 2.0- x 5.5-m section of nylon-based Berber carpet.
	Table dusting	3	The dusting activity required participants to clean an 0.6- x 2.4-m table top by spraying the surface with water using an 1.0 liter spray bottle and then wiping the table dry with a hand cloth.
Locomotion activities[c]	Slow treadmill walking	5	67 $m \cdot min^{-1}$ (2.5 mph; 4 kph) at a level grade.
	Moderate treadmill walking	5	80.4 $m \cdot min^{-1}$ (3.0 mph; 4.8 kph) at a level grade.
	Treadmill jogging	5	20.6 $m \cdot min^{-1}$ (4.5 mph; 7.2 kph) at a level grade.
	Self-paced "slow" walking	5	Indoor track at 59.0 $m \cdot min^{-1}$ (2.2 mph; 3.52 kph) at a level grade.
	Self-paced "fast" walking	5	Indoor track at 85.8 $m \cdot min^{-1}$ (3.2 mph; 5.12 kph) at a level grade.

[a]Children performed hand writing, card sorting, and video game playing while the adults typed instead of playing the video game.
[b]Participants were also instructed to "perform the activity as if to complete the task quickly while not sacrificing quality."
[c]While adults performed treadmill walking and jogging, the children performed either the treadmill walking/jogging or the self-paced overground walking activities, but not both.

and generates an analog voltage signal that is filtered and amplified before being digitized by an A-to-D converter at 32 Hz. The digitized values are then summed over user-specified time intervals (epoch) between 0.25 and 1.0 min. The actual numbers stored by the Actical® are proportional to the magnitude and duration of the sensed accelerations and, thus, roughly correspond to changes in physical activity energy expenditure. Using 1-min sample epochs, the raw data for the Actical® monitor are reported in units of counts•min^{-1}. A total of 10 activity monitors, all calibrated by the manufacturer prior to testing, were randomly assigned to participants for testing. The hip monitor was oriented with the blue arrow (printed on the activity monitor case) pointing upward, while the arrow pointed toward the knee and elbow for the ankle and wrist monitors, respectively. The mass of all equipment (metabolic system, pack, activity monitors) each participant carried weighed 1.14 kg.

Data Treatment and Analysis

Data Transformations. The last 2 min of metabolic and activity monitor data were averaged and used to represent each activity (except supine resting) for all subsequent analyses. Energy expenditure for supine resting (EESR) was determined as an average over the last 5 min. Activity energy expenditure (AEE, kcal•kg^{-1}•min^{-1}) was derived from measures of VO_2 and defined as the relative rate of energy expenditure above EESR:

$$AEE_{ij} = (EE_{ij} - EESR_j)/M_{T(j)},$$

where AEE_i (kcal•kg^{-1}•min^{-1}) was the computed value for the *i*th activity (from Table 1) and participant *j*. Values for AEE_{ij} were derived from the corresponding *i*th mean absolute energy expenditure (EE_i , kcal•min^{-1}) for participant j, the computed $EESR_j$ for participant *j*, and the total mass of participant *j* and equipment ($M_{T(j)}$, kg). Values for EE_i were calculated using Weir's equation (Weir 1949):

$$EE_i = 3.9 \times VO_{2(i)} + 1.1 \times VCO_{2(i)},$$

where $VO_{2(i)}$ (L•min^{-1}) and $VCO_{2(i)}$ (L•min^{-1}) were the average VO_2 and VCO_2 values, respectively, corresponding to the *i*th activity.

Regression Analyses. Multiple regression was attempted using demographic variables (e.g., age, gender, height, weight) and activity monitor output validation as independent variables and AEE as the dependent variable. Other regression techniques included using a single linear regression equation, multiple nonoverlapping linear regression equations, or a single nonlinear equation in which activity monitor output was the only independent variable. Standard residual analyses were used to evaluate each regression equation (Kleinbaum, Kupper, & Muller, 1988).

The typical validation approach taken by previous activity monitor studies has been to infer prediction accuracy of a resulting equation by evaluating the equation's summary statistics (such as *R* and *SEE*) and evaluating Bland-Altman plots (Bland & Altman, 1986) for evidence of bias and a homogeneous scatter of residuals. The present study, in contrast, incorporated the final regression models for the ankle, hip, and wrist monitors into minute-by-minute AEE prediction algorithms using the minute-by-minute activity monitor output from the lab evaluation. The raw minute-by-minute activity data were read into a Visual Basic (V6.0) computer program that performed several analytical steps: (a) the activity data were transformed into units of AEE for each monitor location using the final regression equations; (b) each string of predicted AEE values were searched for predetermined energy expenditure and time-based summary variables; (c) the summary of these data transformations and summarizations were then exported as an ASCII file for statistical evaluation. The energy expenditure variables summarized by the program included the summation of AEE and time values (1-min epochs) within each data string corresponding to sedentary and light (AEE_{SL}, kcal; T_{SL}, min), moderate (AEE_{MOD}, kcal; T_{MOD}, min), and vigorous intensity activities (AEE_{VIG}, kcal; T_{VIG}, min), as well as the total of all AEE and time within the measurement period (AEE_{TOT}, kcal; T_{TOT}, min). Given the lack of consensus in the literature on AEE cut points for defining activity intensity for children, the present study used the cut points defined by Puyau et al. (2002): sedentary and light intensity activities < 0.05 kcal•kg^{-1}•min^{-1}; 0.05 kcal•kg^{-1}•min^{-1} ≤ moderate intensity < 0.10 kcal•kg^{-1}•min^{-1}; vigorous intensity ≥ 0.10 kcal•kg^{-1}•min^{-1}. For adults, the cut points used to define light intensity (< 3.0 METs), moderate intensity (≥ 3.0 and < 6.0 METs), and vigorous intensity (≥ 6.0 METs) physical activity were transformed into units of AEE (sedentary and light intensity < 0.0310 kcal•kg^{-1}•min^{-1}; 0.0310 kcal•kg^{-1}•min^{-1} ≤ moderate < 0.0832 kcal•kg^{-1}•min^{-1}; vigorous ≥ 0.0832 kcal•kg^{-1}•min^{-1}). The adult AEE cut points were determined by creating a plot of mean METs and mean AEE values (using data for all participants across all activities except supine resting) and then using simple linear regression to determine the following (R^2 = 0.99; *SEE* = ±0.004 kcal•kg^{-1}•min^{-1}): AEE = -0.02130 + 0.01743 x MET, which was then used to predict AEE cut points corresponding to 3.0 and 6.0 MET values. Last, the AEE and time summary variables described above were also computed based on minimum bout durations of 1, 3, and 5 min, which allowed the regression models to be evaluated in a manner more consistent with guidelines for minimum daily physical activity levels (Pate et al., 1995). Prior to processing the raw activity monitor data, the computer program was tested for accuracy with a dummy file in which the outcome for AEE (AEE_{SL}, AEE_{MOD}, AEE_{VIG}, AEE_{TOT}) and time-based (T_{SL}, T_{MOD}, T_{VIG}, T_{TOT}) dependent variables were known.

Statistical Analyses. Analysis and modeling of children and adult data were always performed separately. Intraclass reliability (R_{XX}) for internal consistency was computed for the last 2 min of AEE, absolute VO_2, and activity monitor output (ankle, hip, and wrist) for all activities (except supine resting for activity monitor output; Baumgartner & Jackson, 1995). Test-retest reliability for stability was also evaluated for the same variables using the correlation coefficient (R_{XY}). Mean values for the AEE summary (AEE_{SL}, AEE_{MOD}, AEE_{VIG}, AEE_{TOT}) and time variables (T_{SL}, T_{MOD}, T_{VIG}, T_{TOT}) were statistically compared using multivariate repeated measures analysis of variance (ANOVA; Regression Model x Activity Intensity Category x Participant) at the 0.01 alpha level. Significant ANOVA analyses were followed up with planned contrasts to compare measured mean AEE and time values with the predicted values resulting from the different regression models.

Results

Complete data were collected for 24 children and 24 adults, including 14 boys (*M* age = 12 years, *SD* = 3, range: 8–16 years; *M* height = 155.0 cm, *SD* = 14.3, range: 132–173; *M* body mass = 47.5 kg, *SD* = 9.8, range: 32.7–58.6; *M* body mass index [BMI] = 19.5 kg•m^{-2}, *SD* = 1.3, range: 16.5–21.0), 10 girls (*M* age = 13 years, *SD* = 2, range: 10–17; *M* height = 158.8 cm, *SD* = 9.8, range: 145–173; *M* body mass = 48.4 kg, *SD* = 9.3, range: 36.8–64.3; *M* BMI = 19.1 kg•m^{-2}, *SD* = 2.5, range: 15.3–21.6), 12 men (*M* age = 34 years, *SD* = 8; *M* height = 181.4 cm, *SD* = 6.8; *M* body mass = 83.0 kg, *SD* = 8.7; *M* BMI = 25.2 kg•m^{-2}, *SD* = 2.1; range: 22.6–30.1), and 12 women (*M* age = 39 years, *SD* = 10; *M* height = 167.3 cm, *SD* = 4.3; *M* body mass = 60.9 kg, *SD* = 5.3; *M* BMI = 21.7 kg•m^{-2}, *SD* = 1.0, range: 20.5–24.6). Mean values for energy expenditure and activity monitor output variables are provided in Table 2. Scatterplots of the activity monitor output versus AEE are shown in Figures 1A–C for the children and 2A–C for the adults. Children's values for R_{XX} were generally moderate to high for all variables (.757–.997) during cleaning and locomotion activities, high for the physiological variables during seated activities (.817–.932), but considerably more variable (.313–.860) for activity monitor output. Specifically, the ankle and hip monitors had relatively low R_{XX} values (.313–.560) during seated activities, while R_{XX} for the wrist monitor was considerably higher (.729–.860). Adults' values for R_{XX} were generally high for all variables (.81–.998), except for an R_{XX} of .44 for the ankle activity monitor during sweeping.

Regression Analyses

Multiple regression and nonlinear modeling strategies were not successful based on a comparison of residual plots with various linear regression models (described below). Thus, single linear regression models and multiple nonoverlapping linear regression models were developed and evaluated for the remainder of the analyses. For each activity monitor location, a single regression equation (1R model) was fit to predict AEE for each activity monitor location. In addition, two nonoverlapping linear regression equations (2R models) were fit (one equation for the sitting and cleaning activities and a second for the locomotion activities) for each activity monitor location. The resulting regression equations for both 1R and 2R models are provided in Tables 3 and 4 for children and adults, respectively. Modeling the hip and wrist monitor data, both 1R and 2R models best represented the locomotion data with a single regression line (e.g., see Figures 1B and 1C, respectively, for the children's data). Ankle monitor output for walking and jogging, however, covered nearly identical counts•min^{-1} ranges while at different AEE levels (see Figures 1A and 2A). In the interest of creating the best minute-by-minute algorithm for predicting AEE and time-based variables at light and moderate intensities, the locomotion equation for the ankle 2R model was fit only to the walking data (i.e., jogging data were not used). While all the regression equations were statistically significant ($p < .01$), the R^2 and *SEEs* were highly variable (see Tables 3 and 4). Last, excluding the treadmill walking data ($n = 8$) from the overground walking data ($n = 16$) did not meaningfully influence the children's models. Thus, both overground and treadmill walking data were included in developing the final 1R and 2R children's models.

Developing the Data Analysis Algorithms

Algorithms were formulated to analyze the minute-by-minute activity monitor data for comparison to the measured minute-by-minute AEE and time data. First, cut points (CP1) were created for each monitor location (both 1R and 2R models) to objectively distinguish between natural breaks in activity monitor output. Due to the poor predictability of AEE below these cut points for ankle, hip, and wrist monitors (see Table 3 and 4 for CP1 values), the algorithms assumed a constant AEE of 0.0113 (mean AEE for handwriting; see Table 2) and 0.0076 kcal•kg^{-1}•min^{-1} (mean AEE for typing; see Table 2) for children and adults, respectively, when 50 counts•min^{-1} < AC < CP1. This component of the algorithm accounted for the fact that, regardless of activity monitor location, output from the monitors was inconsistent during the seated activities, despite the standardized instructions and structured nature of the tasks.

Values for CP1 reported in Table 3 were determined by evaluating the scatterplots for each monitor location (see Figures 1 and 2) for a CP value that most clearly distinguished between the light-intensity sitting activities and the moderate-intensity cleaning activities. A second cut point (CP2) for the 2R models distinguished between cleaning and locomotion activity monitor output. While both the ankle and hip monitors resulted in fairly clear natural breaks for CP2 (see Figures 1 and 2), the wrist monitor output showed considerable overlap between the slowest walking speeds and the output for the cleaning activities. To address this issue, the algorithm using the 2R model for the wrist monitor output used the lower boundary of the wrist monitor locomotion data (≈ 2,000 counts•min^{-1}) for CP2. Thus, all wrist monitor data > 2,000 counts•min^{-1} were assumed by the algorithm to be related to locomotion activities.

Minute-by-Minute Data Analyses

The minute-by-minute activity monitor output for the ankle, hip, and wrist were processed by the AEE prediction algorithms using both 1R and 2R models in Table 3 (children's data) and Table 4 (adult data). For both children and adults, the results were consistent regardless of minimum bout duration (e.g., 1, 3, or 5 min). Thus, the

Table 2. Summary statistics for energy expenditure variables and activity monitor output in children (n = 24) and adults (n = 24)

Activity	Relative VO_2		AEE		METs		Ankle AC		Hip AC		Wrist AC	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Supine resting in children	5.74	0.92	0.0	0.0	1.0	0.0	3	9	0.1	0.6	8	19
Sitting activitiesin children												
Hand writing	7.95	0.31	0.0113	5.03E-3	1.4	0.2	12	16	11	21	43	60
Card sorting	8.97	1.26	0.0166	3.98E-3	1.6	0.2	81	76	73	58	842	39
Video game playing	8.91	2.30	0.0162	8.79E-3	1.5	0.2	40	53	16	28	210	198
Cleaning activities in children												
Floor sweeping	20.81	4.27	0.0772	0.0198	3.6	0.6	852	337	1,029	336	1,721	579
Carpet vacuuming	19.35	3.70	0.0697	0.0177	3.4	0.6	1,573	557	1,074	342	1,459	229
Table dusting	18.13	3.97	0.0635	0.0175	3.2	0.5	544	409	826	398	1,461	454
Locomotion activities in children												
Treadmill walking at 2.5 mph (4 kph)	18.39	3.92	0.0643	0.0156	3.2	0.4	4,099	579	2,344	556	2,355	395
Treadmill walking at 3.0 mph (4.8 kph)	19.16	3.97	0.0680	0.0143	3.3	0.3	4,772	697	3297	922	2,838	383
Self-paced "slow" walking	17.47	1.51	0.0604	6.65E-3	3.1	0.3	4,836	524	3,008	872	2,569	355
Self-paced "fast" walking	25.78	3.86	0.1030	0.0109	4.6	0.6	6,073	684	5,368	1,613	3,442	506
Treadmill jogging at 4.5 mph (7.2 kph)	35.21	3.51	0.1500	0.0140	6.2	0.8	4,519	699	9,541	1,039	7,598	1,131
Supine resting in adults	4.34	0.65	0.0	0.0	1.2	0.2	0.3	0.8	0.0	0.0	2	7
Sitting activities in adults												
Typing	5.85	0.96	7.56E-3	4.06E-3	1.7	0.3	33	74	29	77	209	459
Hand writing	6.02	1.06	8.40E-3	3.82E-3	1.7	0.3	32	69	17	36	286	422
Card sorting	7.21	2.60	0.0143	0.0129	2.1	0.7	90	217	92	192	1,074	665
Cleaning activities in adults												
Floor sweeping	17.15	3.56	0.0640	0.0170	4.9	1.0	812	159	838	219	2,197	719
Carpet vacuuming	15.00	3.11	0.0533	0.0145	4.3	0.9	861	309	767	354	1,250	427
Table dusting	15.56	2.66	0.0561	0.01280	4.4	0.8	536	213	737	395	1,594	640
Locomotion activities in adults												
Treadmill walking at 2.5 mph (4 kph)	13.54	1.44	0.0462	6.12E-3	3.9	0.4	4,198	444	1,871	548	2,354	1,072
Treadmill walking at 3.0 mph (4.8 kph)	15.25	1.57	0.0548	6.87E-3	4.3	0.5	4,912	735	2,974	897	2,367	792
Treadmill jogging at 4.5 mph (7.2 kph)	30.84	2.51	0.1325	0.0112	8.8	0.6	5,133	906	8,971	1,762	8,640	1,974

Note. Relative VO_2 = relative oxygen uptake (ml•kg^{-1}•min^{-1}); AEE = activity energy expenditure (kcal•kg^{-1}•min^{-1}); METs = metabolic equivalents (unitless ratio), calculated as (relative VO_2 /3.5) in adults and (relative VO_2/supine resting VO_2) in children; AC = Actical® monitor output (counts•min^{-1}); *M* = mean; *SD* = standard deviation.

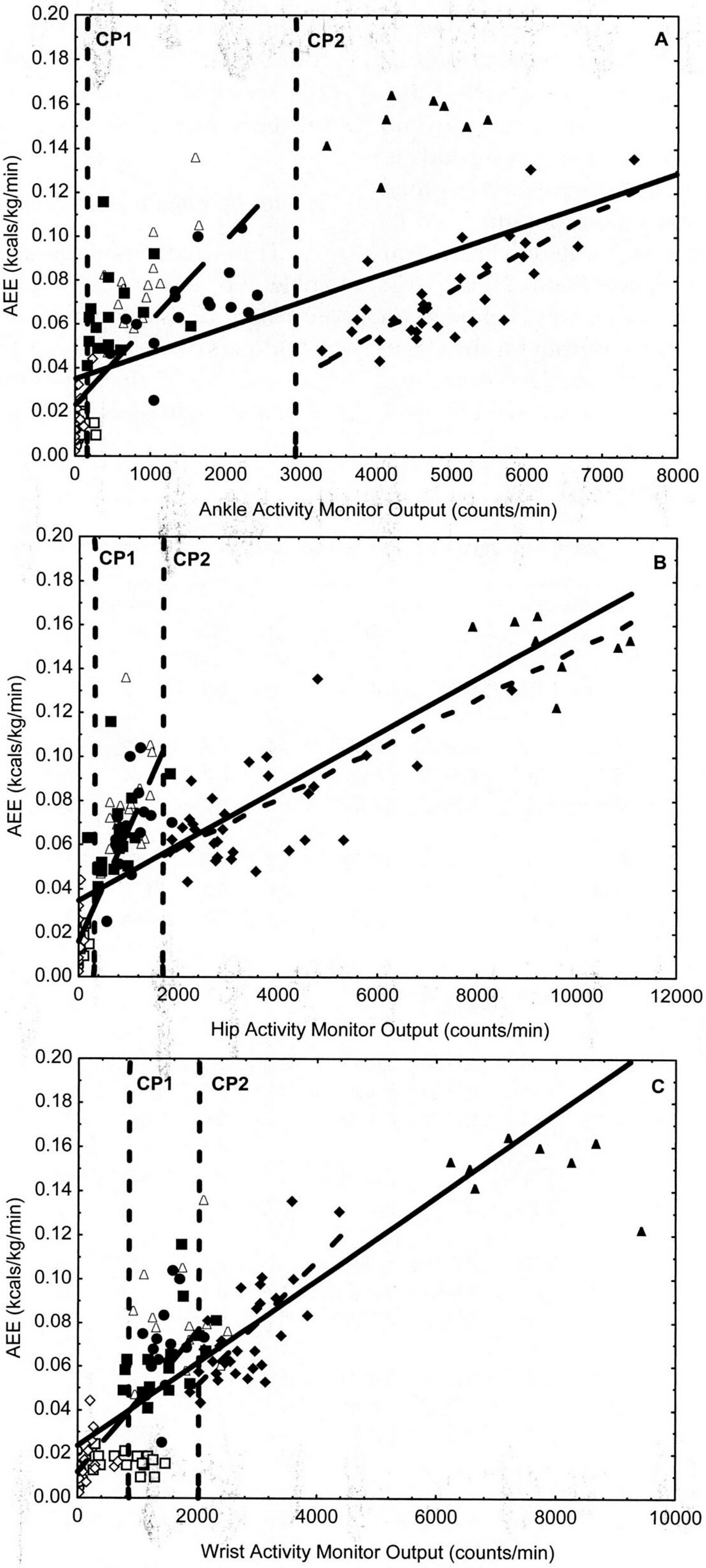

Figure 1. Single and double regression modeling strategies for predicting activity energy expenditure (AEE, kcal•kg^{-1}•min^{-1}) from Actical® activity monitor output at the ankle (A), hip (B), and wrist (C) during nine activities (n = 24 children): hand writing (open circles), card sorting with hands (open squares), video game playing (open diamonds), floor sweeping (open triangles), carpet vacuuming (closed circles), table dusting (closed squares), treadmill and overground walking (closed diamonds), and treadmill jogging (closed triangles). The first vertical dashed line is the cut point (CP1) between sitting activities and cleaning activities, while the second vertical dashed line is the cut point (CP2) between cleaning and locomotion activities. Best fit regression lines shown include the following: (a) solid line for 1R model, (b) long dashed for sitting and cleaning activities in 2R model, and (c) dotted line for locomotion activities in 2R model (line was fit for walking activities only for ankle monitor output).

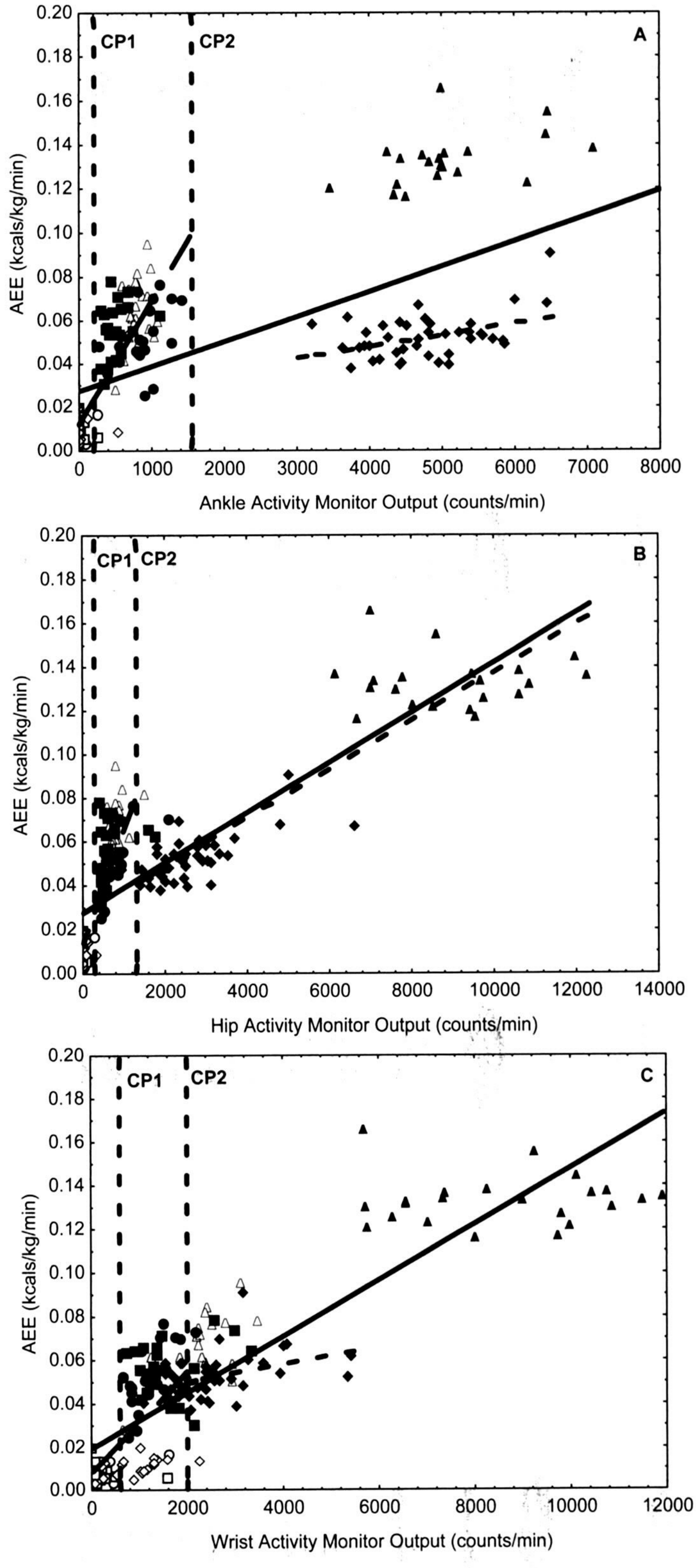

Figure 2. Single and double regression modeling strategies for predicting activity energy expenditure (AEE, kcal•kg^{-1}•min^{-1}) from Actical® activity monitor output at the ankle (A), hip (B), and wrist (C) during nine activities (n = 24 adults): typing (open circles), hand writing (open squares), card sorting with hands (open diamonds), floor sweeping (open triangles), carpet vacuuming (closed circles), table dusting (closed squares), treadmill walking (closed diamonds), and treadmill jogging (closed triangles). The first vertical dashed line is the cut point (CP1) between sitting activities and cleaning activities, while the second vertical dashed line is the cut point (CP2) between cleaning and locomotion activities. Best fit regression lines shown include the following: (a) solid line for 1R model, (b) long dashed for sitting and cleaning activities in 2R model, and (c) dotted line for 2R locomotion activities (walking only for ankle and wrist output).

results for bout duration are shown for the adult algorithms (see Table 6), but results from the children's algorithms were limited to those from a 1-min bout duration (see Table 5). Mean predicted AEE and time sum-

Table 3. Algorithms for predicting activity energy expenditure in children using single and double regression modeling strategies from Actical® activity monitor output[a]

Location	Model	CP1	CP2	AEE constant when 50 < AC < CP1	Predicted AEE for 2R model when CP1 ≤ AC < CP2	Predicted AEE when AC ≥ CP1 (1R) or AC ≥ CP2 (2R)
Ankle	1R	150	NA	0.01130	NA	AEE = 0.03403 + (1.179E-5) x AC (R^2 = .45, *SEE* = 0.028, $p < .001$)
Ankle	2R	150	2,900	0.01130	AEE = 0.02304 + (3.750E-5) x AC (R^2 = .60, *SEE* = 0.020, $p < .001$)	AEE = -0.02268 + (1.939E-5) x AC (R^2 = .60, *SEE* = 0.015, $p < .001$)
Hip	1R	300	NA	0.01130	NA	AEE = 0.03411 + (1.270E-5) x AC (R^2 = .61, *SEE* = 0.024, $p < .001$)
Hip	2R	300	1,650	0.01130	AEE = 0.01667 + (5.103E-5) x AC (R^2 = .75, *SEE* = 0.014, $p < .001$)	AEE = 0.03534 + (1.135E-5) x AC (R^2 = .73, *SEE* = 0.018, $p < .001$)
Wrist	1R	900	NA	0.01130	NA	AEE = 0.02299 + (1.902E-5) x AC (R^2 = .67, *SEE* = 0.022, $p < .001$)
Wrist	2R	900	2,000	0.01130	AEE = 0.01149 + (3.236E-5) x AC (R^2 = .59, *SEE* = 0.020, $p < .001$)	AEE = 0.03115 + (1.581E-5) x AC (R^2 = .69, *SEE* = 0.019, $p < .001$)

Note. AC = activity monitor output (counts•min^{-1}; CP1 = lower AC cut point; CP2 = upper AC cut point; AEE = activity energy expenditure; *SEE* = standard error of estimate; AEE and *SEE* both reported as kcal•kg^{-1}•min^{-1}; 1R = single regression modeling; 2R = double regression modeling; NA = algorithm component not applicable.

[a]2R models when CP1 ≤ AC < CP2 include sitting and cleaning activities but not supine resting; 1R models when AC ≥ CP1 include all activities except supine resting; 2R models when AC ≥ CP2 include walking and jogging activities for the hip monitor, but walking activities only for the ankle and wrist monitors; CP1 distinguishes between sitting and all other activities (e.g., cleaning and locomotion activities); CP2 distinguishes between cleaning and locomotive activities; both modeling strategies assume a constant AEE when 50 < AC < CP1; the coefficient of variation (R^2) and *SEE* are provided as summary statistics for each linear regression equation; all $p < .05$.

Table 4. Algorithms for predicting activity energy expenditure in adults using single and double regression modeling strategies from Actical® activity monitor output[a]

Location	Model	CP1	CP2	AEE constant when 50 < AC < CP1	Predicted AEE for 2R model when CP1 ≤ AC < CP2	Predicted AEE when AC ≥ CP1 (1R) or AC ≥ CP2 (2R)
Ankle	1R	250	NA	0.007565	NA	AEE = 0.02733 + (1.147E-5) x HAC (R^2 = .43, *SEE* = 0.029, $p < .001$)
Ankle	2R	250	1,500	0.007565	AEE = 0.01149 + (5.698E-5) x HAC (R^2 = .74, *SEE* = 0.014, $p < .001$)	AEE = 0.02729 + (5.178E-6) x HAC (R^2 = .17, *SEE* = 0.009, $p = .003$)
Hip	1R	350	NA	0.007565	NA	AEE = 0.02779 + (1.143E-5) x HAC (R^2 = .71, *SEE* = 0.021, p < .001)
Hip	2R	350	1,200	0.007565	AEE = 0.01217 + (5.268E-5) x HAC (R^2 = .75, *SEE* = 0.013, $p < .001$)	AEE = 0.02663 + (1.107E-5) x HAC (R^2 = .85, *SEE* = 0.015, $p < .001$)
Wrist	1R	600	NA	0.007565	NA	AEE = 0.02013 + (1.282E-5) x HAC (R^2 = .75, *SEE* = 0.019, $p < .001$)
Wrist	2R	600	2000	0.007565	AEE = 0.008006 + (2.355E-5) x HAC (R^2 = .61, *SEE* = 0.017, $p < .001$)	AEE = 0.04184 + (3.960E-6) x HAC (R^2 = .14, *SEE* = 0.009, $p = .008$)

Note. AC = activity monitor output (counts•min^{-1}; CP1 = lower AC cut point; CP2 = upper AC cut point; AEE = activity energy expenditure; *SEE* = standard error of estimate; AEE and *SEE* both reported as kcal•kg^{-1}•min^{-1}; 1R = single regression modeling; 2R = double regression modeling; NA = algorithm component not applicable.

[a]2R models when CP1 ≤ AC < CP2 include sitting and cleaning activities but not supine resting; 1R models when AC ≥ CP1 include all activities except supine resting; 2R models when AC ≥ CP2 include walking and jogging activities for the hip monitor, but walking activities only for the ankle and wrist monitors; CP1 distinguishes between sitting and all other activities (e.g., cleaning and locomotion activities); CP2 distinguishes between cleaning and locomotive activities; both modeling strategies assume a constant AEE when 50 < AC < CP1; the coefficient of variation (R^2) and *SEE* are provided as summary statistics for each linear regression equation; all $p < .05$.

Table 5. Measured and predicted activity energy expenditure and time within physical activity intensity categories in children (n = 24)[a]

PA intensity category	Measured AEE		1R Ankle algorithm		1R Hip algorithm		1R Wrist algorithm		2R Ankle algorithm		2R Hip algorithm		2R Wrist algorithm	
	M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
AEE_{SL}	25.7	1.9	45.7	3.1*	43.7	2.5*	32.4	2.2	37.1	3.6	25.1	2.3	24.6	2.4
AEE_{MOD}	62.2	4.2	54.9	4.3	41.5	2.7*	61.8	4.4	60.1	4.2	72.6	5.6	76.5	4.4
AEE_{VIG}	32.5	6.8	10.5	3.5	23.1	4.9	20.0	4.7	11.2	4.0	19.9	4.1	16.5	4.4
AEE_{TOT}	120.4	8.3	111.1	5.5	108.4	7.4	114.1	7.8	108.4	5.0	117.7	7.8	117.6	7.7
T_{SL}	33.8	1.0	40.1	1.0*	40.9	0.9*	35.3	1.2	36.4	1.4	32.6	0.9	31.6	1.3
T_{MOD}	18.1	0.8	14.2	0.8*	12.2	0.6*	18.3	1.0	17.8	1.0	20.8	0.9	22.4	0.9
T_{VIG}	4.4	0.9	2.0	0.6	3.1	0.6	2.6	0.5	2.1	0.7	2.8	0.5	2.2	0.6
T_{TOT}	56.3	0.7	56.3	0.7	56.3	0.7	56.3	0.7	56.3	0.7	56.3	0.7	56.3	0.7

Note. PA = physical activity; 1R = single regression modeling strategy; 2R = double regression modeling strategy; AEE = activity energy expenditure in kcal; T = time in min; *M* = mean; *SE* = standard error; AEE_{SL}/T_{SL} = sedentary and light intensity; AEE_{MOD}/T_{MOD} = moderate intensity; AEE_{VIG}/T_{VIG} = vigorous intensity; AEE_{TOT}/T_{TOT} = sum of all three intensity categories.
[a]Predicted values were based on single and double regression modeling strategies and a 1-min bout duration for activity monitor output from the ankle, hip, and wrist locations.
*Mean predicted value differed significantly ($p < .01$) from mean measured value within the same PA intensity category.

Table 6. Measured and predicted activity energy expenditure and time within physical activity intensity categories for adults (n = 24)[a]

PA intensity category	Bout duration	Measured AEE		1R Ankle algorithm		1R Hip algorithm		1R Wrist algorithm		2R Ankle algorithm		2R Hip algorithm		2R Wrist algorithm	
		M	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*	*M*	*SE*
AEE_{SL}	1	17.8	1.7	14.9	1.0	15.6	0.5	18.4	1.7	15.7	1.1	15.6	0.5	20.6	1.6
AEE_{MOD}	1	89.7	3.4	80.7	6.5	79.2	3.0	77.2	4.7	103.2	6.5	90.4	3.4	96.8	6.4
AEE_{VIG}	1	43.9	3.0	41.3	6.4	42.9	3.6	39.2	5.8	5.2	1.3*	40.3	(4.0	2.9	1.6*
AEE_{TOT}	1	151.4	6.1	137.0	7.8	137.7	6.0	134.9	8.2	124.0	6.3*	146.3	6.0	120.4	6.5*
AEE_{SL}	3	16.7	1.5	14.3	1.0	13.2	0.5	16.7	1.8	14.9	1.1	13.2	0.5	18.9	1.8
AEE_{MOD}	3	87.2	3.5	76.0	6.6	74.5	3.1	73.8	4.6	99.7	6.3	85.4	3.3	94.0	6.2
AEE_{VIG}	3	40.9	3.2	40.0	6.4	42.7	3.7	38.9	5.7	1.0	1.0*	40.3	4.0	2.7	1.6*
AEE_{TOT}	3	144.9	6.0	130.3	7.6	130.4	6.2	129.4	7.9	115.6	6.0*	138.9	6.1	115.6	6.2*
AEE_{SL}	5	16.1	1.4	14.1	1.0	13.0	0.4	15.6	1.7	14.7	1.0	13.0	0.4	17.6	1.8
AEE_{MOD}	5	85.6	3.9	74.0	6.4	74.0	3.0	71.2	4.4	98.0	6.2	84.8	3.2	92.1	6.2
AEE_{VIG}	5	28.4	5.1	39.5	6.4	42.7	3.7	37.8	5.2	1.0	1.0*	40.3	4.0	2.2	1.5*
AEE_{TOT}	5	130.2	7.6	127.6	7.5	129.8	6.2	124.6	7.4	113.7	5.9	138.2	6.0	111.9	6.1
T_{SL}	1	26.5	3.4	25.8	1.4	25.1	0.5	25.3	1.6	26.1	1.4	25.1	0.5	26.8	1.6
T_{MOD}	1	23.2	0.8	23.0	1.7	25.0	0.8	25.0	1.7	27.8	1.6	25.1	0.7	27.5	1.8
T_{VIG}	1	5.2	0.4	6.1	0.9	4.8	0.4	4.5	0.7	0.9	0.2*	4.6	0.4	0.5	0.3*
T_{TOT}	1	55.0	0.2	55.0	0.2	55.0	0.2	55.0	0.2	55.0	0.2	55.0	0.2	55.0	0.2
T_{SL}	3	25.8	0.5	25.2	1.4	24.3	0.4	24.0	1.7	25.6	1.4	24.3	0.4	25.6	1.7
T_{MOD}	3	22.5	0.9	21.6	1.7	23.3	0.8	23.7	1.7	27.1	1.6	23.6	0.8	26.5	1.7
T_{VIG}	3	4.7	0.4	5.9	0.9	4.7	0.4	4.5	0.6	0.1	0.1*	4.6	0.4	0.5	0.3*
T_{TOT}	3	53.0	0.3	52.8	0.6	52.6	0.5	52.3	0.6	52.8	0.5	52.5	0.4	52.6	0.5
T_{SL}	5	25.4	0.5	25.0	1.4	24.1	0.3	23.4	1.7	25.4	1.4	24.1	0.3	24.8	1.7
T_{MOD}	5	22.0	1.0	21.0	1.6	23.1	0.8	22.8	1.6	26.7	1.5	23.4	0.7	25.8	1.7
T_{VIG}	5	3.2	0.6	5.8	0.9	4.7	0.4	4.3	0.6	0.1	0.1*	4.6	0.4	0.4	0.3*
T_{TOT}	5	50.6	0.5	51.9	0.8	52.0	0.6	50.5	0.8	52.3	0.7	52.1	0.6	51.0	0.8

Note. PA = physical activity; 1R = single regression modeling strategy; 2R = double regression modeling strategy; AEE = activity energy expenditure in kcal; T = time in min; *M* = mean; *SE* = standard error; AEE_{SL}/T_{SL} = sedentary and light intensity; AEE_{MOD}/T_{MOD} = moderate intensity; AEE_{VIG}/T_{VIG} = vigorous intensity; AEE_{TOT}/T_{TOT} = sum of all three intensity categories.
[a]Values for AEE and time were evaluated across minimum bout durations of 1, 3, and 5 min.
*Mean predicted value differed significantly ($p < .01$) from mean measured value within the same PA intensity category and minimum bout duration.

mary variables from the children's algorithms (see Table 5) did not differ significantly from actual mean values for each 2R algorithm as well as the 1R wrist algorithm. Mean values for AEE_{SL} and T_{SL}, however, were statistically higher than actual mean values for both the ankle and hip 1R algorithms, as well as AEE_{MOD} for the 1R hip algorithm and T_{MOD} for the ankle and hip algorithms. Mean predicted AEE and time summary variables from the adult algorithms (see Table 5) did not differ significantly from actual mean AEE summary variables for each 1R algorithm or the 2R algorithm for the hip monitor. Mean values for AEE_{VIG}, however, were statistically lower (all bout durations) than actual mean AEE_{VIG} values for the ankle and wrist 2R algorithms. Because AEE_{TOT} was defined as $AEE_{SL} + AEE_{MOD} + AEE_{VIG}$, predicted AEE_{TOT} was also significantly lower than actual AEE_{TOT} for the same ankle and wrist algorithms.

As suggested by Atkinson and Nevill (1998), the mean and standard deviation of the differences between predicted and actual AEE and time summary variables for all dependent variables and algorithms are summarized in Table 7. The positive and negative mean differences represent a tendency to under- and overpredict, respectively, the dependent variable by the prediction algorithm. For comparison to the literature, Bland-Altman plots were also created using the 1R and 2R hip algorithm data for both the children and adult AEE summary variables. The children's 1R hip algorithm data (see Figure 3) demonstrated a significant bias to overpredict AEE_{SL} by 14.7 kcal, underpredict AEE_{MOD} by 16.2 kcal, and predict most accurately AEE_{VIG} and AEE_{TOT}. The children's 2R hip algorithm data (see Figure 4) demonstrated no bias to predict AEE_{SL} or AEE_{TOT} but a nonsignificant tendency to overpredict AEE_{MOD} by 9.6 kcal and underpredict AEE_{VIG} by 8.9 kcal. Both 1R and 2R hip algorithms demonstrated a fairly homogeneous scatter of residuals about the mean difference. The adults' 1R algorithm data (see Figure 5) demonstrate a slight bias to overpredict most variables (residuals of +4.2 to +15.7 kcal for AEE_{SL}, AEE_{MOD}, and AEE_{TOT}, respectively), a homogeneous scatter of residuals for most variables (AEE_{MOD}, AEE_{VIG}, AEE_{TOT}), with only AEE_{SL} showing a clear bias to overpredict as the magnitude of the mean AEE value increased (see Figure 5A). In contrast, the adults' 2R algorithm data (see Figure 6) demonstrated a decreased tendency to overpredict (residuals of -0.7 to +7.1 kcal) and a more homogeneous scatter of residuals for all variables.

Table 7. Means and standard deviations of the differences between measured and predicted activity energy expenditure and time within physical activity intensity categories[a]

PA intensity category	1R Ankle algorithm		1R Hip algorithm		1R Wrist algorithm		2R Ankle algorithm		2R Hip algorithm		2R Wrist algorithm	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Children												
AEE_{SL}	-20.0	8.1	-14.7	10.7	-6.6	7.5	-11.4	11.3	1.3	8.9	1.1	6.8
AEE_{MOD}	7.3	18.4	16.2	16.3	0.4	13.6	2.0	18.6	-9.6	17.5	-14.3	16.1
AEE_{VIG}	22.1	30.3	8.5	28.3	12.5	29.8	21.3	33.7	8.9	21.0	16.0	28.8
AEE_{TOT}	9.3	23.3	10.6	25.9	6.2	27.2	12.0	24.1	1.3	20.5	2.8	27.2
T_{SL}	-6.3	3.5	-7.1	5.0	-1.6	4.2	-2.7	4.9	1.1	5.4	2.1	4.7
T_{MOD}	3.9	4.2	5.8	4.4	-0.2	4.8	0.3	4.7	-2.8	4.9	-4.3	5.2
T_{VIG}	2.4	3.9	1.3	3.8	1.8	3.8	2.4	4.5	1.6	3.8	2.2	3.6
Adults												
AEE_{SL}	2.8	7.0	4.2	7.2	-0.7	8.9	2.1	6.6	1.7	5.1	-2.8	9.1
AEE_{MOD}	9.0	25.6	10.5	14.0	12.4	22.5	-13.5	25.7	-0.7	14.2	-7.1	28.8
AEE_{VIG}	2.6	31.4	1.0	13.6	4.7	23.8	28.8	15.7	3.6	15.2	41.0	14.0
AEE_{TOT}	14.4	30.6	15.7	22.0	16.5	33.2	27.4	26.4	7.1	22.7	31.1	29.4
T_{SL}	1.5	2.8	1.3	2.6	1.1	7.5	0.3	5.6	0.3	1.6	-0.4	7.2
T_{MOD}	-0.1	5.1	-1.8	2.3	-1.8	6.4	-4.7	6.0	-2.0	2.2	-4.3	7.0
T_{VIG}	-1.0	4.9	0.4	1.4	0.7	2.8	4.3	2.3	0.6	1.7	4.7	1.8

Note. PA = physical activity; 1R = single regression modeling strategy; 2R = double regression modeling strategy; AEE = activity energy expenditure in kcal; T = time in min; *M* = mean; *SE* = standard error; AEE_{SL}/T_{SL} = sedentary and light intensity; AEE_{MOD}/T_{MOD} = moderate intensity; AEE_{VIG}/T_{VIG} = vigorous intensity;; results for the T_{TOT} variable were not reported above, because the actual and predicted values were identical for 1-min minimum bout duration (see Tables 5 and 6).
[a]Predicted values were based on single and double regression modeling strategies and a 1-min bout duration for activity monitor output from the ankle, hip, and wrist locations.

Discussion

The present study sought to develop algorithms to predict AEE in children and adults, using the Actical® activity monitor worn at the ankle, hip, or wrist. An algorithm was defined as a set of analytical steps for processing the raw activity monitor data that included one or two AEE prediction equations, cut points to distinguish between active and inactive or between-prediction equations, and a definition of a minimum bout duration. Interestingly, the proposed algorithms for the Actical® appeared to predict both AEE and time-based variables accurately whether worn at the ankle, hip, or wrist. These results, however, are clearly limited by the laboratory nature of the data collection and need to be validated under free-living conditions. In addition, while most group means did not differ significantly from measured values, there was still considerable individual variability in prediction accuracy as previously described for lab (Swartz et al., 2000) and field-based (Strath, Bassett, & Swartz, 2003) activity monitoring.

The most interesting result from this study was the lack of significant differences between measured and predicted AEE and time variables for all three monitor locations using the 2R algorithms in children (see Table 5) and 1R and 2R hip algorithms in adults (see Table 6). The children's algorithms still demonstrated a tendency toward prediction bias, however, with AEE_{SL} overpredicted by the 2R ankle algorithm and AEE_{MOD} by the 2R hip and wrist algorithms, and all 2R algorithms underpredicting AEE_{VIG} (see Table 7). The summation of these biases resulted in a small mean underprediction of AEE_{TOT} by the 2R algorithms ranging from 3 to 12 kcal over the 56-min measurement period. Any biases observed in predicting the AEE variables were mirrored by the same prediction biases in the time variables.

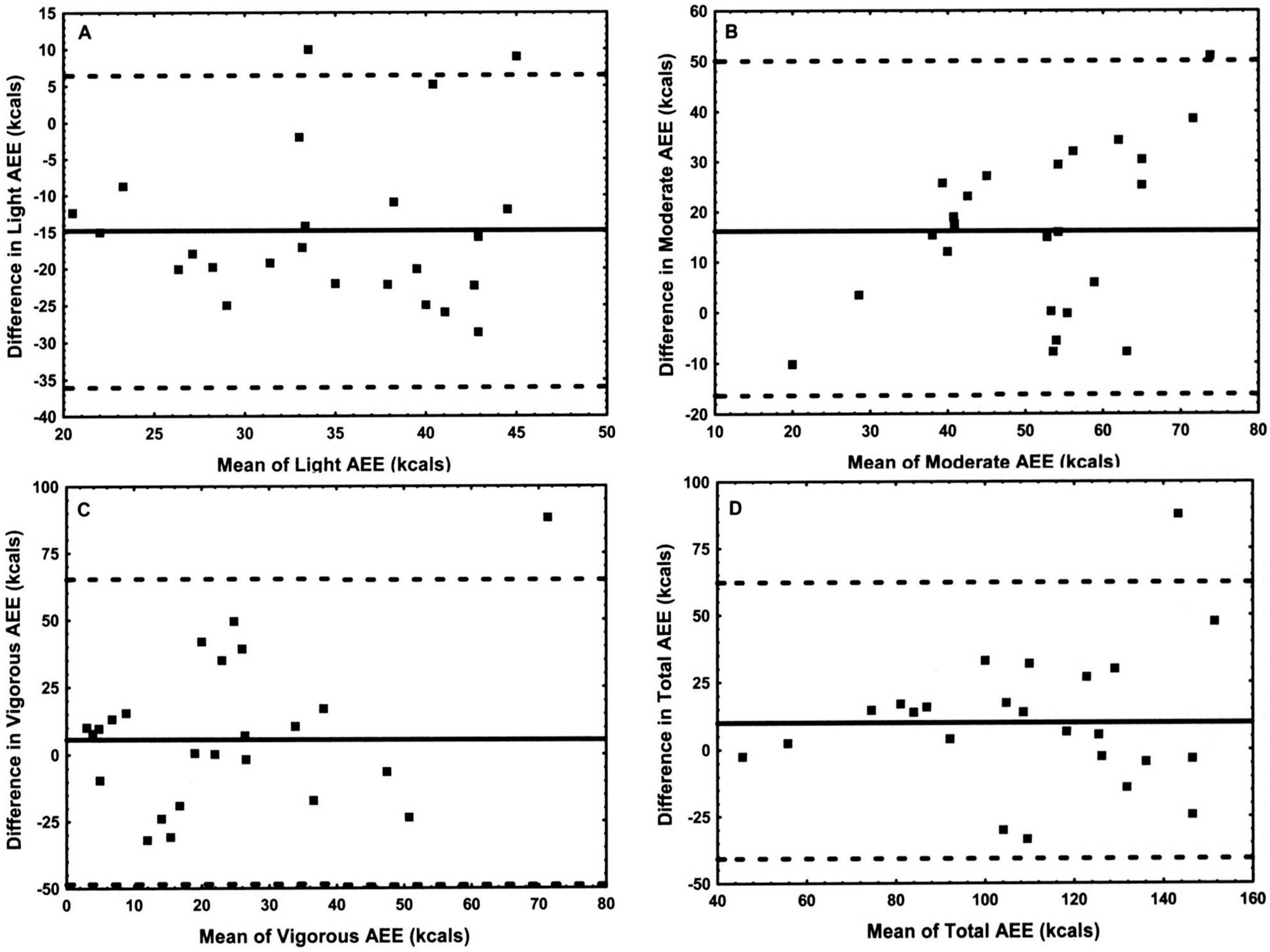

Figure 3. Bland-Altman plots for hip activity monitor (single regression modeling hip algorithm with 1-min bouts) in children showing difference scores (actual-predicted) in activity energy expenditure (AEE) plotted against the average of actual and predicted values for light (A), moderate (B), vigorous (C), and total AEE (D). Solid line = mean of the difference scores; dashed lines = 95% confidence interval for difference scores.

This was expected, because the summation of the time variables was based on the 1-min predicted AEE values within each algorithm. Similarly, the adults' 1R algorithms tended to overpredict both AEE_{VIG} and T_{VIG} as the bout duration increased from 1 to 5 min. The results for the 2R algorithms, in contrast, were not as consistent across monitor locations. While the predictions of AEE and time from the hip 2R algorithm were not different statistically from measured values, the ankle and wrist 2R algorithms could not accurately predict AEE and time in the vigorous category. Table 6, for example, shows that when the ankle and wrist 2R algorithm could not recognize an activity bout as vigorous (e.g., underpredicted mean T_{VIG} values), the result was an underpredicted mean AEE_{VIG} and possibly AEE_{TOT}.

Despite the conclusions above, considerable individual differences still resulted in large standard deviations of the difference scores (see Table 7). Thus, in practice, the algorithms may provide useful predictions of AEE and time-based physical activity variables for groups of children or adults, but the tracking of individuals may still involve considerable error. It does not seem reasonable to expect any activity monitor or data processing algorithm using generalized prediction equations will ever accurately predict AEE for *all activities* in *all people* (Freedson et al., 1998; Hendelman et al., 2000; Puyau et al., 2002; Swartz et al., 2000; Trost et al., 1998) or data processing algorithms (present study). It may be possible, however, to correct for some of the individual prediction outliers by designing a choreographed series of activities that calibrate a particular activity monitor to a specific person. Albeit more time consuming than using generalized algorithms such as those described by this paper, individual calibration of

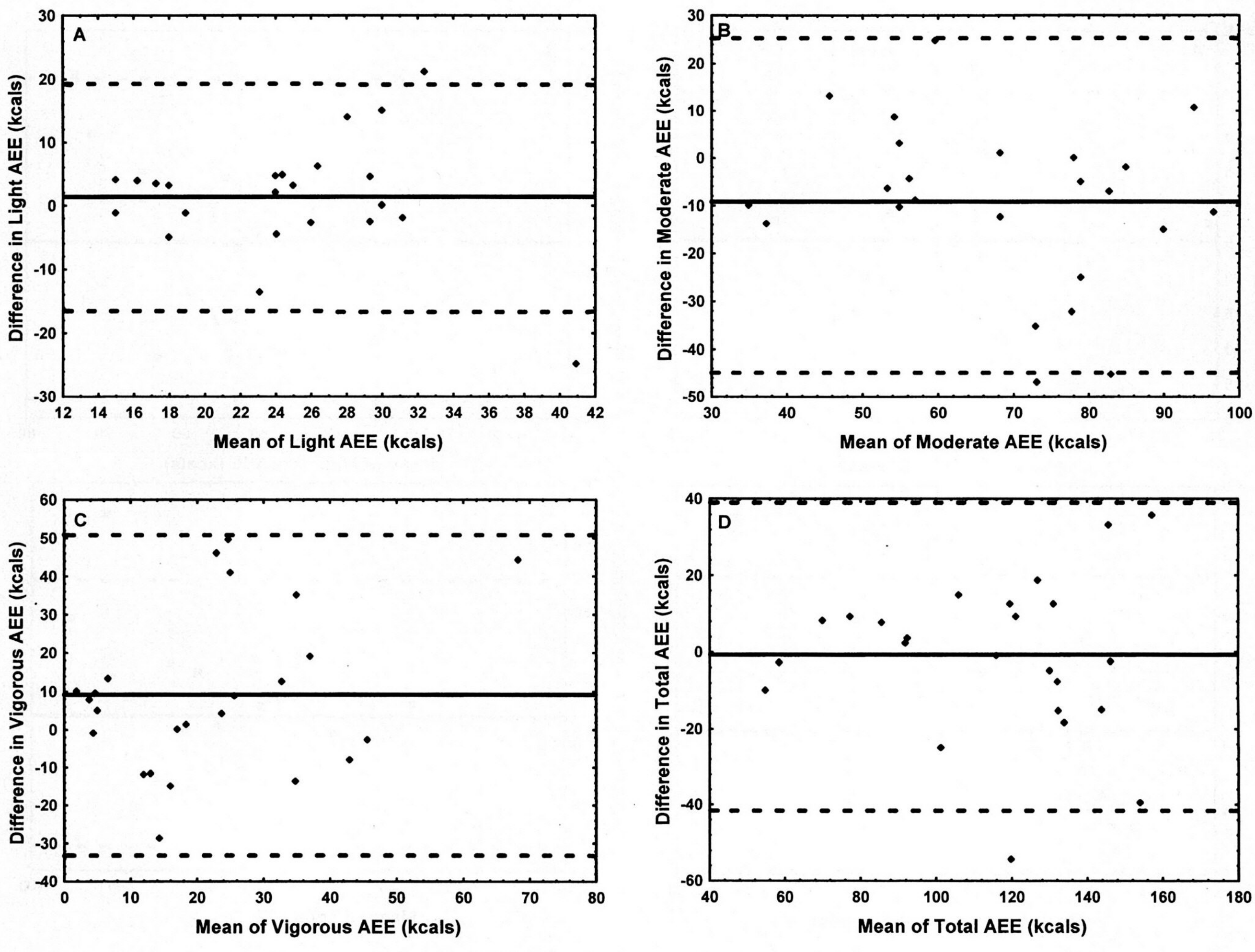

Figure 4. Bland-Altman plots for hip activity monitor (double regression modeling hip algorithm with 1-min bouts) in children showing difference scores (actual-predicted) in activity energy expenditure (AEE) plotted against the average of actual and predicted values for light (A), moderate (B), vigorous (C), and total AEE (D). Solid line = mean of the difference scores; dashed lines = 95% confidence interval for difference scores.

activity monitors may be a necessary step to improve AEE prediction accuracy with any activity monitor.

The relationship between activity counts and AEE demonstrated a clear distinction in Actical® output between simulated household cleaning activities and locomotion activities, especially for the ankle and hip monitors. The hip monitor output for the children (see Figure 1B), for example, showed an almost seamless and nonoverlapping transition between the cleaning (166–1,862 counts•min^{-1} across all participants) and walking activities (1,834–8,680 counts•min^{-1}), with only two AEE data points above the 1,650 counts•min^{-1} value designated as CP2 for the hip algorithm (see Table 3). A more complete demarcation was observed for the ankle monitor (see Figure 1A) output where there was no overlap of output between cleaning (156–2,424 counts•min^{-1}) and walking activities (3,274–7,422 counts•min^{-1}). The ability to distinguish between these activities led to testing the 1R versus 2R methods of modeling the activity data for the present study.

Swartz et al. (2000) reported a different pattern of monitor output, in the form of a large scatter of Manufacturing Technology, Inc. (MTI; ActiGraph, LLC, Fort Walton Beach, FL) activity monitor output at the hip versus METs, in adults using a broad range of activities (including yard work, housework, family care, as well as conditioning and recreational activities). In the same study, an even broader scatter and lower correlation between monitor output and METs (.18 vs. .56) was reported for the MTI monitor on the wrist instead of the hip. It is possible the graphical relationship between Actical® output and AEE in the present study is an artifact of testing relatively few activities. It is also possible, however, that the differences in output between the

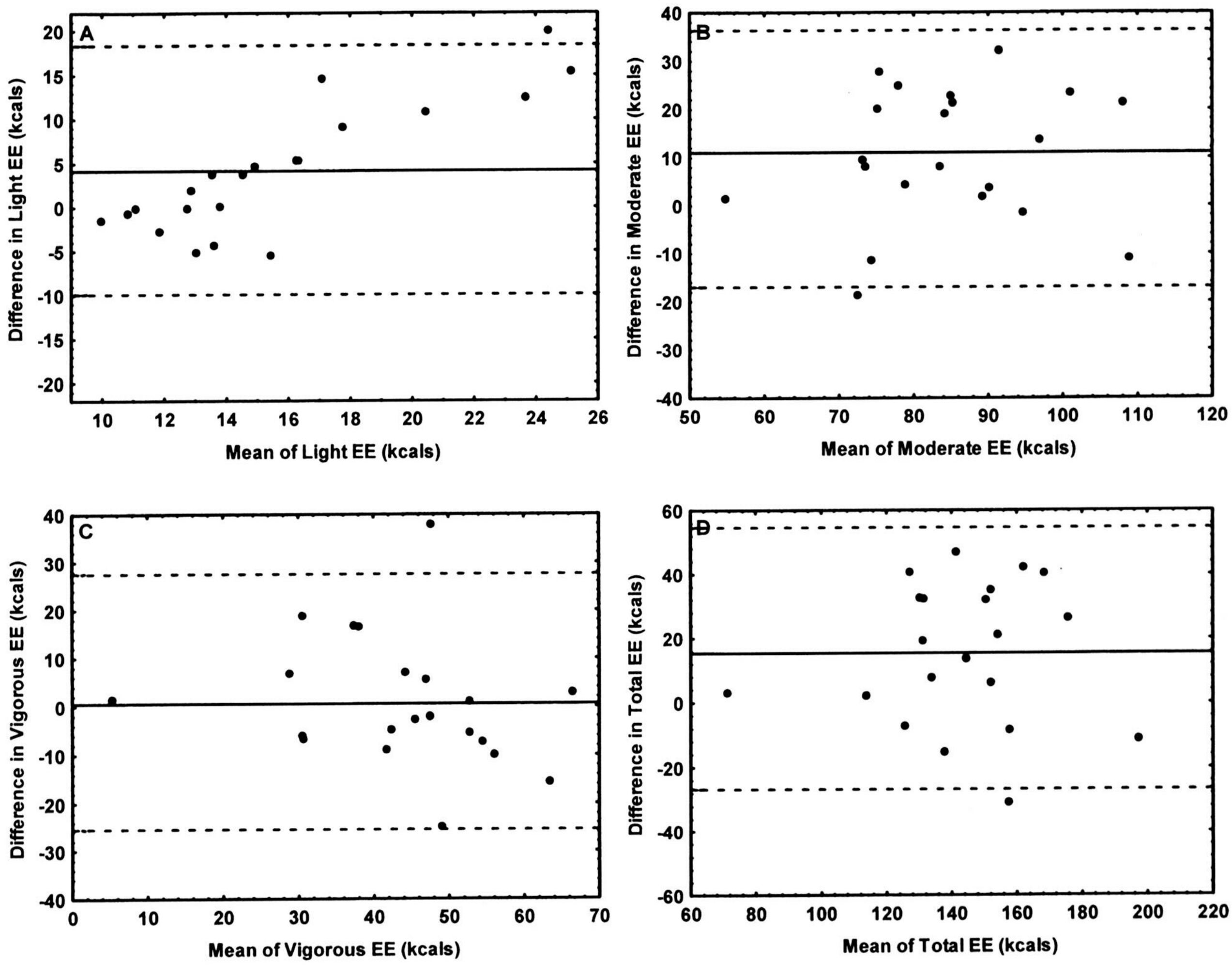

Figure 5. Bland-Altman plots for hip activity monitor (single regression modeling hip algorithm with 1-min bouts) showing difference scores (actual-predicted) in activity energy expenditure (AEE) plotted against the average of actual and predicted values for light (A), moderate (B), vigorous (C), and total AEE (D). Solid line = mean of the difference scores; dashed lines = 95% confidence interval for difference scores.

present study and the Swartz et al. (2000) study may be due to design and sensitivity differences of the activity monitors. The Actical® is described as having an "omnidirectional" accelerometer that is most sensitive in a single plane and less sensitive in other planes, whereas the MTI is designed around a single uniaxial accelerometer that senses motion in only one plane. The sensitivity differences between these monitors is highlighted by Swartz's reported MTI activity monitor output ranges for the hip (0–7,000 counts•min^{-1}) and wrist (0–9,000 counts•min^{-1}) that were lower than Actical® output results at the hip and wrist in adults (0–12,000 counts•min^{-1}) and children (0–12,000 and 0–10,000 counts•min^{-1}, respectively) in the present study.

While several studies have evaluated wrist and ankle monitor locations for predicting energy expenditure in adults (Leenders et al., 2003; Melanson & Freedson, 1995; Swartz et al., 2000), none concluded that these locations were effective alternatives to the standard hip monitor location. Two studies were limited to evaluating walking and jogging (Leenders et al., 2003; Melanson & Freedson, 1995), but Swartz et al. (2000) evaluated a variety of activities and concluded that wrist monitoring with the MTI was not accurate enough by itself or in combination with hip monitoring to be worth the extra time and effort. Puyau et al. (2002) compared hip and lower leg (lateral surface of the right leg at the fibular head) locations for both the MTI monitor and the Actiwatch activity monitors (a predecessor of the Actical® monitor, but originally designed for sleep studies) in 6–16-year-old children. While previous activity monitor studies in children primarily relied on locomotion-based activities

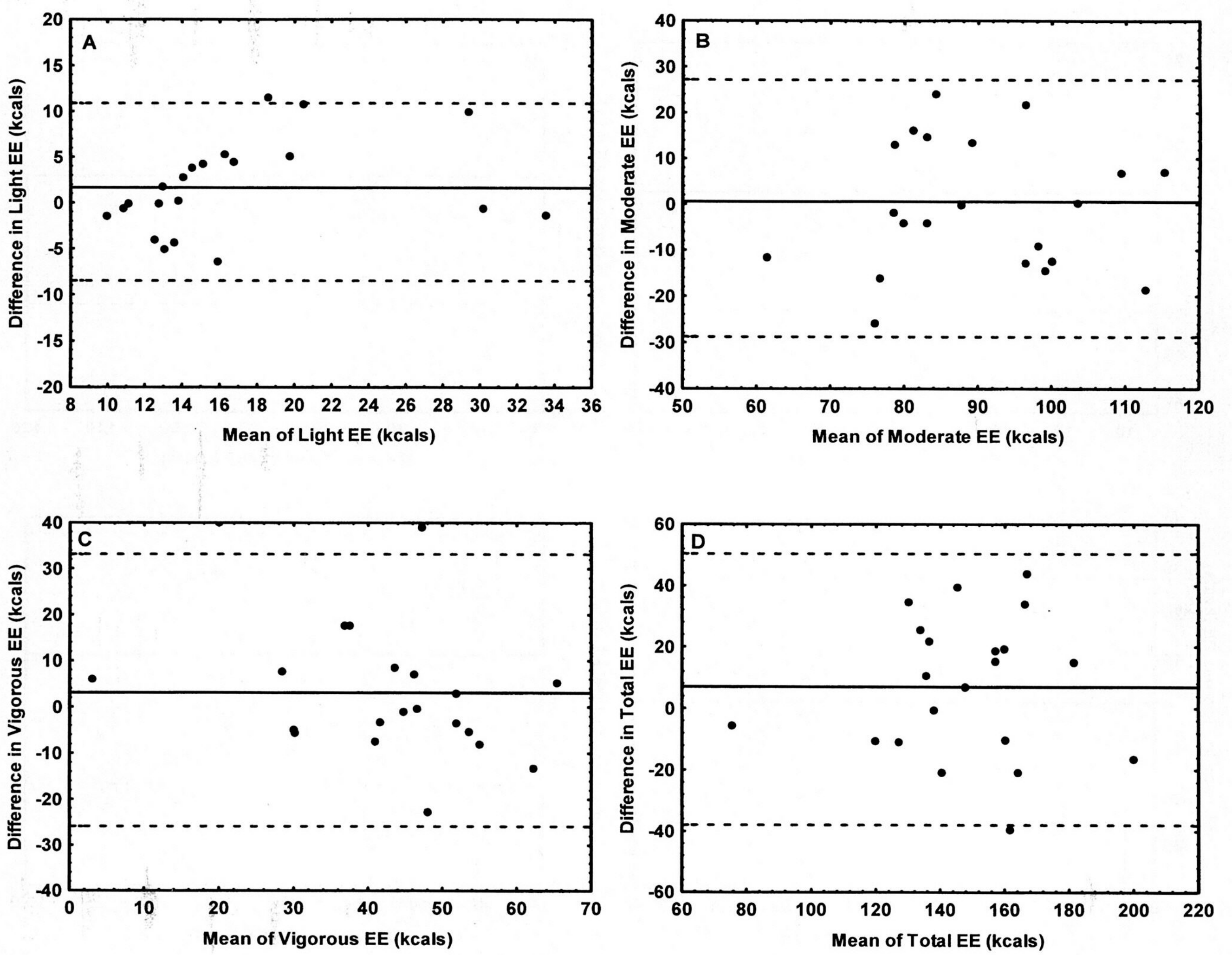

Figure 6. Bland-Altman plots for hip activity monitor (double regression modeling hip algorithm with 1-min bouts) showing difference scores (actual-predicted) in activity energy expenditure (AEE) plotted against the average of actual and predicted values for light (A), moderate (B), vigorous (C), and total AEE (D). Solid line = mean of the difference scores; dashed lines = 95% confidence interval for difference scores.

(Janz et al., 1995; Trost et al., 1998), Puyau's study included many types of free-living activities from sedentary to vigorous intensity over a 6-hr period within a room calorimeter. The study concluded that both MTI and Actiwatch monitors provided reasonable estimates of AEE or time within intensity categories (i.e., sedentary, light, moderate, vigorous) at either the hip or the lower leg. Thus, with the exception of the present study, Puyau et al. (2002) appears to be the only study suggesting that an activity monitor not located on the hip could estimate both EE and time-based variables accurately. Future research could focus on directly comparing the Actical® with another more commonly used activity monitor, such as the MTI, so that procedural versus instrumentation differences can be better understood.

Underlying much of the discussion above is the fact that any activity monitor will best measure human motion (and, thus, estimate EE accurately) when the monitor's accelerometer is attached to the body part responsible for the motion and optimally aligned with the motion itself. Thus, under free-living conditions, activity monitors attached to the ankle or wrist are probably far more likely to record motions not related to the activity being performed (e.g., fidgeting). Example of this type of activity can be clearly seen in both children (see Figure 1) and adults (see Figure 2) in the present study in which the monitors recorded some level of activity at all locations, despite the structured nature of the activities. Activity monitors are also better at detecting whole body weight bearing activity (e.g. walking and jogging) and are relatively insensitive to nonweight bearing activities (such as cycling), lifting heaving objects (e.g., weight training or static muscular contractions), and even surface incline/decline during locomotion (Melanson & Freedson, 1995). Recognizing these known limitations should be critically evaluated when using activity monitors in certain populations (e.g., wheelchair bound individuals), occupational settings (e.g., wildland firefighters; Heil 2002), or when hip-placed monitors are not possible or practical. Thus, despite the suggestion by some that simultaneously wearing multiple monitors is not useful or practical (Melanson & Freedson, 1995; Swartz et al., 2000), this may be the only method to evaluate EE for some experimental questions (e.g., EE differences between mail carriers vs. mail sorters).

The present study appears to be unique in suggesting that AEE and time variables related to assessing physical activity may be assessed at the ankle, hip, and wrist locations in children and adults. In general, the 2R algorithms for children accurately predicted mean values of both AEE and time variables within all intensity categories (sedentary/light, moderate, and vigorous) as well as total AEE accumulated over the measurement period. The 1R algorithms were less consistent in their predictive accuracy. In adults, the 1R and 2R hip algorithms accurately predicted both AEE and time variables within light and moderate intensities for all monitor locations, but only the hip monitor consistently predicted these variables accurately at a vigorous intensity. All the proposed algorithms were developed using lab-based data and should be validated under free-living conditions against a criterion measure of energy expenditure.

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