Physical Activity Assessment in Children

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ABSTRACT

Stookey AD, Mealey LM, Shaughnessy, M. Physical Activity Assessment in Children. JEPonline 2011;14(5):75-84. In the United States, the prevalence of overweight and obesity in children has increased at alarming rates, which suggests that children are experiencing a chronic positive energy balance, with energy intake exceeding energy expenditure. To better understand the contribution of physical activity to daily energy expenditure, it is critical to implement techniques to accurately assess physical activity in children. Implementation of such techniques would facilitate the establishment of more specific physical activity guidelines for children and increase researchers’ ability to monitor the effects of physical activity interventions in youth. This literature review reports the historical evolution of instruments designed to measure energy expenditure in youth and addresses various limitations associated with each assessment tool. A PubMed search was used to locate articles that validated objective activity monitors in children. Only methods validated against criterion methods of indirect calorimetry and doubly labeled water were included in this review. The main outcome was energy expenditure predicted by various activity assessment tools. When relying on the linear relationship of heart rate and oxygen consumption to estimate energy expenditure, errors range from -16.7% to +18.8%. Energy expenditure predicted by accelerometry yields relatively high correlations when compared to criterion methods in a controlled laboratory setting (r = 0.62 to 0.93), but tend to vary with accuracy when analyzing children's free-play activity. Devices that incorporate multiple parameters are promising for improving the accuracy of predicting the energy cost of various activities typical of youth. However, more research is needed to refine algorithms to increase the accuracy and utility of these devices.

Key Words: Energy Expenditure, Childhood, Obesity, Overweight
INTRODUCTION

In the United States, the prevalence of overweight and obesity in children has increased at alarming rates and has become a significant public health concern (14). The percentage of children (6 to 11 yrs of age) who are considered overweight has more than doubled in the last two decades, with some estimates indicating that one in five children in the United States is obese (7). Being overweight or obese during childhood increases the risk for many adverse health outcomes including hypertension, high cholesterol, type II diabetes, bone and joint problems, asthma, sleep apnea, and psychological consequences (9). In addition, approximately 60% of overweight children have at least one risk factor for heart disease and stroke. The risk is directly related to diet and physical activity.

The increasing rates of youth who are overweight and obese suggest that children are experiencing a chronic positive energy balance, with energy intake exceeding energy expenditure (EE) (23). Physical activity accounts for 20% to 30% of total daily energy expenditure (TDEE), and is the most variable component of EE (30). Unfortunately, TDEE has declined in children, a direct result of a decline in physical activity, as well as an accompanying increase in sedentary activities such as playing video games, watching television, and using the internet (1). On average, children spend 5 or 6 hrs per day engaging in some form of sedentary activity, with approximately 25% of children in the United States spending 4 or more hrs a day watching television (13). Additionally, children who watch more than 3 hrs of television a day are 50% more likely to be obese as compared to children who watch fewer than 2 hrs per day (26,30). Engaging in sedentary activity leads to a reduction in time spent participating in physical activity, which leads to a reduction in TDEE (9). Thus, to better understand the contribution of physical activity to TDEE, it is critical to implement techniques to accurately assess EE and, more specifically, physical activity in children. Implementation of such techniques would also facilitate the establishment of more specific physical activity guidelines for children and increase researchers’ ability to monitor the effects of physical activity interventions in youth.

Unfortunately, the accurate assessment of physical activity EE in children has been and still remains a challenge for researchers. In particular, they are faced with challenges associated with the complexity of children's activity, which is characterized by sporadic and intermittent movement patterns. The criterion measures for assessing physical activity in children include indirect calorimetry (IC) and doubly labeled water (DLW). However, due to the expensive nature of these techniques, as well as the expertise needed to conduct such measurements, the use of IC and DLW is impractical for the general population (25,27). As a result, it is a common practice for researchers to rely on less expensive methods of assessing EE in children, which include physiological data, pedometers,
motion sensors, and a combination of these methods in an attempt to determine the most accurate and reliable method for measuring EE in children (25). However, each of these techniques has limitations that can affect the validity, reliability, and/or clinical utility of the EE data obtained. This literature overview: (a) reports the historical evolution of various instruments designed to measure EE in a youth population; (b) addresses the limitations associated with each assessment tool; and (c) suggests future research in this area.

PORTABLE SYSTEMS TO MEASURE ENERGY EXPENDITURE

Heart Rate Method
Heart rate (HR) monitoring relies on the linear relationship between HR and oxygen consumption (VO$_2$) as a means of predicting EE (24,27). During typical, low intensity activities often performed by children (sitting, crayoning, catching, hopscotch, walking at 4 and 6 km·h$^{-1}$), HR is less accurate in predicting EE (13,31). However, during higher intensity activities, HR becomes a more accurate method of assessing EE (31). The linear relationship between HR and VO$_2$ may therefore be a valid measure of EE in children during more intense activity. This highlights a limitation of the HR method for estimating EE in children since their activity patterns are often characterized by rapid transitions between various levels of intensity.

Several factors can impact the accuracy of the HR method to estimate EE in children. For example, although HR is linked to body movement, environmental and psychological stressors, caffeine, and certain medications also influence HR (19,21). These factors can result in an increase in HR without a significant increase in VO$_2$ and, therefore, provide an inaccurate assessment of EE. Additionally, the varying fitness levels of children may limit the ability to estimate EE from HR (5), with more fit children having a lower HR for a given EE compared to their less fit counterparts (12). Heart rate response may also lag behind changes in physical movement (15), especially quick transitions in movement patterns during children's play that may not be captured by HR monitoring. These limitations have lead researchers to question the validity of HR to accurately predict EE in children.

Accelerometry
Accelerometers are electronic devices that detect acceleration produced by a body segment/limb as it moves through space (15). Electric transducers and microprocessors detect this movement and convert the acceleration into digital signals used to predict EE. This technique is based on the theoretical concept that acceleration is directly proportional to muscular force, which represents EE. Accelerometers can be classified as uni-axial or tri-axial. Uni-axial accelerometers record movement in a single, vertical plane of motion. Tri-axial accelerometers detect movement in three planes: mediolateral, anteroposterior, and vertical.

Accelerometers have numerous advantages making them useful tools for assessing physical activity in children. These devices are small, which allows children to wear them for longer periods of time without interfering with normal movement (17). Accelerometers are objective and reusable tools capable of storing data continuously over extended periods of time. As a result, patterns of activity over several days or weeks can be recorded and analyzed.

Uni-Axial Accelerometers
The Caltrac (Muscle Dynamics Fitness Network, Torrence, GA) and Computer Science and Applications Actigraph (CSA; Shalimar, FL) are uni-axial accelerometers commonly used in physical activity research (10). The validity and accuracy of these monitors in children has been analyzed in controlled laboratory settings, as well as in free-living conditions. Research focusing on the validity of uni-axial accelerometers to predict EE during treadmill walking and running in children has yielded
promising results (22,29). Maliszewski et al. (22) and Trost et al. (29) demonstrated that mean EE values predicted by the Caltrac and CSA were strongly correlated to mean EE determined by the criterion method of IC. This research also demonstrated no significant difference between EE measured by IC and EE predicted by the Caltrac and CSA during various speeds of treadmill walking and running in children (22,29). These findings highlight the fact that accelerometers accurately quantify varying intensities of activity in children, which is not always the case with HR monitoring.

Many accelerometer validation studies in children have focused on treadmill walking and running. Thus, it is reasonable that current equations to predict EE are based upon treadmill exercise in a controlled laboratory setting (22,29). However, given the fact that children's activities are often sporadic and non-continuous, it is important to determine the accuracy of these devices during other forms of activity that are typical of children during free play. Various researchers have examined the validity of the treadmill-based prediction equations utilized by uni-axial accelerometers to estimate EE in children during non-treadmill activities (5,12,19). Eisenmann et al. (16) focused on the validity of the Caltrac to estimate EE during activities of daily living (sweeping, bowling, and basketball) compared to portable IC. On average, the Caltrac significantly underestimated EE by 2.80 kcal·min$^{-1}$ during these activities. Similarly, Bray et al. (5) analyzed the validity of the Caltrac to estimate TDEE across 24 hrs in children. When compared to whole-room calorimetry, moderate to strong correlations were reported between TDEE ($r = 0.80$), sedentary daily EE ($r = 0.84$), and walking EE ($r = 0.85$) predicted by the accelerometer and directly measured by IC; however, the accelerometer significantly underestimated TDEE by 13.3%, sedentary daily EE by 6.8%, and walking EE by 30.4%. Johnson and colleagues (19) examined the accuracy of 24-hr EE predicted by the Caltrac accelerometer and used DLW as the criterion measure. Over three consecutive days, the Caltrac method significantly overestimated daily EE ($956$ kcal•d$^{-1}$ vs. $469$ kcal•d$^{-1}$; $P < 0.001$).

These studies demonstrate the limitations of uni-axial accelerometry for predicting EE across a wide spectrum of activities. This may be in part due to the treadmill-based regression equations used by uni-axial accelerometers to predict EE of daily activities in children, which involves more than just walking and running. Inaccurate results may also be the result of uni-dimensional accelerometry’s ability to only detect movement in a single plane rather than multiple planes, which may be necessary to accurately quantify activities typical of children in free-living conditions. As a result, researchers have shifted their focus towards tri-axial accelerometers.

**Tri-Axial Accelerometers**

Tri-axial accelerometers were developed to assess body acceleration in multiple planes of space (mediolateral, anteroposterior, and vertical dimensions), with the assumption that recording motion in more than one plane would increase the accuracy of predicting EE (28). This was thought to be important to address the limitation of uni-axial accelerometers, especially the challenge to accurately assess sporadic physical activity typical of children during normal play. Eston and colleagues (13) sought to directly compare the accuracy of HR monitoring, uni-axial accelerometer (WAM; Computer Science Applications, Shalimar, FL), and tri-axial accelerometer (TriTrac-R3D; Hemokinetics, Inc. Madison, WI) during typical children’s activities, including crayoning, catching, and hopscotch, as well as treadmill walking and running at various speeds. Indirect calorimetry was used as the criterion method. A relatively poor relationship was found between EE predicted by both HR monitoring ($r = 0.64$) and the WAM ($r = 0.61$) when compared to IC (13). Furthermore, both HR monitoring and the uni-axial accelerometer did not accurately predict EE (standard error of $14.91$ mL•kg$^{-1}$•min$^{-1}$ and $15.71$ mL•kg$^{-1}$•min$^{-1}$, respectively). However, the TriTrac-R3D ($r = 0.83$) was better able to predict EE during the variety of activities analyzed, with an average standard error of $10.3$ mL•kg$^{-1}$•min$^{-1}$. When analyzing each dimension of the TriTrac-R3D separately, during activities requiring ambulation (walking, running, and hopscotch), accelerations were largest in the vertical plane. However, during
crayoning and playing catch, the largest accelerations were recorded in the anteroposterior plane. The latter acceleration would not have been detected by a uni-axial accelerometer and, therefore, could partially explain the inability of uni-axial accelerometry to accurately predict EE during these childhood activities.

Eston and colleagues (13) were also interested in determining if combining two measurements techniques would increase the accuracy of predicting EE. Multiple regression equations demonstrated that combining tri-axial accelerometry and the HR method further increased the accuracy of predicting EE (r = 0.85, standard error of 9.7 mL•kg\(^{-1}•\text{min}^{-1}\)) when compared to any single measurement technique. Thus, tri-axial accelerometers, with attention given to three planes of acceleration, provided more appropriate measures of children's free-play physical activity as compared to single-plane accelerometers (13). This investigation also highlighted the advantage of combining multiple measurement parameters to capture children's free-play activity.

Overall, three-dimensional accelerometers provide an accurate assessment of youth physical activity, strongly predicting EE for free-play activities when compared to uni-dimensional accelerometers (13,25,28). Unfortunately, however, accelerometry is not without limitations. The predictive validity of the specific algorithms or count cutoffs used to convert accelerometer data to EE need to be further analyzed, especially in free-living conditions. Over a one-minute period of time, these prediction equations assume steady-state exercise. This is problematic when evaluating physical activity in children since many times a child will alternate between varying levels of intensity within any given minute. Thus, the accumulation of counts for the 1-min represents the average level of activity with no credit given for vigorous activity. This factor limits the utility of these devices to quantify EE during periods of structured and free-living physical activity.

**Method of Combining Multiple Parameters**

With the promising results of combining several methods of assessment, devices that measure multiple parameters improve the accuracy of predicting EE in children. The two most researched and widely marketed devices are the SenseWear Pro Armband\(^{\circledR}\) (BodyMedia, Inc., Pittsburgh, PA) and the Intelligent Device for EE and Activity\(^{\circledR}\) (Minisun LLC, Fresno, CA). The purpose of measuring multiple parameters in a single physical activity assessment device is to overcome the limitations of the other assessment devices (16) and to allow for a more accurate assessment of children's EE. The SenseWear Pro Armband\(^{\circledR}\) (SWA) is a portable device worn on the back of the upper arm. It uses multiple parameters to estimate EE, including dual-axis accelerometry, heat flux, galvanic skin response, skin temperature, and near-body ambient temperature (8). Also, in addition to these data, demographic characteristics such as age, gender, weight, height, right or left handedness, smoker or non-smoker are used in proprietary algorithms to estimate EE.

Validation studies in adults have provided promising results with regards to the accuracy of the SWA to estimate EE (16,18,20). The SWA algorithm was designed for individuals between 18 and 75 yrs of age. Individuals younger than 18 yrs old have different physiology and may require different algorithms (2). Crawford and colleagues (8) examined the validity of the SWA during walking and cycling exercise in subjects with a mean age of 13.8 ± 1.8 yrs. Their results demonstrate that when adult algorithms were applied, there was a significant underestimation in EE compared to the criterion measure of IC. This was the first study to demonstrate that the algorithms for the SWA may not be appropriate for individuals less than 18 yrs of age. Two years later, Arvidsson et al. (3) examined the accuracy of the SWA in 21 healthy children with a mean age of 12.1 ± 0.9 yrs during various activities typical of children's free-play (e.g. lying down, playing games on a cell phone, stepping up and down, bicycling on a stationary bike, jumping on a trampoline, playing basketball, and walking/running on a treadmill at 2.0, 3.0, 4.0, 5.0, 6.0, 7.0, 8.0, and 10.0 km•hr\(^{-1}\)). The children's EE was measured...
simultaneously using the SWA and portable IC (Oxycon Mobile; VIASYS Healthcare, Conshohocken PA). The SWA significantly underestimated EE in all activities except jumping on a trampoline and walking 2 and 3 km•hr⁻¹(29). A point of interest was that the SWA’s underestimation was directly proportional to the intensity of the children’s activity.

Dorminy et al. (11) focused on the accuracy of the SWA to predict 24-hr EE in 21 African American children with a mean age of 11.6 ± 0.9 yrs. The children’s EE was simultaneously measured by the SWA and indirect room calorimetry (IRC). During the 24-hr time period, the children participated in a variety of activities that included walking on a treadmill and reading, writing, doing puzzles, playing computer games, watching television, using the laptop, listening to music, and sleeping. The SWA significantly overestimated EE during the treadmill exercise (p = 0.004), rest before and after treadmill exercise (p = 0.007, p = 0.0001, respectively), sedentary activities (p = 0.0004), sleep (p = 0.0007), resting metabolic rate (p = 0.007), and total 24-hr EE (p = 0.0001). The ratio of EE predicted by the SWA versus EE measured by IRC ranged from 116% during sleep to 143% during rest after exercise. These results contradict the previous study (3). The SWA overestimated EE during similar activities. The use of different versions of the interface software to analyze minute-by-minute data from the SWA may explain this discrepancy. Dorminy et al. (11) used an earlier version of BodyMedia’s InnerView Research Software (version 4.1); whereas, Arvidsson (3) used the 5.1 version.

As new data become available, BodyMedia integrates this information into their proprietary algorithms to increase the accuracy of the SWA in predicting EE of children’s unique movement patterns. Calabro and colleagues (6) analyzed the validity of the most recently updated algorithms (version 6.1) in 22 children (15 boys, 7 girls, mean age = 9.4 ± 1.2 yrs) while resting, coloring, playing computer games, walking on a treadmill at 2.0, 2.5, and 3.0 mph, and while bicycling on a stationary bike. To determine whether modifications in the algorithms were effective in improving the SWA’s accuracy, energy cost estimates using an older version of the software (version 4.2) were calculated and compared to EE estimates provided by the newer version (version 6.1). Energy expenditure was simultaneously measured by the SWA and IC (TrueMax 2400; ParvoMedics, Sandy, UT). Although the older algorithm overestimated EE by 32%, the average error was only 1.7% when the new algorithm was applied (6). No significant differences (P < 0.01) between the new algorithm and IC were observed for rest (0.2 ± 0.26 kcal•min⁻¹), coloring (0.05 ± 0.95 kcal•min⁻¹), playing computer games (0.05 ± 0.41 kcal•min⁻¹), and walking at 2.0 mph (0.02 ± 0.7 kcal•min⁻¹), 2.5 mph (-0.02 ± 0.90 kcal•min⁻¹), and 3.0 mph (-0.09 ± 0.83 kcal•min⁻¹). The only activity that was not accurately quantified was bicycling. The SWA significantly underestimated EE (2.99 ± 0.82 kcal•min⁻¹) as compared to IC (3.99 ± 1.35 kcal•min⁻¹).

Clearly, the initial research on the SWA provided conflicting results, which demonstrated the need to further adjust the algorithm as a means of increasing the accuracy of this device in measuring EE in youth (3,6,8,11). When the algorithms were updated and modeled for children based upon initial research findings, the SWA was able to more accurately predict EE in children. There isn’t any question that it has become a more promising device for quantifying children’s free-play activity.

The Intelligent Device for Energy Expenditure and Activity® (IDEEA) is another device that has combined several parameters in an attempt to increase the accuracy of estimating EE (4). This device consists of five separate sensors worn on the front of each thigh, under each foot, and on the sternum that are all connected with soft cables to a microprocessor/storage unit that is worn on the belt. These sensors detect body motion and behavior patterns to estimate EE during a 24-hr free living condition. The IDEEA can detect a multitude of activities (such as lying, sitting, reclining, standing, leaning over, walking, running, climbing stairs, descending stairs, and jumping on a trampoline). This device is also able to determine the frequency, intensity, and duration of activity.
Arvidsson and colleagues (4) compared the accuracy of the SWA (Version 5.1) and IDEEA against IC (Oxycon Mobile; VIASYS Healthcare) to assess EE in children during rest and periods of physical activity. This was the first study to focus on the validity and accuracy of measuring the energy cost in children by utilizing multisensory activity monitoring. Fourteen children with a mean age of 12.3 ± 1.0 yrs participated in their study. The SWA, IDEEA, and IC were synchronized and worn simultaneously by the children for all activities. The protocol began with a 10-min rest period followed by a series of five different activities: (a) sitting quietly; (b) stationary bicycling; (c) jumping on a trampoline; (d) playing basketball; and (e) stair walking. Each activity was separated by a 5-min rest period in the seated position. Following these activities, each subject rested in a quiet seated position for 10 min followed by walking at three different paces and running at two different paces around a marked 50-meter track.

During rest, sitting quietly, and playing basketball the SWA significantly underestimated EE by 0.01 ± 0.01 kJ•kg⁻¹•min⁻¹ (P = 0.003), 0.01 ± 0.02 kJ•kg⁻¹•min⁻¹ (P = 0.008), and 0.03 ± 0.02 kJ•kg⁻¹•min⁻¹ (P < 0.001), respectively, compared to IC (4). The IDEEA overestimated the energy cost of rest (0.01 ± 0.03 kJ•kg⁻¹•min⁻¹; P = 0.13) and sitting quietly (0.02 ± 0.03 kJ•kg⁻¹•min⁻¹; P = 0.08) and significantly underestimated the energy cost of playing basketball (0.24 ± 0.17 kJ•kg⁻¹•min⁻¹; P < 0.001). However, the IDEEA was the only device to accurately predict the energy cost of stair walking. An intensity-effect was demonstrated by the SWA. This device was accurate during slow walking, but as intensity increased the error of underestimation also increased. No such effect was demonstrated by the IDEEA. In fact, it provided a better estimate of EE during higher intensities of exercise. When examining total energy cost for all activities combined, the IDEEA was the most accurate while still significantly underestimated total energy cost. The SWA and the IDEEA were similar in assessing EE during rest and sitting, and both devices were better in predicting EE during walking and running, as compared to biking, jumping, or playing basketball.

Overall, the IDEEA provided the best estimate of total energy cost since it was more accurate in capturing walking and running EE (4). However, there are limitations associated with both devices that influence capturing various activities in children in a free-living environment. The IDEEA can be a cumbersome device to wear with all of its sensors and cables, which may make it less useful in free-living conditions. This point also raises questions regarding its practicality for use in children. The SWA may be a more feasible option, especially for children since it is easy to put on and wear on the arm. It is a more user-friendly interface for starting, downloading, viewing, and analyzing data. Further research is needed to determine whether more appropriate algorithms should be developed to increase the accuracy of both the SWA and the IDEEA.

**SUMMARY**

Developing EE assessment tools designed to capture the complexity of children's free-play activity has been and continues to be a challenge for researchers. Criterion measures of DLW and IC provide limited data regarding specific physical activity patterns, and they are not feasible for use in free-living environments (27). Portable devices provide an alternative method of assessing EE in children, but are not without limitations. Heart rate monitoring is an easy and simple way to monitor exercise intensity, but relying strictly on the linear relationship between HR and VO₂ to predict EE during children's free-play provides inaccurate estimates (24,27). However, when HR is combined with accelerometry, the estimate for EE is improved (13). Uni-dimensional accelerometers, designed to detect motion in a single, vertical plane, are very useful in children when assessing physical activity during walking and running. But, these devices are limited when children engage in their more typical
play activities (22,29). Tri-axial accelerometers are designed to detect movement in three planes, enhancing their ability to detect diverse activities uni-axial accelerometers may not. This point is very important when capturing children's diverse movement patterns.

More recently, a combination of multiple parameters have been incorporated into devices, such as the SWA and the IDEEA, as a means of improving the overall accuracy of predicting EE in children (3,6,8,11). Although these devices appear to be more accurate in predicting energy cost of various activities typical of youth, more research is needed to refine the algorithms in order to increase their accuracy and utility. Furthermore, it is difficult to compare existing research due to the constant updates in analysis software used in each investigation. More research is needed to analyze the current algorithms used by the newest version of software to determine the validity, accuracy, and clinical utility of these devices.

ACKNOWLEDGMENTS

The authors are grateful and would like to thank the VA RR&D Maryland Exercise and Robotics Center of Excellence (MERCE) and the Department of Veterans Affairs and Veterans Affairs Medical Center Baltimore Geriatric Research, Education and Clinical Center (GRECC).

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