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ORIGINAL RESEARCH

Development and Validation of Energy Expenditure Prediction Models Based on GT3X Accelerometer Data in 5- to 9-Year-Old Children

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***Background*:** Accelerometry has been established as an objective method that can be used to assess physical activity behavior in large groups. The purpose of the current study was to provide a validated equation to translate accelerometer counts of the triaxial GT3X into energy expenditure in young children. ***Methods*:** Thirty-two children aged 5–9 years performed locomotor and play activities that are typical for their age group. Children wore a GT3X accelerometer and their energy expenditure was measured with indirect calorimetry. Twenty-one children were randomly selected to serve as development group. A cubic 2-regression model involving separate equations for locomotor and play activities was developed on the basis of model fit. It was then validated using data of the remaining children and compared with a linear 2-regression model and a linear 1-regression model. ***Results*:** All 3 regression models produced strong correlations between predicted and measured MET values. Agreement was acceptable for the cubic model and good for both linear regression approaches. ***Conclusions*:** The current linear 1-regression model provides valid estimates of energy expenditure for ActiGraph GT3X data for 5- to 9-year-old children and shows equal or better predictive validity than a cubic or a linear 2-regression model.

***Keywords*:** physical activity measurement, value calibration, triaxial accelerometer

Accelerometry has been established as an objective method that can be used to assess physical activity behavior in fairly large groups with a reasonable amount of effort.[1,2] One of the most widely used accelerometers is the ActiGraph. Its uniaxial models have been shown to be valid and reliable for measurements with children.[3–6] However, uniaxial accelerometry reflects locomotor activities (walking and running) better than lifestyle activities (eg, sweeping, children's games, sports) as movement is only registered if the hip moves up and down in a vertical direction.[2,7] Therefore, the triaxial model GT3X was released in mid 2009.[8] In addition to the vertical axis, it features 2 horizontal axes which measure acceleration when the device is moved from left to right or backward and forward. The additional information is expected to provide a more accurate measure of different types of physical activity overcoming the shortfall of uniaxial accelerometry.[9]

Accelerometers integrate the absolute acceleration and deceleration values over a set time interval and thus produce an output referred to as counts. However, the counts are a unit-free figure and need to be translated into physiologically interpretable variables that can be used in epidemiological or intervention studies. The process of determining algorithms for this translation of counts is referred to as value calibration of accelerometers.[10]

To the author's knowledge only 2 value calibration studies with the GT3X have been published so far, 1 in adults[11] and 1 in 8- to 15-year old children.[12] Crouter et al[12] developed algorithms for vertical axis counts and for the composite measure of counts on all 3 axes, the vector magnitude [$VM = (x^2 + y^2 + z^2)^{0.5}$]. The children performed sedentary activities, household chores, track walking and running, video games and sports activities. Their vector magnitude regression equation for locomotor activities explained 39% of the variance in energy expenditure and the equation for all other activities explained 59% of the variance.

Several value calibration studies have been conducted in children with the Tritrac triaxial accelerometer or its successor, the RT3. Their linear regression equations based on the vector magnitude explained between 58%–90% of the variance in energy expenditure.[13–18] With a different device, the ActivTracer, Tanaka et al were able to explain 95% of the variance in energy expenditure per kg body weight for activities of a continuous nature (sedentary activities, standing, walking, running) in 5- to 6-year-old children.[19] They were the only group that computed regression equations with the vertical and horizontal accelerometer axes entered as separate variables

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in the model in addition to developing a model on the basis of vector magnitude. The 2 alternatives showed a very similar model fit in terms of R^2 and standard error of estimate (SEE).

Tanaka et al further argued that nonlinear regression approaches may reflect energy expenditure more accurately.[19] They computed power function models in addition to their linear models, but found very similar values of R^2 and SEE for the 2 alternatives.[19] Similarly, Treuth et al[20] tested several self-developed models with the uniaxial ActiGraph 7164 in teenage girls with a bootstrap cross-validation and found no improvement when quadratic, cubic or polynomial models were used compared with linear models. On the other hand, Crouter et al reported a better model fit with cubic and exponential models for the same accelerometer in adults[21] and for the vertical axis of the GT3X relating to locomotor activities in children but not to intermittent activities.[12] Therefore, it remains unclear, whether nonlinear approaches are more appropriate for interpreting triaxial or even uniaxial accelerometer counts. In addition, Chen and Bassett[22] point out that nonlinear approaches bear the disadvantage of either being unstable or tending to plateau too quickly, thus their predictive validity would be limited. So far, no studies appear to have compared the predictive validity of linear versus nonlinear prediction equations developed with 1 study group and validated with an independent study group.

Guidelines state that studies designed to calibrate accelerometers should include a wide range of activities encompassing locomotion (ie, walking and running), as well as common lifestyle or play activities of an intermittent nature.[2,23,24] In adults, studies have consistently shown lower count outputs at a given energy expenditure value for lifestyle activities compared with locomotion.[7,22,25] Therefore, some authors applied pattern recognition techniques to group activities into appropriate classes first and then developed separate regression equations for each activity class[12,21,26,27] or to calculate energy expenditure directly from counts.[28] Similar observations have been made in studies involving children less than 10 years of age. Lower counts in relation to energy expenditure were seen for play activities with high proportions of static elements and arm movements (ball dribbling, Tae Bo exercises, ball toss, cleaning, and hopscotch) compared with locomotion.[5,13,14,29,30] However, for children's activities involving jumping jacks the opposite was the case.[5,29] To the authors' knowledge only Crouter et al[12] have applied an activity classification before assigning energy expenditure equations in children so far. They showed that their algorithms provided a better predictive power than previous equations based on a single regression equation developed with the ActiGraph model 7164. However, they did not develop a single regression equation in their own study and compare its predictive validity to their 2-regression model. Therefore, it remains unclear, whether distinct regression equations for certain types of activities provide an improvement in energy expenditure prediction based on triaxial accelerometry.

The aim in the current study was thus to develop and validate an accurate equation to translate GT3X accelerometer counts into energy expenditure in 5- to 9-year-old children. This was to be achieved with 3 successive objectives: The first objective was to determine the best possible linear or nonlinear regression model fit by testing meaningful alternatives. The second objective was to provide a classification method to distinguish between locomotor and play activities to develop an algorithm involving 2 separate equations for these activity types. The third objective was to validate the final model and compare its predictive validity to the validity of traditional multiple linear regression models.

Methods

Study Population

Parents of the 5- to 9-year-old children who were enrolled in a holiday sports camp to be held at the first author's institute received written information on the study per e-mail and were asked whether their child would participate. An additional 4 girls were recruited through a local preschool to increase the ratio of girls in the study. Measurements were conducted in July and August 2010 at the physical activity laboratory of the institute. Inclusion criteria were children who were born in the years 2001–2005 and who, according to their parents, did not have any medical condition with contraindications to exercise. Participation was voluntary. The children's guardians signed a written informed consent and the children gave their written assent. Ethical approval was obtained from the competent regional ethics committee.

Measurement Devices

Anthropometric Measurements. The children's weight was measured to the nearest 0.1 kg with a calibrated mechanical scale (seca, Hamburg, Germany). Their height was measured to the nearest 0.1 cm using a portable stadiometer (model 214, seca, Hamburg, Germany).

Accelerometry. Two triaxial ActiGraph GT3X devices (ActiGraph, LLC, Pensacola, FL) were used in the study to measure acceleration. The small (38×37×18 mm) and light (27 g) device was fitted on a belt and strapped around the children's waist so that it was placed on the front slightly to the left of the right iliac crest. The accelerometer was programmed to record counts with the standard filter at an epoch of 5 seconds. This epoch length was chosen as children's daily activity patterns have been shown to be highly transitory with 80% of moderate-intensity activity bouts and over 90% of vigorous-intensity activity bouts being shorter than 10 sec.[31] The GT3X appears to provide valid measurements for energy expenditure in adults exercising on a treadmill[11] and in 8- to 15- year olds,[12] but no studies with younger children have been published so far.

Energy Expenditure. Energy expenditure was measured through indirect calorimetry using the portable Meta Max 3B (Cortex, Leipzig, Germany) breath-by-breath calorimeter. This unit weighs about 500 g and consists of 2 connected parts worn on the front slightly above the left and right breast. It was connected to a pediatric face mask (Hans Rudolph, Inc., Kansas City, KS, USA) with a small tube of 60 cm length. Before each use, the calorimetry unit was calibrated with a 3-point calibration process according to the manufacturer's guidelines including ambient air pressure, gas and volume. The Meta Max 3B has been shown to provide reliable measurements with adequate validity for field-based measurements in young adults,[32] but does not appear to have been validated in children so far.

Measurement Protocol

Two children at a time came to the laboratory for 1 visit lasting 1 hour and were measured simultaneously. At the start, the children were instructed about the procedure of the visit. Weight and height were then measured in light clothing without shoes. Finally, each child was equipped with 1 ActiGraph GT3X, a mask and a Meta Max 3B calorimetry unit. All activities were carried out in the gym space of the laboratory with a size of 11 m × 6 m. To begin with, the participants completed 13 minutes of researcher paced walking or jogging at approximately 2 $km \cdot h^{-1}$, 4 $km \cdot h^{-1}$, 6 $km \cdot h^{-1}$, and 8 $km \cdot h^{-1}$ with 3 minutes and 15 seconds at each speed. For this activity, a researcher held a metronome and walked with a step frequency according to its beats. The beat frequency had been set according to treadmill tests to approximately reflect 2 $km \cdot h^{-1}$, 4 $km \cdot h^{-1}$, 6 $km \cdot h^{-1}$, and 8 $km \cdot h^{-1}$. The children were instructed to follow 1 step behind the researcher at all times. A break of at least 5 minutes followed to allow oxygen consumption values to recover to resting levels. The children then continued with free play, a soccer course around cones, a toy railway course and playing tag for 4 minutes and 15 seconds each with breaks of at least 4 minutes in between. During free play, the children could use a basketball, a skipping rope, and a hoop to play with or climb a ladder mounted to the wall. The soccer course was predetermined with cones to dribble around and a bench to take shots at. For the toy train activity, a box with trains and rail pieces was provided. Tag was played with both researchers and both children.

The activity protocol was designed to cover a scope of low to high intensity activities including locomotion as well as play activities reflecting common activities performed by 5- to 9-year-old children. The order of the activities was set with a tendency from lower to higher intensity activities.

Data Reduction

Data from the Meta Max 3B unit were downloaded with the Meta Soft Program Version 3.9.7 (Cortex, Leipzig, Germany), averaged over 5-second intervals and exported to Microsoft Office Excel 2007 (Microsoft Corporation, Redmond, WA, USA). For further statistical analysis, data were imported into SPSS, version 19 (IBM Corporation, Armonk, NY, USA).

To calculate mean energy expenditure for each activity, the first 2 minutes and the last 15 seconds of each activity measurement were discarded. For the remaining time, mean O_2 consumption and mean CO_2 production per 5 seconds were calculated and converted into energy expenditure in kcal using the equation proposed by Elia and Livesey.[33] According to the literature, an equilibration period of less than 2 minutes is sufficient for O_2 consumption and CO_2 production to reach a plateau, even for activities of an intermittent nature.[34–36] This was confirmed by O_2 and CO_2 diagrams plotted from the current activity data.

Accelerometer data in 5 second epochs were downloaded to an Excel file with the ActiLife Lifestyle Monitoring System Software Version 3.8.3 (ActiGraph, LLC, Pensacola, FL). These data were then integrated into the Excel file with the energy expenditure data. Mean accelerometer counts per epoch were calculated for the same time interval of activity as for the energy expenditure analysis. The vector magnitude integrating all 3 axes was calculated as follows: $VM = (x^2 + y^2 + z^2)^{0.5}$. The horizontal vector was calculated in the same way for the y- and z-axis [$HV = (y^2 + z^2)^{0.5}$]. Mean accelerometer and energy expenditure values for each child and each trial were then collated and imported into SPSS, yielding 256 cases (32 children × 8 activities).

As the conventional value of 3.5 $ml \cdot kg^{-1} \cdot min^{-1}$ oxygen consumption at rest in adults is not appropriate in children, the Schofield weight equation for 3- to 10-year-olds[37] was used to calculate resting energy expenditure. This equation was chosen on the basis of the recommendation by Rodriguez et al,[38] who compared the validity of 5 equations in a study with 116 children and adolescents. The Metabolic Equivalent (MET) value was determined by dividing mean total energy expenditure for each activity by resting energy expenditure.

Statistical Analysis

Development of the Regression Model. The study group was divided into 5 age groups. Two-thirds of the children from each age group were randomly chosen yielding a development sample of 21 children. The remaining 11 children served as the validation sample. To develop the energy expenditure prediction models, 8 activity measurements from 21 children were thus available for analysis, yielding 168 cases. Independence of the errors was verified through a scatter plot of the residuals and the Durbin-Watson statistic.[39]

Multiple linear regression analyses were performed in a forward stepwise manner with energy expenditure in MET as dependent variable. Based on the findings of previous literature, separate regression models were computed for the 4 locomotor activities and the 4 play activities.[5,13,14,21,29,30] This analysis yielded a power of >

.99 to detect statistical significance for an alpha level of 0.05 based on the assumption that an R^2 of at least 0.50 was to be expected.

Figure 1 shows the sequence of steps taken to determine the best model fit in a flowchart. The best model fit was defined as the one with the highest R^2 and the lowest standard error of estimate. Step one tested whether the vector magnitude counts or counts of the vertical axis and the horizontal vector entered separately should be used as the current evidence is inconclusive on this point.[19,40] Counts of the y- and z-axis were taken together as horizontal vector because the placement of the accelerometer differs between studies. In some studies it is placed over the hip facing the front, in others facing the side, which produces a different pattern of counts on the y-axis and z-axis. Furthermore, during the course of a study where children wear an accelerometer over several days, it may easily slip from the front to the side or even to the back and vice versa.

In a further step, 5 different model alternatives emerging from the current literature[19–21,40] were tested with vertical counts as the independent variable: linear, quadratic, cubic, power function and exponential. The best alternative, which was a cubic equation for both data sets (locomotor and play activities), was then chosen and the additional variables that had explained less than 5% of variance previously were added in a linear function to make up the final cubic 2-regression model (see Figure 1).

Validation of the Regression Model. For validation of the cubic 2-regression model, the energy expenditure predicted by the model was calculated for the 11 children (88 cases) who served as validation group. As skewness values and Q-Q plots (quantile-quantile plots) revealed that the data were not normally distributed even after logarithmic transformation, the Spearman correlation between the 2 variables was calculated to determine the association between predicted and measured energy

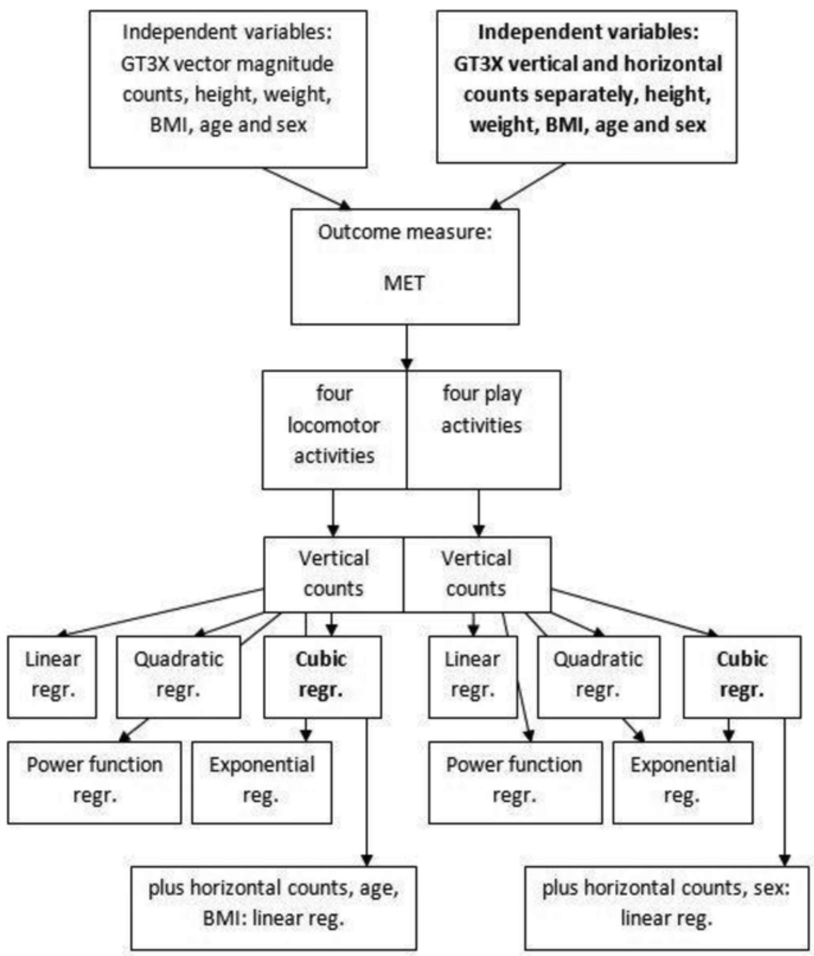

Figure 1 — Development of the regression model: Alternatives that produced the highest R^2 and lowest SEE are presented in bold letters and were chosen for the next step in developing the model, n = 168 cases.

expenditure. Bland-Altman plots were graphed to assess agreement.[41]

Furthermore, a linear 2-regression model (with separate equations for locomotor and play activities) and a linear 1-regression model (with the same equation for all activities) were also validated in the same manner for comparison.

Classification System

To be able to decide whether to use the regression equation for locomotor activity or the equation for play activity, a classification system to distinguish between the 2 categories is needed.

Box plots for 1 minute averages per activity were computed for vertical counts, horizontal vector, vector magnitude, steps, the sum of all 3 axes and the ratio of the vertical counts to the sum of all 3 axes. These plots revealed that horizontal counts and steps were the features with the least overlap between locomotor and play activities. Various alternatives for decision trees based on these 2 variables were then tested. Figure 2 shows the structure of the final decision tree and the thresholds used to classify activities at the decision points. These thresholds were found by testing various values with increasing increments of 1 horizontal count at a time and 0.1 steps at a time. The decision tree with the highest rate of correctly classified locomotor and play activities was then chosen.

Results

Study Population Characteristics

The data of 1 boy had to be discarded due to an equipment failure. Table 1 shows the characteristics of the remaining 20 boys and 12 girls. One child was overweight according to the international standard definition provided by Cole et al.[42]

Energy Expenditure and Accelerometer Count Values

Mean energy expenditure values in MET and mean count values for each accelerometer axis and steps per activity are shown in Figure 3.

Regression Model Fit. The multiple linear regression model with vertical and horizontal counts entered separately as independent variables provided a better fit for locomotor activities (R^2 = .822 and SEE = 0.450) and for play activities (R^2 = .639 and SEE = 1.048) than the model with vector magnitude as independent variable (locomotor activities: R^2 = .709, SEE = 0.569; play activities: R^2 = .582, SEE = 1.120). Vertical counts was the only variable that contributed more than 5% of explained variance to each model. No stratified analyses for age or sex were conducted because age and sex only explained a small percentage of variance in only 1 of the 2 models: age explained 2% of variance in energy expenditure for locomotor activities and sex 2% of the variance in energy expenditure for play activities. As seen in Table 2, a cubic regression for vertical counts provided a slightly better fit for locomotor as well as play activities than other linear and nonlinear equations.

Table 3 presents the final cubic 2-regression model with separate equations for locomotor and for play activities. It further shows the linear 2-regression model and the linear 1-regression model that were computed for comparison. Independence of errors was verified in these models.

Classification System. Horizontal counts and steps showed the best distinctive power between locomotor and play activities. The resulting decision tree for

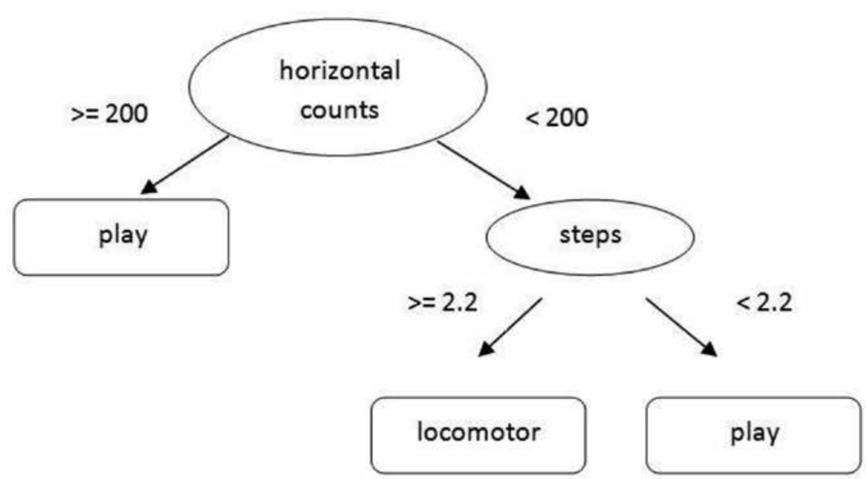

Figure 2 — Decision tree for classifying 1-minute averages.

Table 1 Study Population Characteristics

Variable	Mean (SD)	Range
Age (yrs)	7.55 (1.35)	5.14–9.23
Height (cm)	125.38 (11.97)	104–152
Weight (kg)	25.37 (6.76)	16.0–42.5
BMI (kg·m^{-2})	15.85 (1.67)	13.07–20.84

Note. n = 32 (20 boys, 12 girls).

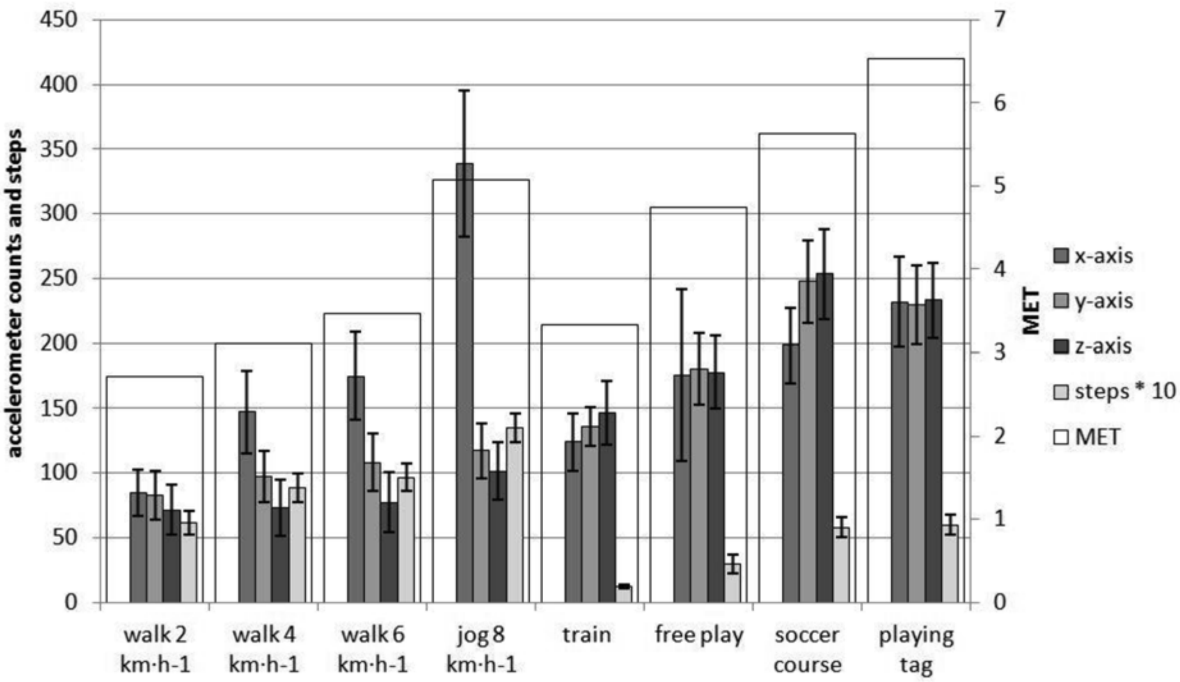

Figure 3 — Mean values and standard deviations per 5 seconds for the x-axis (vertical), y-axis (left-right), z-axis (back-front), and steps per activity; MET per activity are indicated with the large white column.

Table 2 R^2 and Standard Error of Estimate (SEE) for the Linear and Nonlinear Regression Models With Vertical Counts as the Independent Variable and Energy Expenditure as the Dependent Variable

	Locomotor activities		Play activities	
	R^2	SEE	R^2	SEE
Linear	.768	0.505	.575	1.123
Quadratic	.781	0.493	.670	0.995
Cubic	.799	0.477	.672	0.999
Power function	.587	0.173	.617	0.217
Exponential	.740	0.137	.537	0.239

Note. The independent variable for the power function and exponential model is ln (MET). Therefore, the SEE is not directly comparable to the SEE of the other models.

Table 3 Results of the Multiple Stepwise Regression Procedure for 3 Different Models With Energy Expenditure as Dependent Variable and Counts for Vertical Axis, Horizontal Vector as Well as Height, Weight, BMI, Sex, and Age as Independent Variables

	Activities	Predictors	R^2	SEE	Regression equation
Cubic 2-regression model	Locomotor activities	Vertical Horizontal Age BMI	.829	–	2.804 – 0.00000002346 × vertical counts^3 + 0.00002289 × vertical counts^2 + 0.002 × vertical counts – 0.003 × horizontal counts – 0.121 × age + 0.056 × BMI
	Play activities	Vertical Horizontal Sex	.685	–	1.904 – 0.00000001724 × vertical counts^3 + 0.000004669 × vertical counts^2 + 0.019 × vertical counts + 0.001 × horizontal counts – 0.398 × sex
Linear 2-regression model	Locomotor activities	Vertical Horizontal Age BMI	.822	0.450	2.370 + 0.008 × vertical counts – 0.004 × horizontal counts – 0.140 × age + 0.071 × BMI
	Play activities	Vertical Horizontal Sex	.639	1.048	2.282 + 0.010 × vertical counts + 0.004 × horizontal counts – 0.531 × sex
Linear 1-regression model	All activities	Vertical Horizontal	.644	.948	1.504 + 0.007 × vertical counts + 0.007 × horizontal counts

Note. n = 84 observations for locomotor activities and 84 observations for play activities, accelerometer counts per 5 seconds, age in years, BMI = kg/m^2, sex: 0 = girl, 1 = boy.

classifying activity trials based on these variables is shown in Figure 2.

Validation of Models. In the validation group, the decision tree was able to correctly classify 89% of locomotor activities and 100% of play activities. Strong significant correlations were seen between predicted and measured MET for all 3 algorithms. The Spearman rho was .83 for the cubic 2-regression model, .85 for the linear 2-regression model and .85 for the linear 1-regression model ($P < .001$ for all 3).

The Bland-Altman plots showed acceptable agreement between predicted and measured MET with a mean bias (predicted – measured MET) of 0.23 ± a standard deviation of 1.10 MET for the cubic 2-regression model. Agreement was good for the other 2 models with a mean bias of -0.17 ± 0.84 MET for the linear 2-regression model and –0.11 ± 0.86 MET for the linear 1-regression model (Figure 4). The 95% limits of agreement ranged from –1.97 to 2.43 MET for the cubic 2-regression model, from –1.85 to 1.52 MET for the linear 2-regression model and from –1.82 to 1.60 MET for the linear 1-regression model. For all 3 models the plots show slightly increasing biases with increasing MET values.

Discussion

The aim of the current study was to develop and validate energy expenditure equations for the GT3X accelerometer in 5- to 9-year-old children. The children performed 4 locomotor and 4 play activities that are typical for their age group. An energy expenditure algorithm involving separate cubic regression equations for locomotor activities and for play activities was developed on the basis of model fit (Figure 1 and Table 2). A clearly distinct pattern of vertical and horizontal acceleration counts between locomotor and play activities was seen (Figure 3). However, this did not lead to better validation results when separate regression equations were applied to locomotor and play activities. Furthermore, applying cubic regression equations did not provide more accurate predictions compared with linear equations (Figure 4).

In accordance with the existing literature on adults[2,7,22] and children,[5,12–14,29,30] the current results showed lower mean accelerometer counts for vertical acceleration in relation to energy expenditure values when play activities were compared with locomotor activities (Figure 3). For horizontal counts on the y- and z-axis the opposite was the case. Therefore, separate regression equations were developed for locomotion versus play activities as suggested by Crouter at al.[12,21] A simple decision tree with very promising classifying qualities to distinguish between locomotor and play activities on the basis of counts and steps measured by the GT3X was found (Figure 2). However, the validation showed that the energy expenditure prediction on the basis of 2 separate regression equations was not superior to the prediction based on 1 single equation for all activities (Figure 4).

In the development group, the R^2 for the cubic regression equation was 1% higher than for the linear

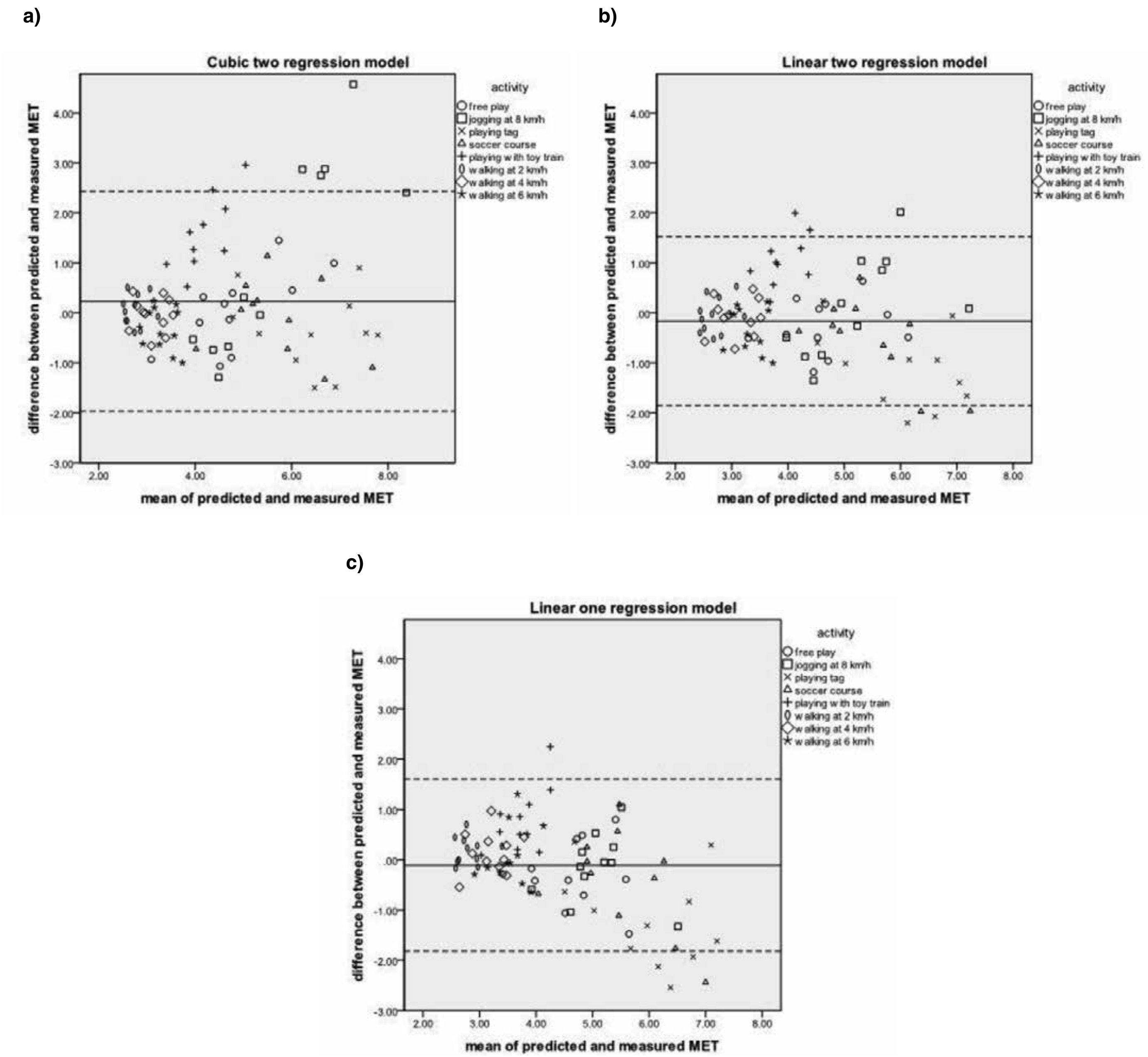

Figure 4 — Bland-Altman plots comparing observed and predicted energy expenditure in METs for a) the cubic 2-regression model, b) the linear 2-regression model, and c) the linear 1-regression model; n = 88 observations.

equation in locomotor activities and 5% higher in play activities (Table 2). However, this small advantage led to a disadvantage in terms of agreement between predicted and measured energy expenditure when the equations were applied to the validation group. Therefore, this study supports the findings by Tanaka et al[19] indicating that nonlinear approaches are not superior to linear approaches in estimating energy expenditure from triaxial counts. Chen and Sun,[40] on the other hand, found a better predictive accuracy for a power function model when validating the model with the same group on a different day. In the current validation on an independent group of children, the Bland-Altman plot for the cubic 2-regression model shows a small mean bias but wider limits of agreement than the linear regression models (Figure 4). No other studies that developed and validated linear versus nonlinear regression approaches appear to have been published so far.

With an R^2 of .64, the current 1-regression model explained a lower percentage of variance than 6 out of 8 other child studies that have developed regression models with other types of triaxial accelerometers so far (R^2 of .70–.95).[13–17,19] However, the current study included a greater variety of activities in the protocol than these 6 studies and examined a younger study group with the exception of Tanaka et al's group.[19] The variance explained in our cubic 2-regression model with an R^2 of .83 for locomotor activities and .69 for play activities (Table 3) is comparable to the results of the 6 studies. Nevertheless, it showed a poorer predictive validity for the independent validation group than the current linear regression models. The 6 previous studies did not provide a validation with an independent group of children and none of the studies were conducted with the ActiGraph GT3X.

The 2 child studies that did not show higher R^2 values than the current study both developed 2 distinct regression equations and provided a validation with an independent study group. Sun et al's[18] study involved 25 adolescents aged 12–14 years wearing the RT3 accelerometer. The indoor equation was developed on mostly continuous activities (sitting, writing, standing, sit-stand, stepping, stationary cycling and treadmill walking) and explained a variance of 90%. The outdoor equation was based on structured outdoor activities (3 minutes each: picking up tennis balls, passing basketballs, kicking soccer balls, shooting basketballs, walking relaxed, jogging lightly, and jogging fast) and yielded an R^2 of .58. The outdoor equation was validated on a separate group of 10 children performing the same activities. Their correlation of r = .78 between predicted and measured energy expenditure is slightly lower than the correlation coefficients for the current 3 algorithms (ρ = .83–.85).

The second study was the only one conducted with GT3X accelerometers. Crouter et al[12] developed a 2-regression model with 73 children aged 8–15 years. The first regression equation was based on locomotor activities (track walking and running at different speeds and walking with a backpack). With an R^2 of .39 the locomotor equation for vector magnitude counts explained a much lower percentage of variance than all previous models. The second equation was based on a range of different activities (sedentary activities, household chores, video games and sports activities) and yielded an R^2 of .59, which is comparable to the current R^2 for play activities. In their validation with 33 children performing the same activities, Crouter et al found a mean bias of 0.06 MET with 95% limits of agreement (–2.18 to 2.30 MET) that are comparable to the current ones for the cubic 2-regression model (–1.97 to 2.43 MET). However, limits of agreement were narrower for both linear regression algorithms in the current study (Figure 4). Crouter et al showed that their 2-regression model yielded a better predictive validity than previous 1-regression models. However, they did not develop a 1-regression model of their own for comparison with their 2-regression model. As in the current study, Crouter et al also found an increasing bias as the MET value increases.

The results of the current study may have been influenced by a few limitations. Firstly, mostly lean children took part in this study which may limit the applicability of the equations to a group of overweight children. Secondly, data points in our data set were not independent, as each child was measured for each of the 8 activities. However, this limitation did not lead to a violation of regression assumptions as the independence of errors was verified. Finally, the current study focuses on energy expenditure during light to vigorous activity excluding sedentary activities. Studies aiming to provide energy expenditure equations for various sedentary activities may need to include additional features such as inclinometer data in separate analyses. However, as Basset and colleagues[10] point out in their recent guideline on the calibration and validation of wearable monitors, no single study can address every aspect of a monitor's validity and the overall picture should be gained from multiple studies.

Strengths of the current study, on the other hand, include the fact that the protocol consisted of a range of typical child activities of continuous as well as intermittent nature. Furthermore, an advanced regression algorithm was developed on the basis of the current acceleration data and existing evidence. In addition, the algorithm was validated with an independent group of children including a comparison with simpler models. Lastly, this study is the first to the authors' knowledge that provides a validated regression model to translate GT3X accelerometer counts into energy expenditure in children as young as 5–9 years of age.

Conclusion

In this study with 5- to 9-year-old lean children who performed 4 locomotor and 4 play activities, a cubic 2-regression model with a good model fit and a simple yet promising classification system was developed and validated. The model showed a strong correlation and acceptable agreement between predicted and measured energy expenditure in the validation group. However, better agreement was seen for a linear 2-regression model with a similar model fit and a linear 1-regression model. We thus conclude that our linear 1-regression model (Table 3) can be used to translate accelerometer counts from the triaxial GT3X into energy expenditure in 5- to 9-year-old children.

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