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4 authors, including:

Mirko Brandes
Leibniz-Institute of Prevention Research and Epi…

Vincent T Van Hees
Netherlands eScience Center

Soren Brage
University of Cambridge

SPECIAL COMMUNICATIONS

Estimating Energy Expenditure from Raw Accelerometry in Three Types of Locomotion

MIRKO BRANDES[1], VINCENT T. VAN HEES[2], VIVIANE HANNÖVER[3], and SOREN BRAGE[2]

[1]Institute of Sports Science, University of Oldenburg, Oldenburg, GERMANY; [2]MRC Epidemiology Unit, Institute of Metabolic Science, Cambridge, England, UNITED KINGDOM; and [3]Institute of Sports Science, University of Bremen, Bremen, GERMANY

ABSTRACT

BRANDES, M., V. T. VAN HEES, V. HANNÖVER, and S. BRAGE. Estimating Energy Expenditure from Raw Accelerometry in Three Types of Locomotion. *Med. Sci. Sports Exerc.*, Vol. 44, No. 11, pp. 2235–2242, 2012. **Purpose**: Accuracy of estimating activity-related energy expenditure (AEE) from raw body acceleration may improve by using prediction equations that are specific for the type of activity. The current study aims to improve published equations by deriving an equation for overground walking and to evaluate whether overground cycling and stair walking require specific prediction equations. **Methods**: Participants (91 male/95 female, 8–81 yr old) were equipped with a triaxial accelerometer (DynaPort MiniMod; McRoberts BV, The Hague, The Netherlands) on their lower back. Total energy expenditure (TEE) was measured using a mobile oxygen analyzer (MetaMax 3b; Cortex Biophysik, Leipzig, Germany). Resting energy expenditure (REE) was measured for 30 min, following which a physical activity course was completed involving walking on level ground at slow (8 min), normal (8 min), and fast speed (3 min), stair walking (3 min), and cycling (8 min). AEE was calculated as TEE − REE, expressed in both absolute (kJ·min^{-1}) and relative (J·min^{-1}·kg^{-1}) units. Mixed linear regression analysis was used for developing regression equations for walking, stair walking, and cycling. **Results**: Acceleration contributed 76% and 93% ($P < 0.001$) to explained variance in walking AEE for absolute and relative AEE models, respectively. Age and gender improved estimation accuracy by <1%. Applying a conservative walking equation, AEE (J·min^{-1}·kg^{-1}) = -40.19 + 816.11 acceleration (*g*) (root-mean-square error = 34.00 J·min^{-1}·kg^{-1}), to cycling and stair walking resulted in mean bias (95% limits of agreement) of -253 (-449, 46) and -276 (-442, 109) J·min^{-1}·kg^{-1}, respectively (approximately 50% bias). Acceleration added 35% and 42% to explained variance in relative AEE (J·min^{-1}·kg^{-1}) during cycling and stair walking, respectively; this fraction was approximately 20% for absolute AEE (kJ·min^{-1}) in both activities. **Conclusion**: AEE during walking can be predicted across a wide age range using raw acceleration, but activity-specific equations are needed for cycling and stair walking. **Key Words:** OXYGEN CONSUMPTION, ACCELERATION, WALKING, BICYCLING, STAIR WALKING

Physical activity (PA) is believed to play an important role in the prevention of cardiovascular disease, weight gain, obesity, Type II diabetes, and skeletal and mental health problems similarly in children, adolescents, and adults (1,3,13,15). Although subjective and complex phenomena such as mental health or eating habits are usually evaluated using self- or proxy-report measures, various instruments such as pedometers, accelerometers, and global positioning systems are available to measure PA objectively (18,20–22).

Currently, accelerometers are the most commonly used objective tools for the assessment of PA (17). It is broadly agreed that accelerometers allow for an unobtrusive, cost-effective, and reliable estimation of PA-related energy expenditure (AEE) (17). Most of the published methods for estimating AEE from accelerometer output use the magnitude of acceleration as input parameter, sometimes combined with basic participant characteristics such as age, gender, and body weight. Various studies have shown that high-resolution accelerometry can also be used to estimate the types of PA (12,14). It has recently been shown that the estimation of energy expenditure can be improved under sedentary conditions when activity type–specific prediction equations are used for lying, sitting, standing, and walking (24). The main limitations of that study were as follows: 1) The walking equation was developed from a walking experiment on a treadmill, which may not be representative for walking on level ground. 2) The study was based on a small group of young adult female participants. 3) The model as reported did not include specific prediction equations for overground cycling and stair walking, and as a consequence, the prediction equation for walking would have to be used in all types of locomotion. Previous research indicates that count-based accelerometer models underestimate AEE during ergometer cycling (8,11,29), but it is unclear if this would also hold true for raw accelerometry models

Address for correspondence: Mirko Brandes, Ph.D., Institute of Sports Science, University of Oldenburg, Ammerländer Heerstraβe 114-118, 26129 Oldenburg, Germany; E-mail: mirko.brandes@uni-oldenburg.de.
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derived during overground walking and applied to overground bicycling and stair walking.

The present study aims to improve the published prediction model for AEE that uses raw accelerometer data in SI units (g) and activity type as its input, by taking the limitations as listed previously into account and confirming whether or not there is a need for specific prediction equations for overground cycling and stair walking. If activity-specific prediction equation is found to be needed, it is important to recognize that accurate and precise estimation of energy expenditure will then require accurate activity type identification, either by automatic detection from the accelerometry data or by other direct/indirect assessment tools. The latter is not part of the current investigation.

METHODS

Participants. One hundred eighty-six participants were recruited by newspaper announcements and telephone calls. Before given written informed consent, the participants were carefully informed about and familiarized with the procedures of the study, which was approved by the local ethics committee. Inclusion criteria were a body mass index of 27.5 $kg \cdot m^{-2}$ or lower and at least 6 yr of age. Participants were excluded if they had any impairment related to the PAs tested metabolic disorders (e.g., hypothyroidism and diabetes) or any disorders of the cardiovascular system.

Study design. The participants were fasted for at least 3 h but were allowed to drink water. Anthropometric data of the participants were measured in the laboratory at the beginning of the procedures (Table 1). Afterward, participants were equipped with an accelerometer (DynaPort MiniMod; McRoberts BV, The Hague, The Netherlands) on their lower back and a mobile oxygen analyzer as described in the latter part of this article. Resting energy expenditure (REE) was measured in lying posture for 30 min in a temperature-controlled room at 21.9°C. A blanket was provided if the participant felt cold. Finally, participants were asked to complete a PA course. In total, 2.5 h was allocated for the measurements of one subject. Throughout the study, the participants were allowed to wear their own clothing and shoes.

PA course. The course was placed in a restricted area at the open space of the University of Bremen (Bremen, Germany), providing sufficient space for conducting the activities in a regular manner. After a measurement of sitting (8 min) and standing (8 min), the participants were asked to ride a bicycle at their regular pace for 8 min. Different city bikes for adults and children were available and adjusted to participants' satisfaction. Afterward, the participants were asked to walk for 8 min on a walkway around the area at their preferred speed. Subsequently, participants were requested to walk 8 min at a slower speed ("you have plenty of time, watch the scenery") and 3 min at a faster speed ("you want to catch a bus, but do not run"). Finally, the participants repetitively ascended and descended a flight of 22 steps (step height = 0.17 m) for 3 min. Participants younger than 18 yr were only asked to walk at regular and fast speed. All tasks were separated by a break of at least 2 min. The beginning and the end of each task was indicated by setting markers in the oxygen analyzer and accelerometer. Data obtained from minutes 5:00 to 8:00 during sitting, standing, bicycling, and normal and slow walking were extracted for analysis. For fast walking and stair walking, data from minutes 2:00 to 3:00 were considered for further analysis. All included periods fulfilled the criteria of steady state defined as rate of change in oxygen consumption (mL $O_2 \cdot min^{-2}$) being less than 10% of the average oxygen consumption (mL $O_2 \cdot min^{-1}$) for a given period. Acceleration recordings of less than 0.05g in walking, stair walking, or cycling were regarded as outliers and excluded from analysis.

Physiological measures. In both the resting test and the PA course, oxygen consumption and carbon dioxide production were measured using a mobile gas analyzer (MetaMax 3b; Cortex Biophysik, Leipzig, Germany). The analyzer was warmed up and calibrated according to the manufacturer instructions before each measurement. During the PA course, the participants wore the mobile gas analyzer in a neoprene belt around their neck, by which the operating units (telemetry, gas analyzer) were placed on the frontal upper body Supplemental Digital Content, http://links.lww.com/MSS/A170). The total weight of the gas analyzer including batteries did not exceed 850 g. Gas analyses were carried out breath by breath, smoothed with a three-breath rolling median, and converted to REE in kilojoules per minute using Weir's equation (27). REE was defined as the lowest 5-min rolling average during the supine rest. Finally, AEE for the activity

TABLE 1. Participant characteristics.

Age Group	6–11 yr	12–17 yr	18–54 yr	≥55 yr
N (female/male)	31 (14/17)	26 (10/16)	75 (40/35)	53 (31/23)
Age (yr)	9.3 ± 0.6	14.9 ± 1.2	33.6 ± 11.4	63.6 ± 5.5
Weight (kg)	34.6 ± 6.3	63.3 ± 10.8	71.5 ± 11.6	69.9 ± 10.2
Height (cm)	142.1 ± 5.6	173.9 ± 10.5	174.4 ± 9.4	169.9 ± 7.7
BMI ($kg \cdot m^{-2}$)	17.1 ± 2.4	20.8 ± 2.7	23.5 ± 2.8	24.2 ± 2.6
REE ($kJ \cdot min^{-1}$)	4.8 ± 0.8	5.7 ± 1.0	5.3 ± 1.0	4.7 ± 1.0
TEE sitting ($kJ \cdot min^{-1}$)	4.9 ± 0.7	6.8 ± 1.1	6.1 ± 1.1	5.7 ± 1.1
TEE standing ($kJ \cdot min^{-1}$)	NA	8.9 ± 1.6	7.3 ± 1.9	7.0 ± 1.5

Values are presented as mean ± SD.
BMI, body mass index; NA, not applicable.

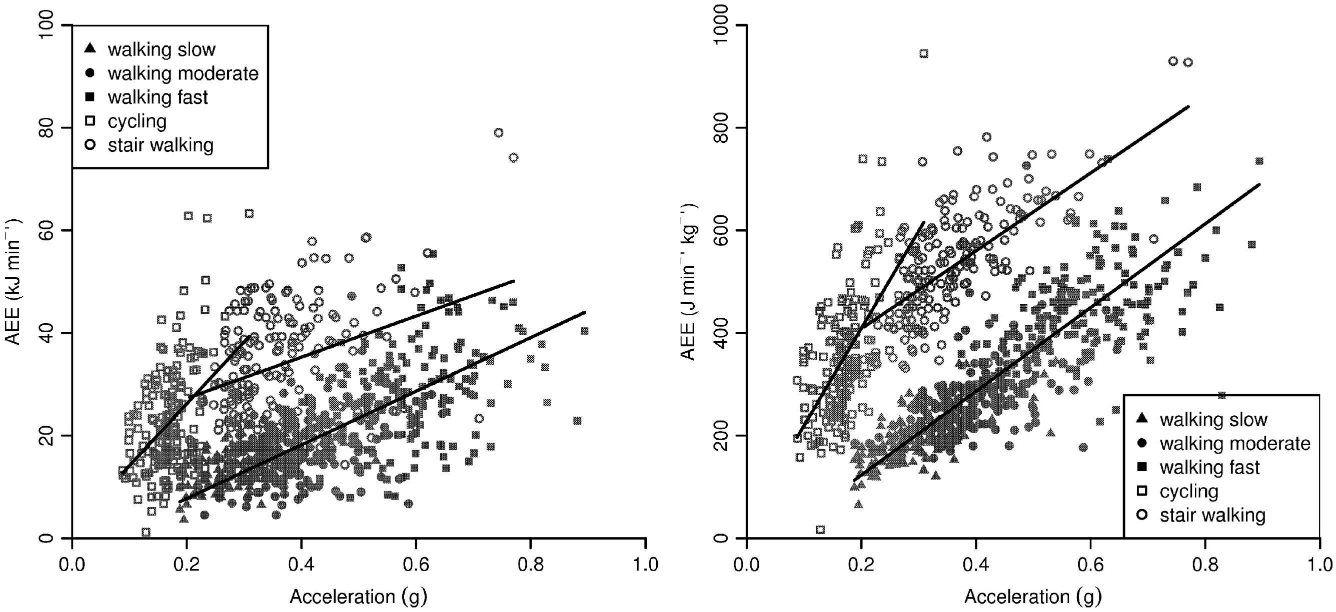

FIGURE 1—AEE in kilojoules per minute (left panel) and in joules per minute per kilogram (right panel) as a function of acceleration for three walking speeds, cycling, and stair walking. Straight lines indicates regression lines within each activity.

course was calculated from REE and total energy expenditure (TEE) as AEE = TEE − REE. AEE was then expressed in both kilojoules per minute and in joules per minute per kilogram.

Accelerometer. The acceleration sensor (DynaPort) contains three orthogonally mounted acceleration sensors collecting data at 100 Hz. The dimensions of the sensor including two batteries (AAA, 1.5 V) are 70 × 62 × 15 mm, and the weight is 78 g. Data are stored on a secure digital card and downloaded to a PC. The sensor was attached on the participants' skin over the lower lumbar spine, close to the sacrum, using double-sided adhesive tape. Further information on technical aspects and signal processing has been described elsewhere (23,24). Acceleration was summarized by applying a fourth-order band-pass frequency filter to each acceleration axis (ω_0 = 0.1–15 Hz), following which the vector magnitude was calculated as $\sqrt{a_x^2 + a_y^2 + a_s^2}$.

Statistical analysis. Mixed linear regression analysis was used to develop a prediction equation for AEE in walking. A mixed linear regression analysis takes into account the dependence of data points obtained from the same individual on the three walking speeds. The following variables were evaluated with respect to their contribution: acceleration, body weight, gender, and age, including interaction effects. Leave-one-out cross-validation was used to estimate the robustness of the model for application outside the training data set (25). Walking models were cross-validated in cycling and stair walking using agreement analysis (4); mean bias was tested using a paired sample *t*-test. Activity type–specific regression models for stair walking and for cycling were derived using linear regression analysis with same set of predictor variables as for walking models. All statistical analyses were carried out in the open-source tool R (http://www.r-project.org); specifically, the nlme package was used for mixed linear regression. An alpha level of $P < 0.05$ was regarded as statistically significant.

RESULTS

Resting measures. Sitting and standing energy expenditures were on average 15% and 48% higher than supine rest, respectively (Table 1). Supine REE was significantly ($P <$ 0.05) higher than predicted values (10). Median (95% reference range) nongravity acceleration during sitting was

TABLE 2. Activity energy expenditure by activity type and participants' age.

Age Category	6–12 yr	12–17 yr	18–54 yr	≥55 yr
AEE slow walking (kJ·min^{-1})	NA	NA	12.9 ± 4.0	14.8 ± 3.6
AEE regular walking (kJ·min^{-1})	9.3 ± 2.5	18.1 ± 7.1	18.1 ± 5.4	20.3 ± 5.2
AEE fast walking (kJ·min^{-1})	14.9 ± 4.7	26.0 ± 5.4	32.5 ± 7.9	29.0 ± 8.0
AEE stair walking (kJ·min^{-1})	20.4 ± 4.0	34.9 ± 9.7	38.2 ± 10.9	35.4 ± 10.6
AEE cycling (kJ·min^{-1})	11.9. ± 3.4	20.2 ± 7.0	25.7 ± 11.4	25.3 ± 9.2

Values are presented as mean ± SD.

measured at 0.004g (0.002g–0.015g), and this was 0.015g (0.005g–0.035g) for standing.

Walking. Mean velocities for slow, regular, and fast walking were 1.3 ± 0.2, 1.5 ± 0.2, and 1.9 ± 0.3 $m{\cdot}s^{-1}$, respectively. Observed AEE is given in Table 2 and shown graphically against acceleration in Figure 1. For all participants, AEE averaged 13.7 ± 3.8 $kJ{\cdot}min^{-1}$ for slow walking, 17.3 ± 6.4 $kJ{\cdot}min^{-1}$ for walking with regular pace, and 27.6 ± 9.4 $kJ{\cdot}min^{-1}$ for fast walking.

Table 3 provides an overview of evaluated models for walking AEE. Acceleration, body weight, and their interaction explained 95% of the variation in absolute AEE ($kJ{\cdot}min^{-1}$), with acceleration terms contributing an additional 76% to the 19% explained by body weight alone. The interaction between acceleration and body weight was highly significant (P < 0.001), so the model containing this term was used as the basis for evaluating the additional contribution of gender and age; this was significant for gender as a mediator however very small, but not for gender as an interaction term. There was no significant contribution of age as a mediator, but there was a significant contribution for age as an interaction term. In the leave-one-out cross-validation, the simple model with acceleration, body weight, and their interaction explained 56% of the variance in absolute AEE (95% limits of agreement, −12.5; 12.9 $kJ{\cdot}min^{-1}$).

For relative AEE ($J{\cdot}min^{-1}{\cdot}kg^{-1}$), acceleration alone explained 93% of the variation, which decreased to 70% in the leave-one-out cross-validation (95% limits of agreement, −133; 139 $J{\cdot}min^{-1}{\cdot}kg^{-1}$). Identical with absolute AEE gender and age contributed marginally to the explained variance (Table 3). The regression coefficients for the models based on acceleration and body weight are shown in Table 4. Bland–Altman plots for the cross-validation are shown in Figure 2.

Stair walking and cycling. Participants ascended/descended stairs with an average step frequency of 109.8 ± 8.6 (range, 82.6–136.8) steps per minute and cycled with an average velocity of 4.7 ± 0.9 $m{\cdot}s^{-1}$. AEE averaged 33.9 ± 11.5 $kJ{\cdot}min^{-1}$ in stair walking and 22.5 ± 10.5 $kJ{\cdot}min^{-1}$ during bicycling (Table 2). Data from three participants were excluded because of procedural error; in each case, acceleration in either cycling or stair walking was below 0.05g.

When walking equations were applied to overground bicycling and stair walking, mean biases (95% limits of agreement) were −16.4 (−33.1, 0.3) $kJ{\cdot}min^{-1}$ (P < 0.001) and −17.6 (−31.9, −3.4) $kJ{\cdot}min^{-1}$ (P < 0.001), respectively (Fig. 2). This equates to about −73% bias in cycling and −50% in stair walking activities for absolute AEE. Performing the same cross-validation for relative AEE yielded biases of −253 (−449, −46) $J{\cdot}min^{-1}{\cdot}kg^{-1}$ (P < 0.001) for cycling and −276 (−442, −109) $J{\cdot}min^{-1}{\cdot}kg^{-1}$ (P < 0.001) for stair walking, corresponding to −72% and −52%, respectively. Consequently, regression equations were derived for cycling and stair walking (Table 3). Acceleration contributed significantly to the explained variances in cycling and stair walking AEE, 35% and 42%, respectively, when AEE was expressed relative to body weight, and 21% and 18% for absolute AEE, in addition to the contribution from body weight alone. In both activities, age and gender terms made significant contributions to the models, although the improvements in accuracy were small, for example, reductions in SEs for both cycling and stair walking AEE of 0.23 $kJ{\cdot}min^{-1}$ (<5%). In the leave-one-out cross-validation analysis, the more conservative models based on only acceleration and body weight information (Table 4) explained 32% and 41% of the variance in relative cycling and stair walking AEE, and the corresponding values for absolute AEE being 57% and 76%, respectively.

DISCUSSION

This study developed a prediction equation for predicting energy expenditure from raw accelerometry of the lower back in walking on level ground. Furthermore, we analyzed whether the predicted energy expenditure is applicable also for stair walking and bicycling. In contrast to previous studies investigating less heterogeneous samples with

TABLE 3. Overview of models for predicting AEE during walking, cycling, and stair walking.

		Walking[1]		Cycling[2]		Stair Walking[2]	
Dependent	Independent	r^2	RMSE	r^2	RMSE	r^2	RMSE
AEE ($kJ{\cdot}min^{-1}$)	Weight[a]	0.188	8.37	0.36	8.36	0.57	7.58
	Weight[a] + Acc[a]	0.934	2.39	0.57	6.90	0.75	5.80
	Weight + Acc + weight × Acc[a]	0.946	2.16	0.59	6.67	0.77	5.57
	Weight + Acc + weight × Acc[a] + gender[a]	0.947	2.15	0.61	6.48	0.79	5.31
	Weight + Acc[s] + weight × Acc[a] + gender + gender × Acc	0.947	2.15	0.62	6.44	0.79	5.30
	Weight + Acc + weight × Acc[a] + age	0.946	2.16	0.60	6.67	0.77	5.57
	Weight[s] + Acc + weight × Acc[s,w] + age[c,s] + age × Acc[c,s]	0.947	2.15	0.61	6.51	0.78	5.45
AEE ($J{\cdot}min^{-1}{\cdot}kg^{-1}$)	Acc[a]	0.927	34.00	0.35	97.22	0.42	84.36
	Acc[a] + gender[a]	0.928	33.76	0.39	94.27	0.45	82.40
	Acc[a] + gender[w] + gender × Acc	0.928	33.74	0.40	93.58	0.45	82.18
	Acc[a] + age	0.927	34.00	0.35	97.15	0.43	84.19
	Acc[a] + age[c,s] + age × Acc[c, s]	0.927	33.97	0.39	93.80	0.46	81.65

All models were significant at the P < 0.01 level. Significance (P < 0.05) indicated for individual terms in models is as follows: a, all types of locomotion (walking, cycling, and stair walking); w, walking; c, cycling; s, stair walking.

[1] Based on 507 observations (186, 136, and 185 observations at normal, slow, and fast speed, respectively).

[2] Based on 179 observations.

RMSE, root-mean-square error; Acc, acceleration.

TABLE 4. Regression coefficients for selected models of walking, cycling, and stair walking AEE.

Dependent	Independent	Walking			Cycling			Stair walking		
		Coefficients (95% CI)	SE	*P* value	Coefficients (95% CI)	SE	*P* value	Coefficients (95% CI)	SE	*P* value
AEE (kJ·min^{-1})	Intercept	−18.61 (−21.02 to −16.20)	1.23	<0.001	−23.44 (−29.59 to −16.4)	3.14	<0.001	−20.20 (−25.17 to −15.21)	2.54	<0.001
	Weight (kg)	0.24 (0.20 to 0.28)	0.02	<0.001	0.39 (0.33 to 0.45)	0.03	<0.001	0.55 (0.49 to 0.61)	0.03	<0.001
	Acc (*g*)	53.97 (51.60 to 56.34)	1.21	<0.001	125.91 (98.94 to 152.88)	13.76	<0.001	51.55 (42.57 to 60.53)	4.58	<0.001
AEE (kJ·min^{-1})	Intercept	−3.24 (−6.98 to 0.50)	1.91	0.09	10.50 (−9.04 to 30.04)	9.97	0.29	6.52 (−7.75 to 20.79)	7.28	0.37
	Weight (kg)	0.01 (−0.05 to 0.07)	0.03	0.76	−0.15 (−0.44 to 0.14)	0.15	0.33	0.15 (−0.07 to 0.37)	0.11	0.17
	Acc (*g*)	8.97 (−0.28 to 18.22)	4.72	0.06	−65.95 (−174.32 to 42.42)	55.29	0.23	−15.21 (−49.90 to 19.48)	17.70	0.39
	Weight (kg) × Acc (*g*)	0.68 (0.54 to 0.82)	0.07	<0.001	3.02 (1.35 to 4.69)	0.85	<0.001	1.02 (0.51 to 1.53)	0.26	<0.001
AEE (J·min^{-1}·kg^{-1})	Intercept	−40.19 (−52.75 to −27.63)	6.41	<0.001	29.83 (−35.87 to 95.53)	33.52	0.38	256.17 (207.2 to 305.2)	24.99	<0.001
	Acc (*g*)	816.11 (783.0 to 849.2)	16.88	<0.001	1895.23 (1516.7 to 2273.8)	193.12	<0.001	759.25 (629.9 to 888.6)	66.01	<0.001

Acc, acceleration; CI, confidence interval.

respect to age and sex (11,19,26,29), this is the first study developing prediction equations for energy expenditure from raw accelerometry for walking, bicycling, and stair walking in a large number of male and female participants with a broad range of age.

An important finding of the present study was how little age and gender contribute to acceleration-based prediction models for AEE, when examined in a large and sufficiently diverse sample. This was evident, regardless how AEE was expressed. Compared with a previous study that used a treadmill for deriving the prediction equation for walking, the explained variation in AEE by magnitude of acceleration was higher in the present study, and the slope and the 95% confidence interval of the predicted AEE with respect to acceleration magnitude was slightly lower in the current data set at 831 (796–866) J·min^{-1}·kg^{-1} per 1*g* versus 987 (831–1143) J·min^{-1}·kg^{-1} per 1*g* (24). Three parameters may account for the slight differences in the slope of the regression line: the study sample, the experimental setting, and the method of fixation of the device. Given the larger number of participants measured in the present study, the applied method is relatively stable if the participants walk under controlled conditions outside a laboratory. Furthermore, a larger sample allows for a more accurate estimation of model coefficients as reflected by the narrower confidence interval. Furthermore, it is suggested that the use of adhesive tape for fixation of the device directly to the skin at the lower trunk allows for a more direct transition of body acceleration to the acceleration sensors of the device. Potentially, using a neoprene belt could result in cushioning of body movement and body acceleration if the neoprene is compressed or extended by the body movement.

Applying the prediction equations derived from overground walking to the activities “overground cycling” and “stair walking” resulted in significant underestimation of AEE. These findings are in line with the results of a previous study published by Calabró et al. (7) who reported cycling to be the only activity showing significant differences in AEE between stationary cycling (on ergometer) and various activities, for example, treadmill walking. Arvidsson et al. (2) validated three different activity monitors with respect to their ability to accurately assess energy cost of different activities. It was reported that none of the activity monitors were able to satisfactorily assess energy cost of stationary cycling, and only one device was able to accurately assess the energy cost of stair walking. However, it should be noted that translating findings from studies using stationary cycling (8,29) to overground bicycling is somewhat questionable because of the negligible acceleration along the anterior–posterior and contralateral axes when cycling on ergometer. Nonetheless, our study demonstrates that the inaccuracy of estimating AEE with prediction equations derived from walking is also evident in overground cycling, even though additional acceleration along the aforementioned axes is included in the predictor variable. Hence, there is a need to apply activity-specific prediction equations including

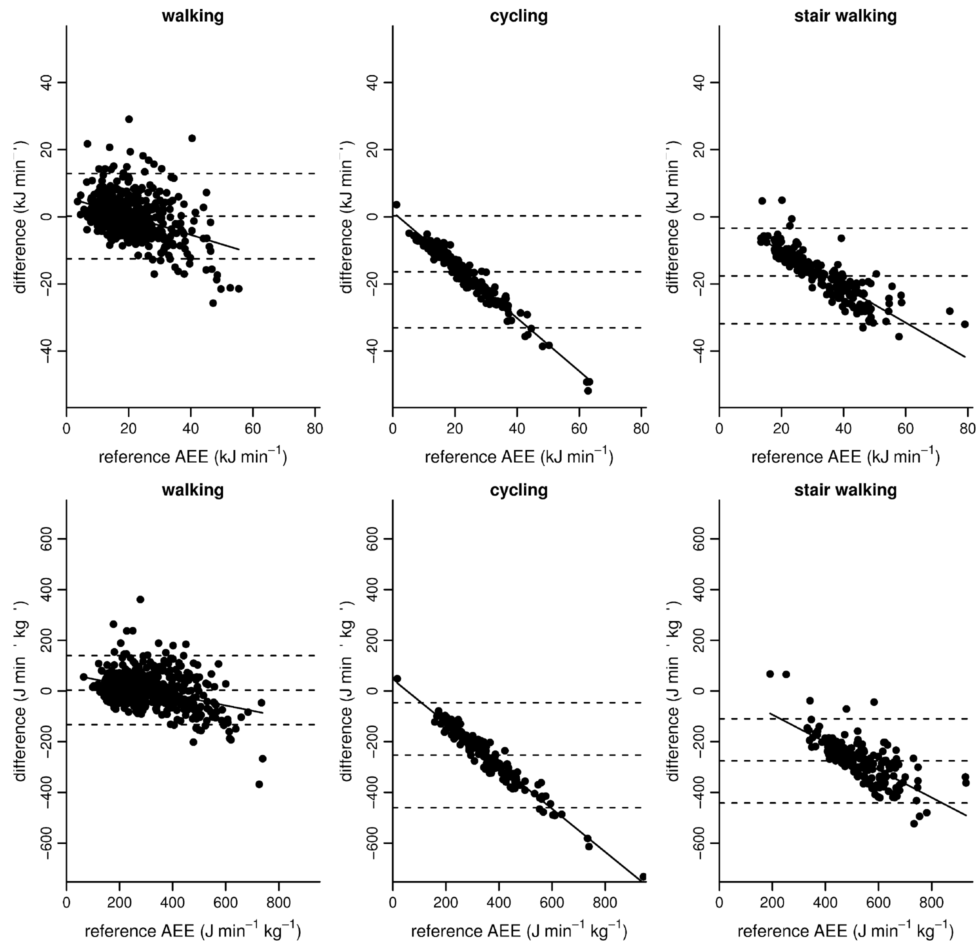

FIGURE 2—Modified Bland and Altman plots for walking-based model estimations of AEE in kilojoules per minute (*top row*) and joules per minute per kilogram (*bottom row*). Lines represent dynamic bias (*solid*), mean bias, and 95% limits of agreement (*broken lines*). All error trends are significant (P < 0.001).

the activities cycling and stair walking from a biomechanical point of view, but this is also relevant in health research, because the amount of cycling in daily life has been reported to be different, for example, for obese and nonobese adolescents (16). Furthermore, Bonomi et al. (6) found out that 60% of the variation of Dutch participants' PA level, calculated as TEE divided by sleeping metabolic rate, could be explained by the duration of cycling. Therefore, reducing the error in estimating AEE induced by cycling is important for assessment of total PA within populations with higher prevalence of cycling. Within the same context, encouraging subjects to use stairs as an alternative to escalators or elevators has been reported to be a cost-effective intervention for increasing AEE in daily life (28). Consequently, there is a need to automatically detect these types of activities in the analysis of raw acceleration signals at the lower back and to implement specific equations allowing for an accurate estimation of AEE during cycling and stair walking.

The developed models for predicting AEE, regardless if expressed in absolute or relative units, demonstrate that the explained variance of AEE by accelerometry is smaller in stair walking and cycling compared with level walking. For example, 93% of the variation in AEE ($J \cdot min^{-1} \cdot kg^{-1}$) is explained by acceleration during level walking, but only 39% and 28% of the variation in AEE ($J \cdot min^{-1} \cdot kg^{-1}$) is explained by acceleration in stair walking and bicycling, respectively. Data volume was less for cycling and stair walking in this study because we did not induce within-individual variance in these activities but relied solely on between-individual variance for examining the relationship with acceleration. However, the observed range of AEE was still reasonably high in these activities, and similar to that of walking, suggesting that the explanation for the observed differences is likely to be mainly biological. For stair walking, the increased metabolic demands are not indicated in the acceleration signals, which are similar to those observed during level walking. The center of mass has to be elevated during ascending and lowered during descending by the skeletal muscles to a larger extent compared with level walking. Although it is metabolically less costly to descend stairs, this does not compensate for the increased cost of ascending stairs because the center of mass has to be decelerated against gravity while descending. The unique style and rate by which individuals ascend and descend stairs are very likely explanations for the higher interindividual variability of the acceleration–AEE relationship during stair walking compared with level walking. In bicycling, the center of mass is supported by the seat, and no whole-body lift work is involved, only the movement of the legs that a waist-worn accelerometer does not directly measure. Thus, mainly horizontal accelerations (fluctuations in two-dimensional speed including changes in direction) contribute to our model for predicting AEE.

With the intention to create robust prediction equations, we suggest to use the prediction equation based solely on acceleration if AEE expressed as joules per minute per kilogram is aimed. This would result in losing 0.1% of explained variance during walking and 5% and 6% of explained variance in cycling and stair walking, respectively. If AEE expressed as kilojoules per minute is desired, the interaction term of weight and acceleration was significant in all activities, again with age and gender adding very little beyond this basic model. Thus, a pragmatic recommendation is to use this model when predicting AEE as kilojoules per minute. Irrespective of model type, it is recommended to implement safeguards against nonplausible AEE values when extrapolating beyond the ranges of acceleration and body weight observed in the present study, in particular, at very low levels of accelerations (9). It should also be noted that AEE predictions of very light intensity activities would be relatively more influenced by the definition of the resting state, which in this study is higher than basal metabolic rate.

In this study, we included only nonobese, healthy participants. Therefore, the current findings may not generalize to obese people and certain patient groups. We used a standard band-pass filter for initial processing of the raw acceleration signals, from which we calculated vector magnitude, but this is by no means the only way to do this. Furthermore, derived models must be combined with an appropriate activity classification scheme, for example, as suggested by Bonomi and Plasqui (5). To this end, it should be noted that the reported accuracy of the prediction equations is dependent on accurate activity type classification; this is hardly ever true during free living and so the prediction accuracy during these circumstances is likely to be substantially less when activity types are misclassified.

CONCLUSION

Estimation of AEE from raw acceleration signals measured at the lower back can be successfully achieved in walking with only acceleration and body weight parameters in the model, but the regression equation derived from walking significantly underestimates AEE for cycling and stair walking. These activities require specific prediction equations, but even so, one must accept that acceleration-based estimation accuracy of AEE is lower. Future studies are needed to combine these models with appropriate activity classification models and evaluate such complete inference schemes under free-living conditions using the doubly labeled water method as a reference.

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