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Validation of algorithms for energy expenditure evaluation in children using raw acceleration data.

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ABSTRACT

Backround: The relation between energy expenditure (EE) in childhood physical activity and childhood or later adult health status is not clearly established. Thus, a better understanding of relation between energy expenditure and health in children are needed. An accessible approach for estimation of energy expenditure is important and may be established by using acceleration data. **Aim:** Determine the accuracy of Brandes´ linear regression equation for estimation of EE when applied to children (7-15 years old) using raw acceleration data. Furthermore, stepwise regression equations will be developed to improve accuracy of estimating EE from children acceleration data. **Method**: A cross-sectional study examining 42 children (20 girls and 22 boys; 7-15 years) wearing two accelerometers (to the lower back and thigh) and a portable indirect calorimetry as reference measure for total EE estimation was performed. The children performed several physical activities including walking with different speed, jogging and running. The accuracy of an existing data model (1) for evaluation of EE was tested. Further, stepwise regression analysis was used for developing new regression equations based on walking activities ($NTNU_{walking}$), vigorous activities ($NTNU_{vigorous}$) and all activities combined ($NTNU_{all\ int.}$). The accuracy of the different equations was assessed using correlation, coefficient of determination and Bland-Altman plots. Further, Bland-Altman plots is presented as mean bias and limits of agreement (LoA). EE is presented both as an absolute measure (kJ/min) and relative to body mass (J/kg/min). **Results:** The smallest difference between measured and estimated EE using Brandes et al.´s equation was found when walking moderately both for absolute (mean bias -0.78 and 95% LoA -9.80 to 8.24) and relative measures (mean bias -57.24 and 95% LoA -213.92 to 99.44). Further, $NTNU_{walking}$ presented a greater accuracy for walking activities compared to Brandes et al.´s equation (absolute units: mean bias 0.24 and 95% LoA -3.23 to3.72. Relative units: mean bias 18.06 and 95% LoA -43.71 to 79.84). In addition to $NTNU_{walking}$, $NTNU_{all\ int.}$ presented the greatest accuracy for jogging and running when absolute values for EE were used ($NTNU_{walking}$: mean bias -1.23 and 95% LoA -12.88 to 10.40. $NTNU_{all\ int.}$: mean bias 1.22 and 95% LoA -9.29 to 11.75). **Conclusion**: Brandes´ equations estimated EE in children most accurately for absolute values when walking moderately. However, newly developed equations were more accurate for both walking and vigorous intensities, supporting child-specific regression equations for estimating EE in children. The above equations worked reasonably well for estimating group estimates. However, further adaptations are needed to enhance accurate individual EE estimation.

SAMMENDRAG

Bakgrunn: Sammenhengen mellom energiforbruk (EE) under fysisk aktivitet hos barn og barnehelse eller senere helse i voksenlivet er uklar. En bedre forståelse av forholdet mellom EE og barnehelse en derfor nødvendig. For å estimere energiforbruk ønskes det en tilgjengelig og lett håndterlig metode. En mulighet er derfor å bruke akselerometer som måler akselerasjon. **Problemstilling:** Se på nøyaktigheten av Brandes regresjonslikning for å estimere EE hos barn (7-15 år) der det brukes råakselerasjonsdata. I tillegg vil det lages nye regresjonslikninger for å se om de kan estimere energiforbruk mer nøyaktig. **Metode**: Dette er en tverrsnittstudie basert på 42 barn (20 jenter og 22 gutter; 7-15 år) som hadde på seg akselerometer (på nedre rygg og lår) og et bærbart indirekte kalorimetriutstyr som referanse for måling av totalt energiforbruk. Barna gjennomførte ulike fysiske aktiviteter som jogge, løpe, gå sakte, normalt og fort. Nøyaktigheten av en allerede eksisterende datamodell for estimering av EE ble evaluert. I tillegg ble det utført en "stepwise" regresjonsanalyse for å utvikle nye regresjonslikninger for ganghastighetene ($NTNU_{walking}$), de vigorøse aktivitetene ($NTNU_{vigorous}$) og alle aktivitetene kombinert ($NTNU_{all\ int.}$). Nøyaktigheten av de ulike likningene ble deretter evaluert ved bruk av korrelasjon, forklart varians og Bland-Altman plots. Bland-Altman plots ble presentert ved bruk av gjennomsnittlig feil og "limits of agreement" (LoA). EE ble presentert i absolutte verdier (kJ/min) og relativt til kroppsvekt (J/kg/min). **Resultat:** Den minste forskjellen mellom målt og estimert EE ved bruk av Brandes likning var for normal ganghastighet, både for absolutte (gjennomsnittlig forskjell -0.78 og 95% LoA -9.80 til 8.24) og relative verdier (gjennomsnittlig forskjell -57.24 og 95% LoA -213.92 til 99.44). $NTNU_{walking}$ estimerte ganghastigheter med større nøyaktighet enn Brandes likning (absolutte verdier: gjennomsnittlig forskjell 0.24 og 95% LoA -3.23 til 3.72. Relative verdier: gjennomsnittlig forskjell 18.06 og 95% LoA -43.71 til 79.84). I tillegg til $NTNU_{walking}$ predikerte $NTNU_{all\ int}$. aktivitetene jogge og løpe med like stor nøyaktighet for absolutte verdier ($NTNU_{walking}$: gjennomsnittlig forskjell -1.23 og 95% LoA -12.88 til 10.40. $NTNU_{all\ int.}$: gjennomsnittlig forskjell 1.22 og 95% LoA -9.29 til 11.75). **Konklusjon:** Brandes likning estimerte EE hos barn mest nøyaktig for absolutte verdier når barna gikk i normal hastighet. De nye regresjonslikningene estimerte uansett ganghastigheter og vigorøse aktiviteter med større nøyaktighet, noe som kan tyde på at spesifikke regresjonslikninger for barn er nødvendig. Likningene predikerte EE godt på gruppenivå, men trenger videre tilpasninger for å kunne estimere EE like nøyaktig for barn på et individuelt nivå.

ACKNOWLEDGEMENT

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At last, a special thank you to all the children who volunteered their participation in this project.

Thank you!

TABLE OF CONTENT

1. INTRODUCTION

It is well known that regular physical activity is central for improving health and reducing risk of disease (2, 3). This association is broadly documented in the adult population (2). However, the evidence linking physical activity with health is more ambiguous for children and adolescents. A review of the physical activity, fitness and health of children concluded that even though studies had shown several benefits of physical activity, the supporting evidence for the assertions were weak (4). The main benefits of childhood physical activity discussed in this review included that active children had generally healthier cardiovascular profiles and higher peak bone masses than their less active peers. Higher peak bone masses in children was also associated with reduced risk of osteoporosis in old age and promoted health benefits difficult to catch up later in life. Furthermore, children learning movement skills such as jumping, cycling and running early in life were more likely to feel the joy of an active lifestyle, and thereby become more active and healthy adults. A later systematic review published by Janssen and co-workers (2010) found that childhood physical activity was associated with numerous health benefits, but added that existence of a particular threshold value for obtaining a better health seemed unclear when examining health benefits of physical activity and fitness in school-age children.

Despite this uncertain dose-response relation, the World Health Organization recommends at least 60 minutes of moderate- to vigorous- intensity physical activity every day for children and adolescents in order to improve health status at an early stage in life (5). Commissioned by the Norwegian directorate of health, Norges Idrettshøyskole (NIH) examined the number of school children that met these recommendations. Among 6-years-olds 87.0 % of girls and 95.7% of boys met the recommendation and in the age of 9 years the numbers had decreased to 69.8% and 86.2%. The corresponding number for 15 year-old girls and boys were 43.2% and 58.1% (6). To evaluate the consequences of these results and the relevance of physical activity recommendations, we need a better understanding of the dose-response relation between physical activity and health outcomes. In such, precisely measurement technique of both health and physical activity outcomes is needed. Accurately quantifying physical activity in children and adolescents also allows further evaluation of the effectiveness of intervention that aim to increase childhood physical activity.

Physical activity refers to any bodily movement produced by skeletal muscles leading to a significant increase in energy expenditure (EE) from rest (7). The variables of frequency, intensity and duration are commonly used to describe physical activity. However, positive health benefits of physical activity are mostly related to physiological adaptations during increased intensity physical activity (3). As exercise intensity increase, a greater demand in the muscle tissue is met by physiological adaptations such as an increase in cardiac output and greater oxygen extraction from the vasculature (8). These physiological adaptations result in increasing or maintaining physical fitness, which is associated with positive impacts on general health (9). Measuring intensity of physical activity accurately is therefore important in terms of studying the relation between physical activity and health.

There is a diversity of methods for estimating intensity of physical activity, but they vary in validity and reliability. Some of the issues are common for all population, while other methodological challenges arise from the unique developmental and behavioural aspects of children (10, 11). The methods are often divided into subjective and objective approaches. Subjective measurements, such as self-report of physical activity level are often used due to the low cost and time efficiency. However, there is a widespread concern about the accuracy of self-report data from children due to the lack of ability for a detailed recall (12). Additionally, the physical activity pattern in children tends to be sporadic and intermittent, which increase the need for a more sensitive and objective measurement approach (10). Objective measures of intensity of physical activity include estimations of EE (e.g. indirect calorimetry and doubly labelled water) and acceleration of movement (e.g. activity monitors). Indirect calorimetry is often referred to as the most objective "gold standard" in controlled settings. In a free-living situation, it is more suitable to use doubly labelled water as a reference standard. However, both indirect calorimetry and doubly labelled water are not always appropriate techniques because they are expensive, time consuming and associated with complex organization (13).

The most popular objective measurement device used to assess intensity of physical activity is activity monitors and in particular accelerometers. They are small, light weighted and capable of large memory storage, making them practical for extended measurement periods (14) and are particularly appealing for use on children. Accelerometers detect acceleration which is the change in velocity over a given time. In such, when a child is being physically active, the accelerometer gives information about volume and intensity of the child's movement. The information can further be calibrated to derive point estimates of EE.

Up until recently the most standard output from the accelerometer has been activity counts and cut-points to categorize time spent in different activity intensities (14, 15). This analytic approach is appealing because of the simplicity of applying ready-to-use software. However, this simple method has shown not to be accurate enough for calculating EE for different individuals and activities (15). Firstly, different personal factors such as age, height or body mass may result in different metabolic cost for these individuals, although activity count values may be the same (14). Secondly, there is currently no consensus on how to select cut-of points to define activity intensities (16). Thirdly, it seems to be no linear relationship between acceleration and EE in free-living environments (17). Consequently, the method fails to explain a considerable portion of EE estimation in daily living. Another drawback is that the algorithms calculating counts have been protected and specific for different activity monitors, making it problematic to easily compare the different manufacturer's devices and thereby directly compare different study results (14).

Using raw accelerometer data may overcome these problems. More advanced mathematical algorithms can estimate EE from the raw acceleration signal and does not relay on cut of points as for the computation of activity counts. Consequently, methods of analysis such as more flexible regression equations (1, 18) and artificial neural network (19, 20) have been established, and are still being developed and optimised to reach for a consensus analytical approach (14). However, existing studies are mostly based on adults conducting different free-living activities. This is questionable, as we know children tend to have a more sporadic activity pattern in free-living communities and varies in growth and maturation (21, 22). Though, being able to estimate EE with high accuracy in adults and in such distinctive movement patterns builds optimism for more complex free-living activities and other study populations, such as children and adolescents. One study presented by Brandes and colleagues (2012) used a mixed linear regression analysis for EE estimation in three different walking speed (slow, moderate and fast) in addition to stair walking and cycling. The study targeted notable 180 study participants (91 males and 95 females) ranging from 6–81 years old. They concluded that acceleration, body weight, and their interaction explained 95% of the variation in the absolute EE in walking (1). In this regard, raw acceleration may represent a good replacement for indirect calorimetry and achieve the request for objective and accurate physical activity measuring technique.

The aim of this thesis is therefore to determine the accuracy of Brandes´ linear regression equations for estimation of EE when applied to children (7-15 years old) using raw acceleration data. Furthermore, stepwise regression equations will be developed to improve accuracy of estimating EE from children acceleration data.

2. METHOD

2.1 Participants

The study took place in October –December 2016 at Lundamo Skole, which is a primary and secondary school in Mid-Norway. A total of 310 children from second to tenth grade and their caregivers were informed about this study and asked to participate. This resulted in 61 children from primary and 28 children from secondary school that gave written consent. To meet recommendation for validation of activity monitors in children (15) 3 girls and 3 boys from each class were randomly chosen to participate in this study. Descriptive statistics of the participants are presented in Table 1.

This study is a part of a larger validation study from raw acceleration sensors in children. The validation study was approved by Norwegian Centre for Research Data (NSD-nr:50683). In addition, the study was reported to the Regional Ethical Committee (REK-nr:2016/707/REK nord) but was not classified under the act on medical and health research.

2.2 Protocol and equipment

The children performed several physical activities including walking with different speed, jogging and running. Gas exchange measures, acceleration of back and thigh, heart rate and video were recorded for all activities (see Figure 2).

2.2.1 Axivity AX3

The main instrumentation used for estimation of EE was the Axivity AX3 activity monitor (Axivity, UK). The activity monitor measures acceleration in three directions (x, y, z). The monitors are small (23 x 32.5 x 7.6 mm), light weighted (11 gram) and capable of large memory storage (512 MB). Acceleration was sampled at 100 Hz, within a range of ± 8g.

During the measurement period, one sensor was attached to the right mid-thigh, approximately to the front midline and between the anterior superior iliac spine and the patella. A second sensor measured acceleration at the lower back central for the lumbar vertebrae 3. Sensor placements are illustrated in Figure 1. The monitors were attached to the skin using double-adhesive tape, Fixomull (brand: BSN Medical) and sport tape (Scansport). Further, the accelerometers were orientated with the x-axis equalled to the vertical axis, the y-axis to the mediolateral axis, and the z-axis to the anterioposterior axis.

Figure 1. Axivity AX3 monitors placed to the mid thigh and lower back.

2.2.2 Indirect calorimetry

A portable gas exchange system (Metamax 11 Cortex Biophysik GmbH, Leipzig, Germany) was used as the reference method for estimation of EE. The entire system weighted approximately 980 g and had a dimension of 189 x 160 x 47 mm. It was attached to the children's back using a chest harness (see Figure 2.). A pedriatic face mask (held in place by a mesh cap) was placed over nose and mouth, and attached to a digital turbine flow meter that registered inspired and expired air volume for the calculation of VO_2 and VCO_2. This system offered the participants good mobility, and made it possible performing free-living activities. The Metamax was calibrated before testing according to the manufacturer's guidelines. After each test, the collected data were downloaded to a laptop with the manufacturer software (Metasoft).

Figure 2. A participant wearing measurement equipment and ready for testing (pictures used with permission).

2.2.3 Validation protocol

All participants performed 6 different ambulatory activities. The activities were performed in the following fixed order: walking slow, walking moderately, walking fast, jogging and running. The duration of each activity was set to 5 minutes although subjects' physical fitness and age had to be considered. However, the duration of each activity had to overcome 3 minutes in order to ensure steady state measures of VO_2 and VCO_2. Subjects were allowed to rest between the activities, and the resting period was individualized to each subject's own preferences. If the weather outside was good (no rain or snow) the protocol was implemented outside on an athletic track. If not, the protocol was performed at an indoor handball field.

Anthropometrical measurements of participants were noted from previous testing in the larger validation study. This included measuring weight on a digital scale (Tanita) to the nearest 0.1kilogram and measuring height using a measuring tape to the nearest 0.1centimetre (both without shoes or heavy clothes). Before the test started, children were fitted with axivity monitors, Metamax, a GoPro camera and heart rate monitor.

The GoPro camera (HERO +, with video resolution of 720 pixels and 30 frames per second) was placed to the subjects' chest with a chest harness making it possible capture the subjects' legs and thereby differentiate between the different activities. Additionally, heart rate was continuously recorded for all activities using a polar heart rate monitor (Polar M400, H7 Heart Rate Sensor). Walking speed was assessed by measuring time spent on a given distance. Walking distance was measured using a measuring wheel (Binkrn AS, Gressvik, Norway).

The test leader gave a standardized verbal instruction of the content and order of the test protocol. This included familiarizing the subjects to the equipment (particularly the face mask). When introducing the different activities, the test leader used standardized instructions to decrease the risk of interfering preferred speed; “walk slower than you usually do”, “Walk as you usually do”, “walk faster than you usually do”, “jog” and “run, but not as fast as you can”. The subjects were asked to restrain from talking during the activity protocol, as this could affect the gas exchange measurement. However, if they felt any discomfort while completing protocol they were asked to show a “thumb down”. If they did, the equipment was immediately taken off. The protocol took approximately 60 minutes to complete.

2.3 Synchronization

The start and end time of the protocol were indicated by setting markers in the GoPro camera, polar clock and Axivity monitors accomplished by performing a heel drop (rise up on toes and rapidly drop the heels towards the ground) three times and standing still at least five seconds in between each heel drop. For example, for the Axivity monitors, this would set undoubtedly marks in the acceleration signal, making it easier to find the right period of time for later data analysis (Figure 3). Furthermore, the test leader made a lap in the child's polar clock and wrote down the relative time at the first heel drop. During the testing, the test leader made a marker in the oxygen analyser and polar clock before and after each activity to easily separate activities. Consequently, this would set marks in the equipment to easier ensure synchronised data material for further data analysis.

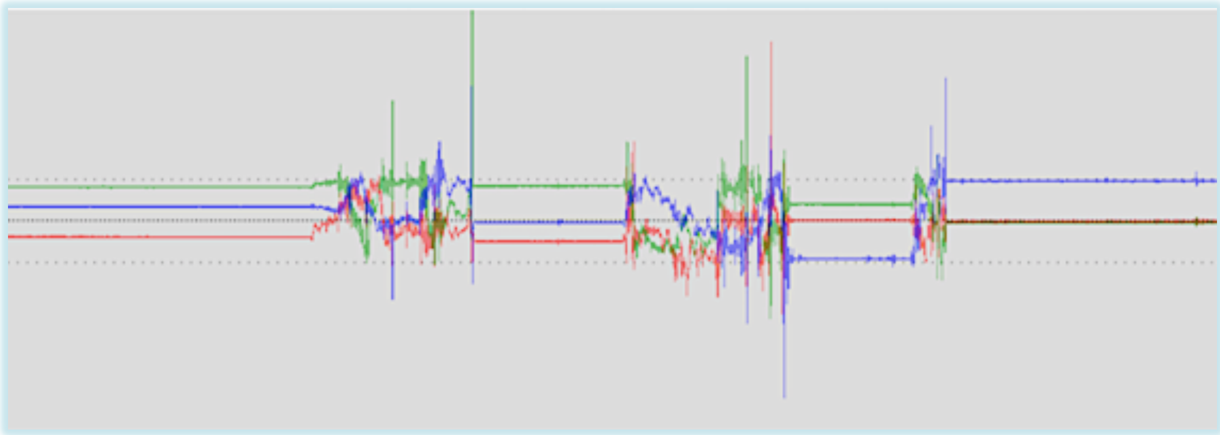


Figure 3. Acceleration signal from the lower back when performing the heel drops before test start. The blue (z), green (y) and red (x) curves represent the different acceleration axis.

2.4 Data analysis

Acceleration data, heart rate data and gas exchange data for the activity periods were extracted from the remaining data material, and a one minute steady state period was identified in the gas exchange data for all activities. Further, a steady state period was defined as the most stable one-minute period from the last two minutes of testing. Furthermore, average VO_2 and RER from the selected minute was calculated. In addition, the acceleration signal for the same period was evaluated. The acceleration signal should display a repetitive and rhythmic activity pattern. If the acceleration was non-period for the selected steady state period, a new time period was selected. The video recordings were able to reveal deviating activities (e.g. tie shoelaces) resulting in an intermittent non-periodic acceleration signal.

2.4.1 Energy expenditure

Gas exchange data was converted to absolute and relative EE using already existing equations (23). Equation 1 represents relative EE, while equation 2 represents absolute EE.

$$\text{Relative EE-O}_2\text{ (J/kg/min)} = \frac{(4960 * \text{RER} + 16040) * \text{VO2 [l/min]}}{\text{Body mass [kg]}} \qquad \text{(Eq. 1)}$$

With VO_2 in l/min, respiratory exchange ratio (RER) as VCO_2/VO_2, Body mass in kilograms.

$$\text{EE-O}_2\text{ (KJ/min)} = 4.96 * \text{RER} + 16.04 * \text{VO2 (l/min)} \qquad \text{(Eq. 2)}$$

With VO_2 in l/min, respiratory exchange ratio (RER) as VCO_2/VO_2.

2.4.2 Accelerometer signal

Brandes et al.´s method was followed for the acceleration signal processing (1). The raw acceleration signal was filtered using a fourth-order band-pass frequency filter (0.1- 15Hz) to each acceleration axis. Furthermore, the raw acceleration signals were converted into vector magnitude (see equation 3), which gives information about size of the signal using all three axis. Finally, mean vector magnitude from the one-minute analyze window represented the acceleration signal in the different equations.

$$\text{Vector magnitude (g)} = (x^2+y^2+z^2)^{1/2}-1 \qquad \text{(Eq. 3)}$$

2.4.3 Brandes et al.´s equation

The equations by Brandes et al. (2012) were used to estimate relative and absolute EE (J/kg/min and kJ/min). The equations are presented in Table 4. They are based on 57 children and 128 adults with an age range of 6-81 years. The equations estimated activity EE, and it was therefore necessary to add resting EE (REE) to calculate total EE. Mean REE values from Brandes et al.'s study was applied. Accordingly, we added a mean REE of 4.8 kJ/min or 107 j/kg/min for 7-11 years old children and 5.7 kJ/min or 107 j/kg/min for 12-17 years old children.

2.4.4 NTNU developed equations

We developed 3 new regression equations for estimation of EE. One was based on walking activities only ($NTNU_{walking}$) one was based on jogging and running ($NTNU_{vigorous}$) and one was based on all activities conducted ($NTNU_{all\ intensities}$). The new equations for EE estimation were developed using stepwise linear regressions. In order to develop equations explaining as much as possible of the variance in EE, several variables were evaluated in respect to their contribution due to their theoretical relation to EE. The variables were: acceleration (on both thigh and lower back), body weight, gender, age, BMI, step frequency, velocity and heart rate. If the stepwise regression not entered acceleration output into the equations automatically, acceleration from the lower back was entered manually. The equations were developed on 70% of the children and validated on the remaining 30%. The regression equation is presented in Table 4.

2.5 Statistics

Statistical analyses were conducted in Excel (Microsoft excel for mac 2011), Matlab (MATLAB R2016a, The MathWorks, Inc., Massachusetts, US) and SPSS statistics (IBM SPSS statistics, version 24). Mean and standard deviation (± SD) were used to presents participant characteristics, activity velocities and EE values.

Normal distribution of the data was examined using Kolmogorov-Smirnov and visual assessment of histogram and normal Q-Q plots. The association between measured and estimated EE was further assessed with spearman correlation (r). A greater strength of linear relationship would give a correlation closer to +1.0 or -1.0. For newly developed equations, coefficient of determination (r^2) was presented as an indication of how much variation in the measured EE that could be explained by the regression equations. A p-value of <0.05 was considered to be significant.

In addition, accuracy of the EE estimation was presented as root-mean-square error (RMSE) values, which is the square root of the variance of the residuals and indicates the absolute fit of the model to the data. In other words, the difference between observed and estimated values. For example, a RMSE value of 0 would suggest that it is no spread in the values of the dependent variable around the regression line.

To be able to evaluate the differences between the two methods, Bland-Altman plots were conducted. Y-axis represents the differences in EE for the two measurement approaches while the x-axis is the mean EE for the two measurement approaches. Consequently, this would give us the opportunity to study the differences between the methods and reveal any systematic pattern of error and individual deviations. Previous studies have suggested that measuring gas exchange with a Metamax 11 analyser gives a random variation of 5% (24). Therefore, a ±2.5% deviation line was calculated for the different activities and added to the bland-Altman plots as an indication of measurement error.

3. RESULTS

From the 54 participants, instances of irregular acceleration signals (n= 3), malfunction or measurement error of Metamax analyser (n=7), not conducting the protocol (n=1) and not reaching one-minute steady state (n=1) were excluded from further analysis. Furthermore, when analysing the data, 2 participants walked significantly faster than the rest, and had to be excluded in all walking activities. This resulted in 42 participants. Participant characteristics are presented in Table 1.

Subject characteristics	Mean (±SD)
N (female/male)	42 (20/22)
Age (years)	10.6 (±2.62)
Weight (kg)	43.52 (±12.47)
Height (cm)	149.98 (±15.94)
BMI ($kJ*m^{-1}$)	19.13 (±3.03)
Walking speed	**Mean (±SD)**
Walking slow (m/s)	0.96 (±0.25)
Walking moderate (m/s)	1.33 (±0.2)
Walking fast (m/s)	1.54 (±0.22)
Jogging (m/s)	2.35 (±0.41)
Running (m/s)	2.84 (±0.56)
Energy expenditure	**Mean (±SD)**
Walking slow (kJ/min)	14.1 (±2.9)
Walking moderate (kJ/min)	16.3 (±3.1)
Walking fast (kJ/min)	18.72 (±3.7)
Jogging (kJ/min)	30.45 (±7.81)
Running (kJ/min)	34.52 (±9.7)

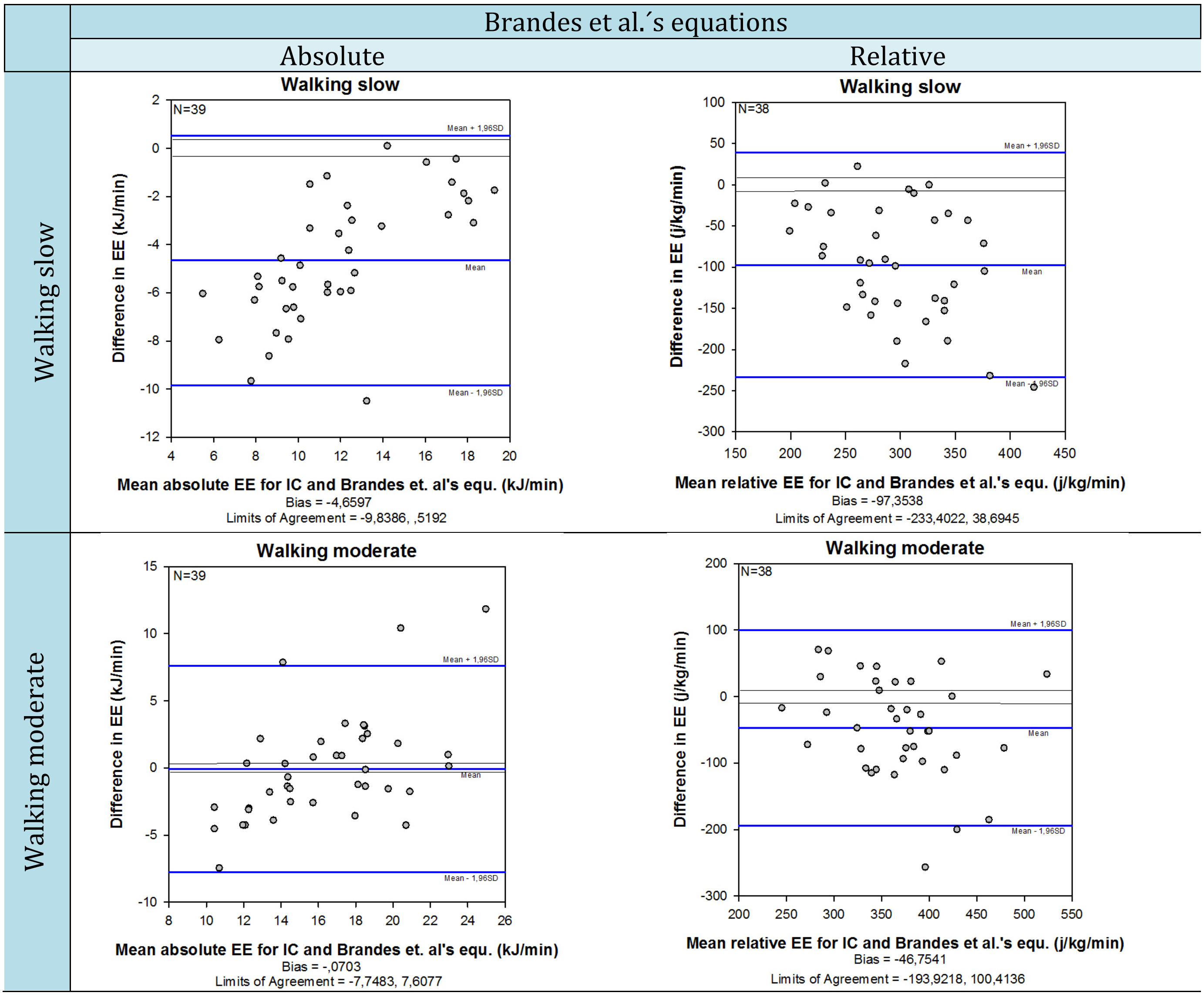
Table 1. Subject characteristics, walking speed and energy expenditure presented as mean (±SD).

3.1 Brandes et al.´s equation

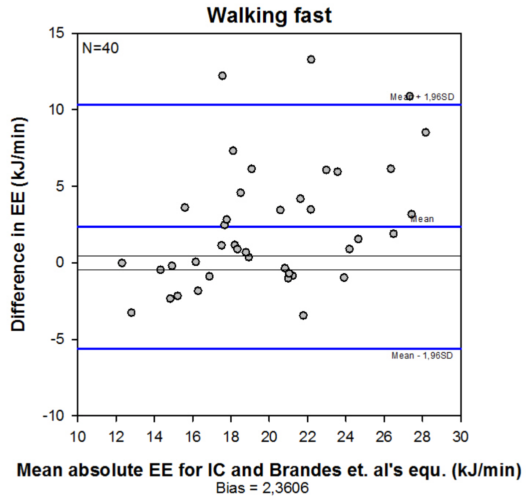
The correlation between EE estimated from Brandes et al.´s equation and estimations from ergospirometry for activities separately, both in absolute and relative units was: walking slowly = 0.8 ($p < 0.001$) and 0.44 ($p < 0.006$), walking moderate= 0.68 ($p < 0.001$) and 0.42 ($p < 0.008$), walking fast = 0.65 ($p < 0.001$) and 0.38 ($p < 0.017$), jogging= 0.43 ($p < 0.004$) and 0.14 ($p < 0.388$), running= 0.63 ($p < 0.001$) and 0.26 ($p < 0.126$).

A significant positive correlation was found between measurement output for both combined walking and vigorous activities. Overall, the strongest correlation was shown for absolute values, and particularly for the combined walking category. In addition, the lowest RMSE values were found when the equation estimated walking activities in absolute units. Correlation coefficients and RMSE values when walking activities and more vigorous activities are combined can be found in Table 3.

The Bland-Altman plots for the different activities when using Brandes´ estimation equation are shown in Figure 4. and show that Brandes equation underestimated walking slow, and overestimated walking fast, jogging and running. For relative units, Brandes equation underestimated walking slow, moderate and fast and overestimated jogging and running. Overall, the smallest difference between measured and estimated EE was found when walking moderately both for absolute and relative units.



Walking fast



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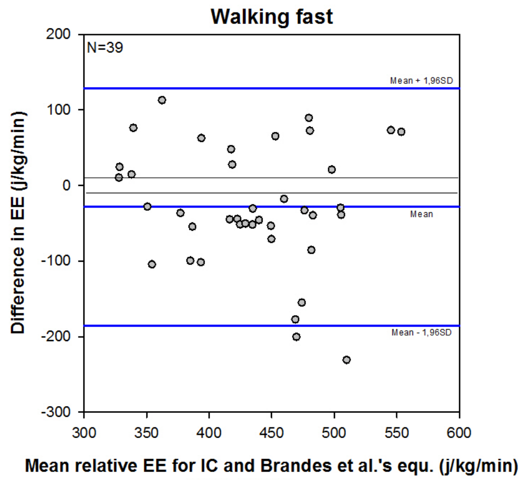

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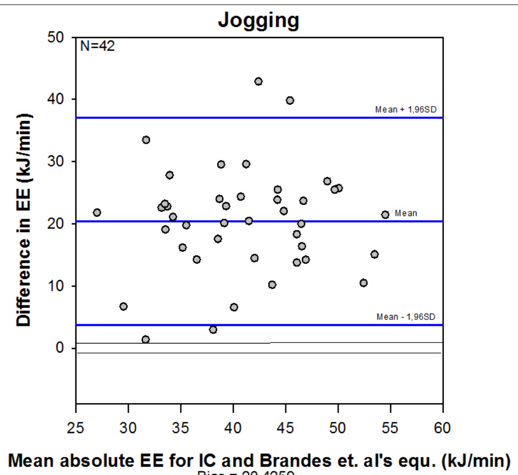
Jogging



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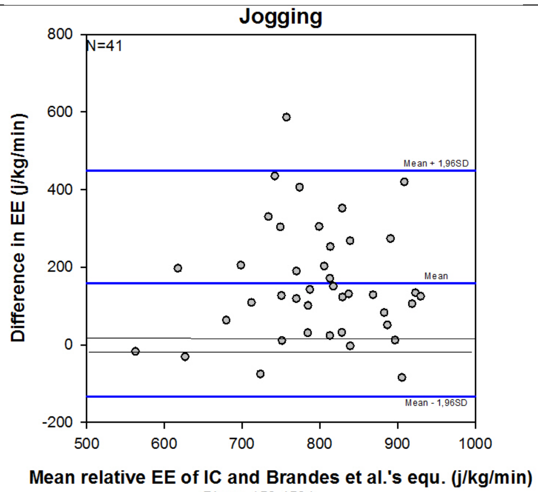

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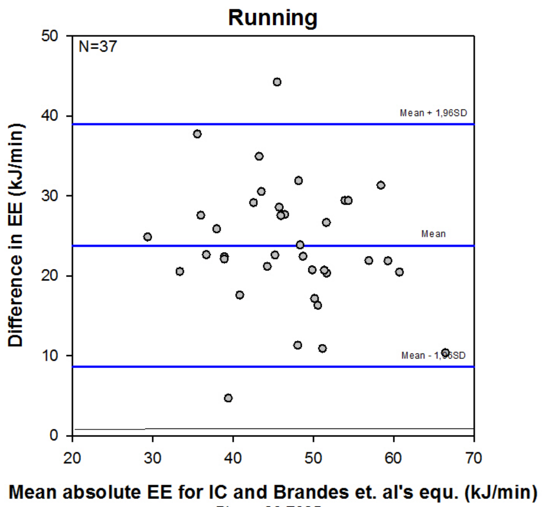
Running



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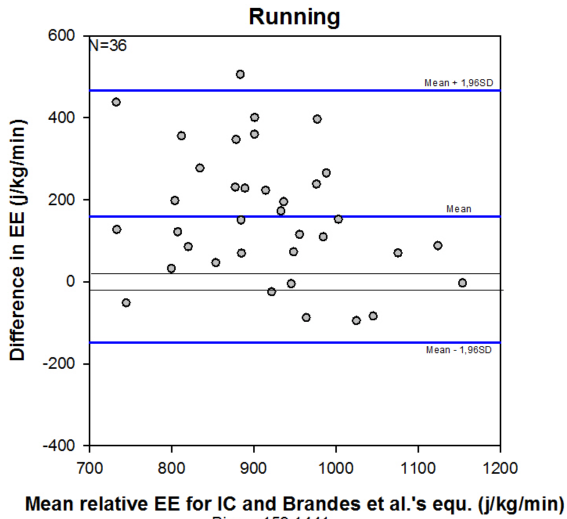

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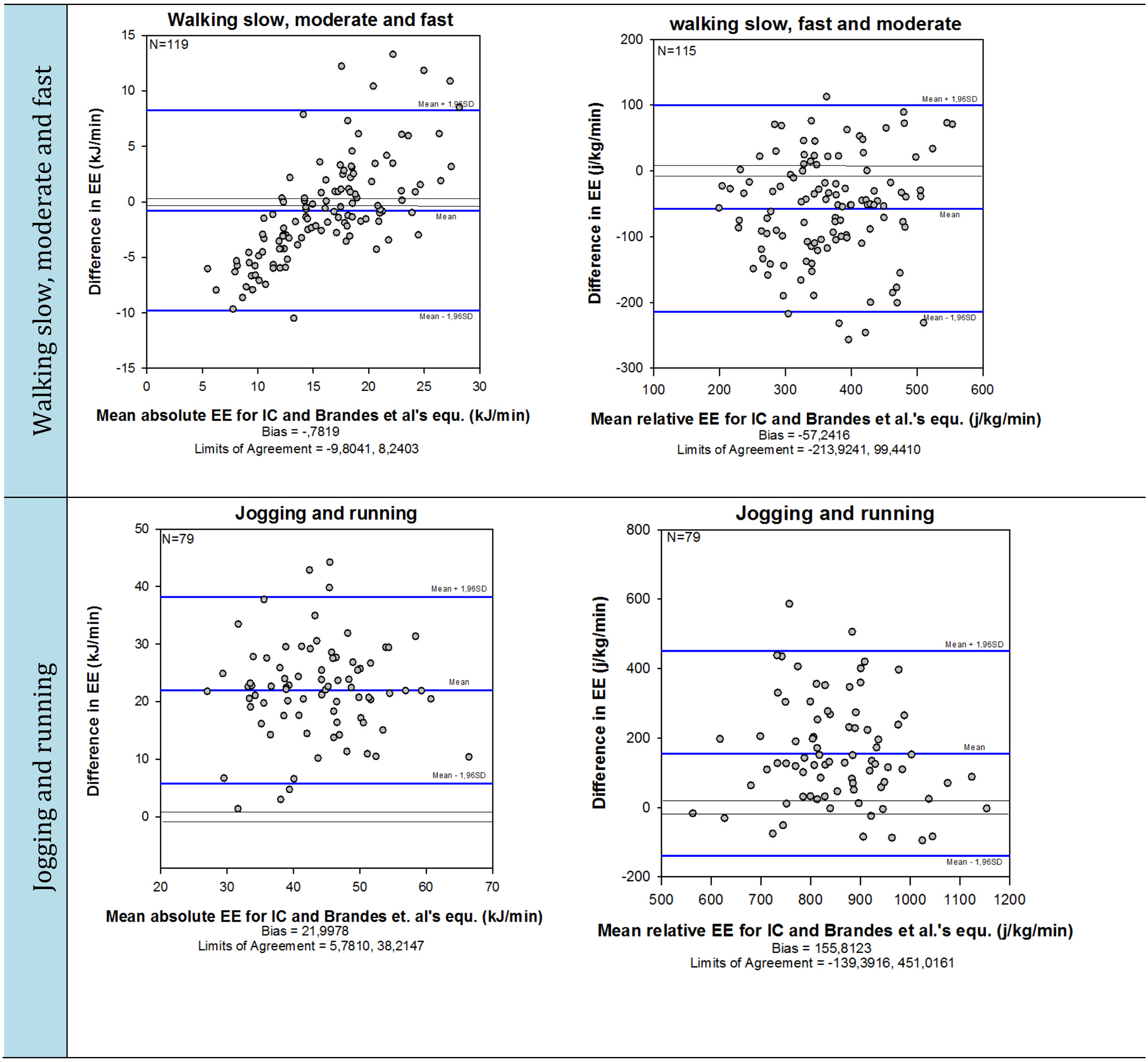


Figure 4. The outermost solid blue lines represent 95% limits of agreement (1.96SDs), whereas the solid blue line in between is the mean bias between measured and estimated EE. The grey lines represent ±2.5% deviation.

3.2 NTNU developed equations

When estimating EE for walking activities, $\text{NTNU}_{\text{walking}}$ and $\text{NTNU}_{\text{all int.}}$ presented the greatest correlations and lowest RMSE values. In addition, $\text{NTNU}_{\text{vigorous}}$ and $\text{NTNU}_{\text{all int.}}$ presented the greatest correlations and RMSE values when estimating jogging and running. EE estimation from the newly developed equations compared with the EE estimation from indirect calorimetry is presented in Table 3.

3.2.1 NTNU$_{walking}$ (walking slow, moderate and fast)

Table 2. displays selected regression equation from the regression development. For NTNU$_{walking}$, acceleration and weight explained 73% (kJ/min) and 75% (j/kg/min) of the variation in EE. After the split sample validation, the explained variances were 69% (kJ/min) and 78% (j/kg/min) for walking activities. Bland-Altman plots are presented in Figure 5. presenting 95% limits of agreement of -3.23 to 3.72 (kJ/min) and -43.71 to 79.84 (j/kg/min). Bland-Altman plots for the different activities separately, are presented in Appendix 1.

3.2.2 NTNU$_{vigorous}$ (jogging and running)

For NTNU$_{vigorous}$, the most robust equation included acceleration and height, which explained 72% (kJ/min) of the variance in EE. After the split sample validation, the explained variance increased to 74% for jogging and running activities and the Bland-Altman plots presented 95% limits of agreement of 11.72 to 26.29 for absolute values (Figure 6.). For relative units, the relation between NTNU$_{vigorous}$ and indirect calorimetry was not statistical significant (p= 0.96). Bland-Altman plots for the different activities separately, are presented in Appendix 2.

3.2.3 NTNU$_{all\ int.}$ (jogging, running, walking slow, moderate and fast)

For NTNU$_{all\ int.}$ the most robust equations included acceleration and weight, which explained 83% (kJ/min) and 85% (j/kg/min) of the variance in EE. After the split sample validation, acceleration and weight explained 70% (kJ/min) and 78% (j/kg/min) of the variance in EE when walking. For vigorous intensities, the explained variances for absolute units were lower (43% kJ/min) whereas the explained variance for relative units was not significant (p =0.102). Bland-Altman plots for walking activities and vigorous activities combined are presented in Figure 7. whereas Bland-Altman plots for the different activities separately, are presented in Appendix 3.

3.2.4 NTNU developed equations summary

Compared to NTNU$_{vigorous}$ and NTNU$_{all\ int.}$, NTNU$_{walking}$ presented a lower mean bias and narrower 95% limit of agreement when estimating walking activities in both relative and absolute units. This indicates that NTNU$_{walking}$ estimated EE during walking more accurate both on an individual and population based level.

Compared to NTNU$_{vigorous}$, NTNU$_{all\ int.}$ and NTNU$_{walking}$ presented a lower mean bias and narrower 95% limit of agreement for absolute values, which indicates that NTNU$_{all\ int.}$ and

$NTNU_{walking}$ estimated EE during vigorous activities more accurate both on an individual and population based level for absolute units.

3.3 NTNU developed equations compared to Brandes et al.´s equation

Compared to Brandes´ equation, $NTNU_{walking}$ presented mean bias closer to zero and a narrower 95% limit of agreement both in absolute and relative units. In addition, compared to Brandes´ equation, $NTNU_{all\ int.}$ and $NTNU_{walking}$ presented a mean bias closer to zero and a narrower 95% limit of agreement for absolute values.

Activities	Dependent	Independent	R^2	RMSE
$NTNU_{walking}$	EE (kJ/min)	Acc.	0.28	3.36
		Acc. * weight	**0.73**	**2.07**
		Acc. * weight * velocity	0.78	1.89
	EE (J/min/kg)	Acc.	0.34	76.97
		Acc. * weight	**0.75**	**47.58**
		Acc. * weight * heart rate	0.82	41.08
		Acc. * weight * heart rate * velocity	0.84	38.2
$NTNU_{vigorous}$	EE (kJ/min)	Acc.	-0.02	9.71
		Acc. * height	**0.72**	**5.15**
		Acc. * height * velocity	0.72	5,18
		Acc. * Height * velocity * BMI	0.76	4.75
	EE (J/min/kg)	Acc.	0.23	130.3
		Acc. * BMI	**0.40**	**115.08**
		Acc. * BMI * velocity	0.41	113.9
$NTNU_{all\ intensities}$	EE (kJ/min)	Acc.	0.67	6.03
		Acc. * weight	**0.83**	**4.39**
		Acc. * weight * velocity	0.87	3.8
		Acc. * weight * velocity * heart rate	0.89	3.79
	EE (J/min/kg)	Acc.	0.76	110.7
		Acc. * weight	**0.85**	**88.33**
		Acc. * weight * velocity	0.89	71.45
		Acc. * weight * velocity * heart rate	0.91	65.68

Table 2. Overview of models estimating EE.

Activity	R								RMSE							
	Brandes et al.´s equation		$NTNU_{walking}$		$NTNU_{vigorous}$		$NTNU_{all\ intensities}$		Brandes et al.´s equation		$NTNU_{walking}$		$NTNU_{vigorous}$		$NTNU_{all\ intensities}$	
	(kJ/min)	(J/kg/min)	(kJ/min)	(J/kg/min)	(kJ/min)	(J/kg/min)	(kJ/min)	(J/kg/min)	(kJ/min)	(J/kg/min)	(kJ/min)	(J/kg/min)	(kj/min)	(J/kg/min)	(kj/min)	(J/kg/min)
Combined walking	0.77*	0.61*	0.84*	0.88*	0.79*	0.83*	0.84*	0.88*	2.44	71.7	1.8	31.42	2.0	37.76	1.77	31.43
Jogging and running	0.6*	0.36*	0.59*	0.35*	0.87*	0.35	0.68*	0.35	7.20	133,6	5.95	89.46	3.68	89.27	5.44	89.48

Table 3. Correlation coefficients and RMSE for walking activities and vigorous activities combined. Significant $P < 0.05$

Dependent	Independent	Brandes et al.´s equation		$NTNU_{walking}$		$NTNU_{vigorous}$		$NTNU_{all\ intensities}$	
		Coefficient (95% CI)	P-value	Coefficient (95% CI)	P-value	Coefficient (95% CI)	P-value	Coefficient (95% CI)	P-value
EE (kJ/min)	Intercept	-18.61 (-21.02 to -16.20)	<0.001	1.634 (-0.41 to 3.68)	0.116	-44.068 (-57.71 to -30.43)	<0.001	-4.351 (-7.12 to -1.58)	0.002
	Weight	0.24 (0.20 to 0.28)	<0.001	0.194 (0.16 to 0.23)	<0.001	-		0.307 (0.25 to 0.36)	<0.001
	Acceleration	53.97 (51.60 to 56.34)	<0.001	19.327(15.56 to 23.1)	<0.001	19.175 (4.74 to 33.61)	0.010	22.716 (20.77 to 24.66)	<0.001
	Height	-		-		0.487 (0.4 to 0.57)	<0.001	-	
EE (J/kg/min)	Intercept	-40.19 (-52.75 to -27.63)	<0.001	438.048 (389.68 to 486.42)	<0.001	1027.396 (778.31 to 1276.78)	<0.001	444.285 (388.23 to 500.33)	<0.001
	Weight	-		-4.351 (-5.124 to -3.58)	<0.001	-		- 4.907 (-6.01 to -3.8)	<0.001
	Acceleration	816.11 (783.0 to 849.2)	<0.001	454.817 (359.5 to 550.134)	<0.001	559.576 (226.0 to 893.14)	0.001	519.403 (480.21 to 558.6)	<0.001
	BMI	-		-		-20.416 (-31.2 to -9.63)	<0.001	-	

Table 4. Values integrated in the regression equation developed by Brandes and NTNU.

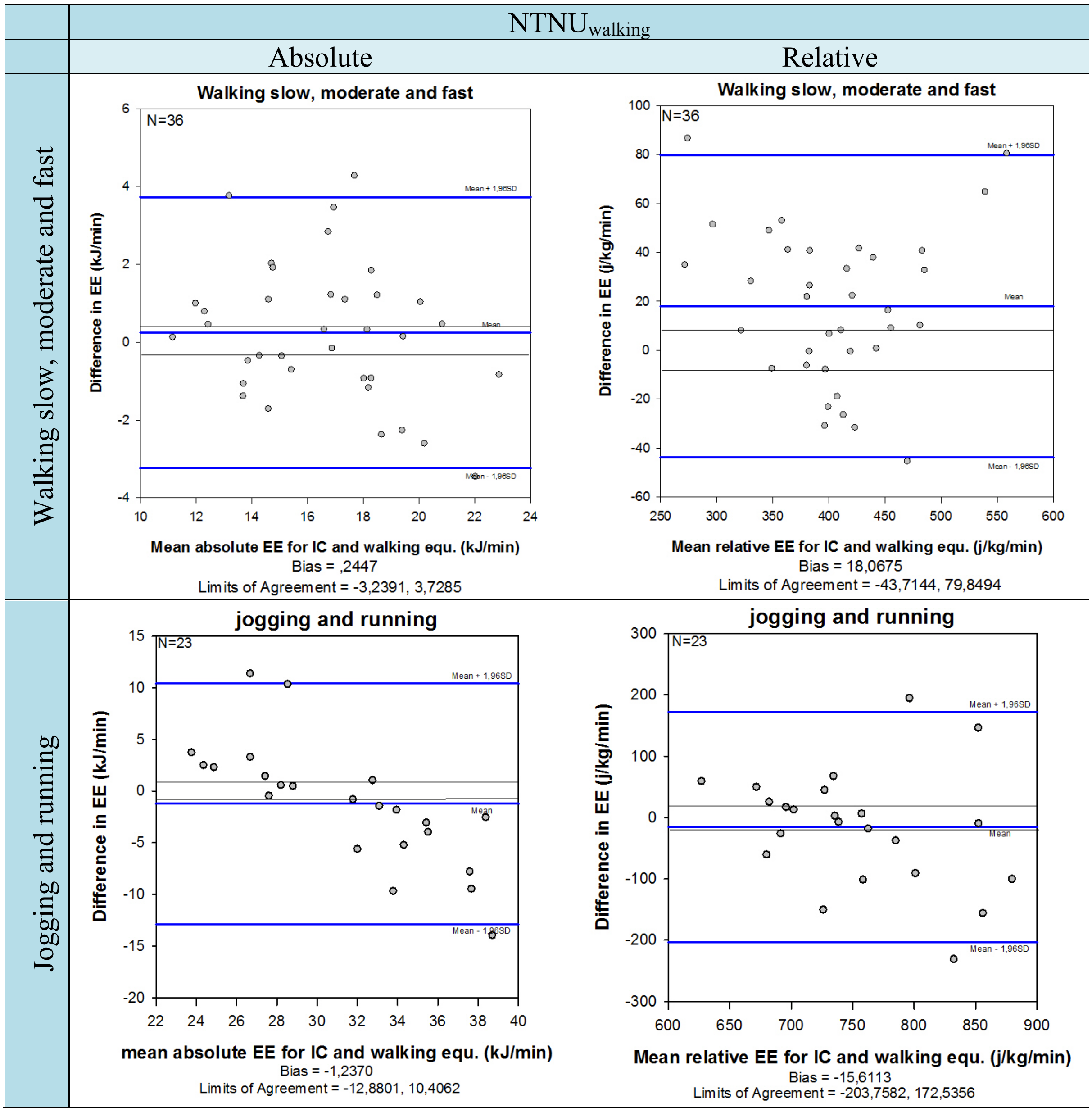


Figure 5. The outermost solid blue lines represent 95% limits of agreement (1.96SDs), whereas the solid blue line in between is the mean bias between measured and estimated EE. The grey lines represent ±2.5% deviation.

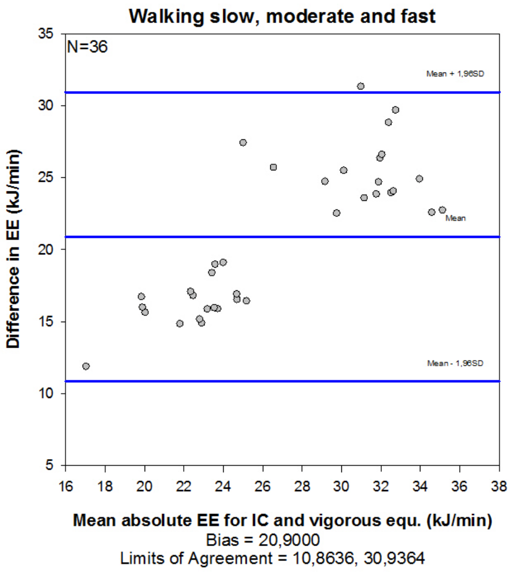
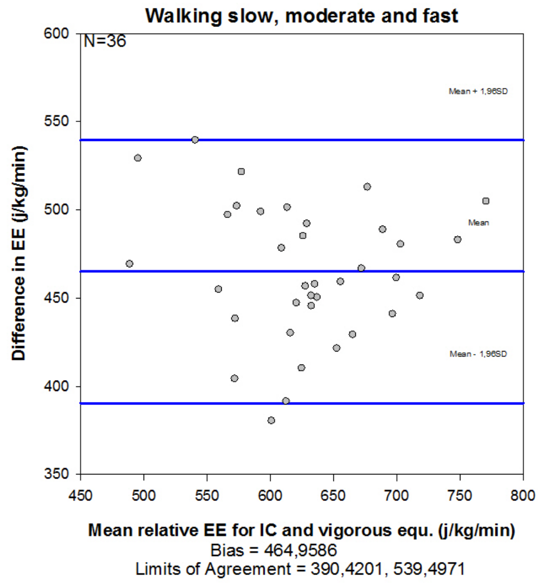
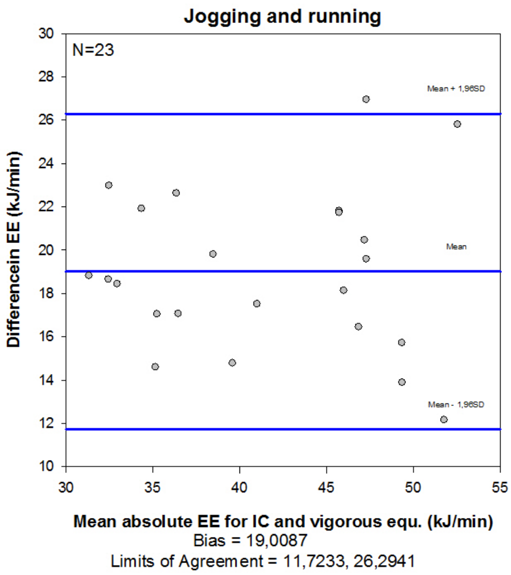
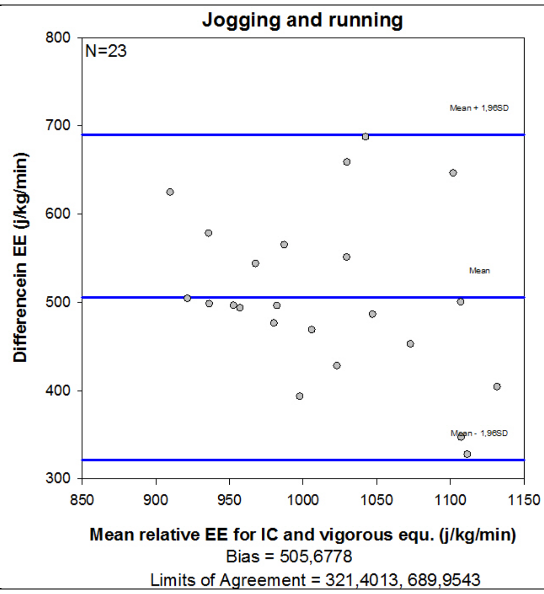
<table>
<tr><th></th><th colspan="2">NTNU$_{vigorous}$</th></tr>
<tr><th></th><th>Absolute</th><th>Relative</th></tr>
<tr><td>Walking slow, moderate and fast</td><td>
</td><td>
</td></tr>
<tr><td>Jogging and running</td><td>
</td><td>
</td></tr>
</table>

Figure 6. The outermost solid blue lines represent 95% limits of agreement (1.96SDs), whereas the solid blue line in between is the mean bias between measured and estimated EE. The grey lines represent ±2.5% deviation.

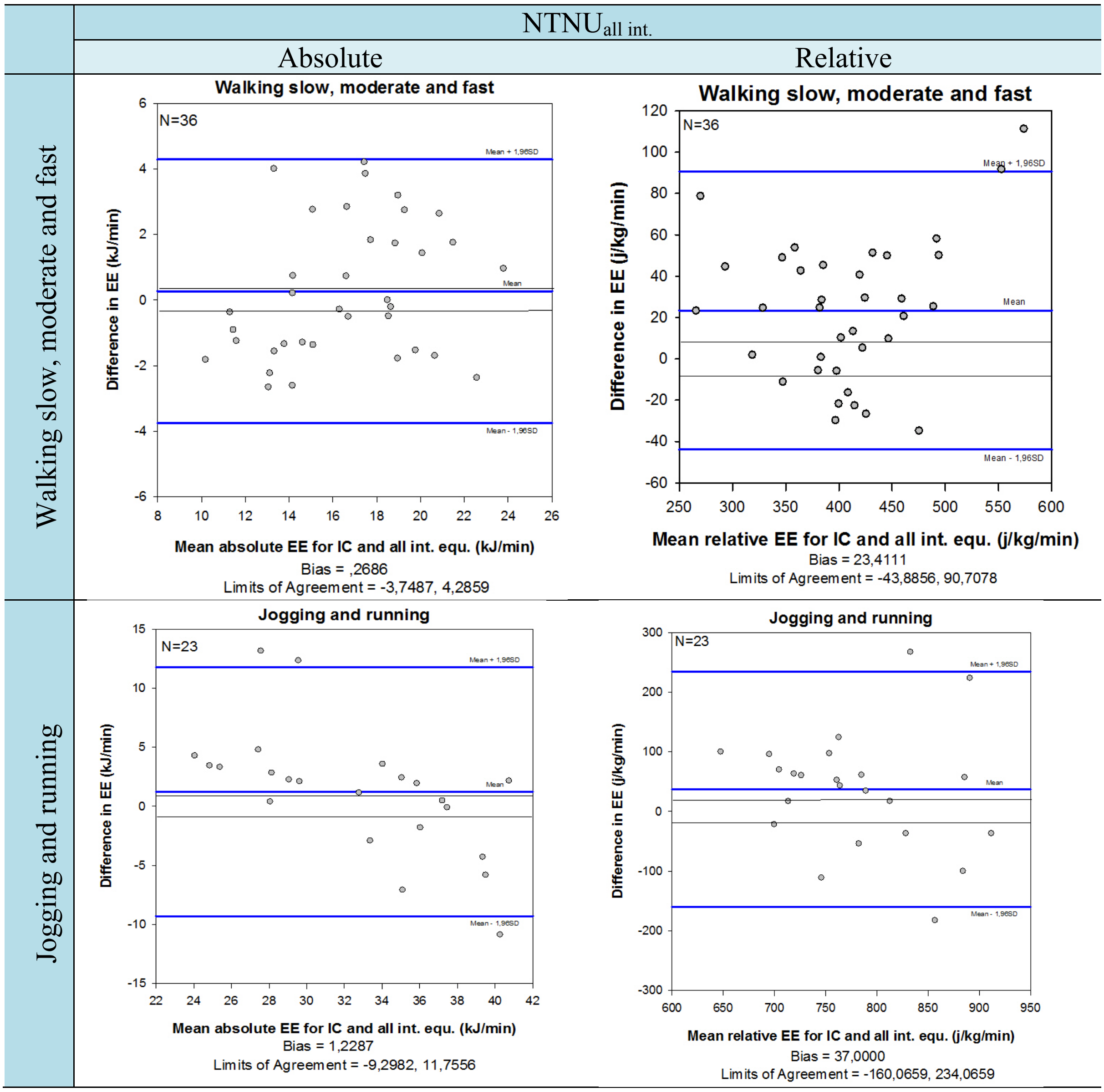


Figure 7. The outermost solid blue lines represent 95% limits of agreement (1.96SDs), whereas the solid blue line in between is the mean bias between measured and estimated EE. The grey lines represent ±2.5% deviation.

4. DISCUSSION

The aim of this study was to 1) examine the validity of Brandes´ estimation equations for EE detection in children using raw acceleration data and to 2) develop stepwise regression equations for EE estimation to improve accuracy. Results from the current study indicate that Brandes´ equation manages to estimate EE accurately for a specific range of EE values, corresponding to the children´s preferred walking speed. For absolute units, Brandes et al.´s equation underestimated walking slow, and overestimated walking fast, jogging and running. For relative units, Brandes´ equation underestimated walking slow, moderate and fast and overestimated jogging and running. Further, the newly developed equations for walking activities ($NTNU_{walking}$) presented a greater accuracy for walking activities compared to Brandes et al.´s equation. In addition to $NTNU_{walking}$, the new equations for all intensities ($NTNU_{all\ int.)}$ presented the greatest accuracy for jogging and running when absolute values for EE were used.

4.1 Brandes et al.´s equation

When using the equation by Brandes and co-workers to estimate EE the greatest correlation and lowest RMSE between measured and estimated EE was found for walking activities. This might be explained by the fact that the equations of Brandes and co-workers were originally developed using a protocol only including walking intensities. Still, the current study presented a weaker relation between measured and estimated EE during walking compared to Brandes et al.´s own results. Brandes et al.´s study reported an explained variance of 95% in absolute EE using acceleration, body weight, and their interaction as contributing factors. For relative units, acceleration alone explained 93% of the variance (1) whereas in the present study, a correlation of 0.77 was found for absolute values and 0.61 for relative units. Both studies had relatively similar experimental settings placing the accelerometer to the lower back and conducting the same activities. However, using correlation as evaluation statistics alone could be uninformative when the aim is to identify systematic bias in measures (25).

Accordingly, compared to our results, Brandes et al. reported a broader limit of agreement for absolute values suggesting lower agreement between methods, which is important considering validity of two measurement approaches. Their paper reported 95% limits of agreement of -12.5 to 12.9 for absolute units (kJ/min) and -133 to 139 for relative units (j/kg/min), respectively. In comparison, the current study reported 95% limits of agreement of -9.80 to 8.24 for absolute units (kJ/min) and -213.92 to 99.44 for relative units (j/kg/min). This may indicate that the individual differences for absolute values were more accurate explained in our results. A possible explanation is the observed difference in walking speed. Brandes study population had an average slow, moderate and fast walking speed (SD) at 1.3 (0.2) m/s, 1.5 (0.2) m/s and 1.9 (0.3) m/s. Compared to our findings, Brandes et al.´s walking speed was notably higher for all walking trials. However, Brandes included both children and adults in his study sample, which could increase the range of preferred walking speed. In such, it may be that the regression equation is more accurate for lower walking speed (more represented in children) and for that reason our study sample estimated individual accuracy better.

However, any range in limit of agreement itself does not give sufficient information to confirm that acceleration and weight estimates EE accurately enough. For example, a greater amount of observed data would narrow the limits and therefore, we can only conclude that 95% of the differences between the two measurement approaches lies within these limits. For this purpose, limits based on clinical relevance should be used. A previous study suggested that EE reported by Metamaxes presents a random variation of approximately 5% (24). Therefore, the upper and lower limits based on this random variation were added to the Bland-Altman plots suggesting that values between these limits might be due to error reported by Metamax, and not necessarily inaccurate regression equations. In addition, there exist no clear definition of clinical relevant change in EE. However, a previous study used 10% as a clinical significant change in energy cost (26). For example, adding these limits to $\text{NTNU}_{\text{walking}}$ (kJ/min) results in an upper and lower limit of 1.647 to -1.647. Consequently, all the data points do not lie between these limits, suggesting that there still is some error related to this regression equation.

The equation by Brandes and co-workers is estimating activity related EE, which is total EE (as measured with indirect calorimetry during activities) minus their individual resting EE (REE). We did not record REE in the present study, but used the mean age related REE from Brandes to be able to compare methods. Resting energy expenditure is simply defined as the energy expended at rest by a fasted individual in a thermo-neutral environment and is known to play an important role in the total energy expenditure output (27). However, because individual measurements in children tend to be time consuming and are associated with participant burdens (28), we used mean individual measures calculated from Brandes et al.´s study. Consequently, this could have affected the association between measured and estimated values, and caused higher differences between the two measurement approaches.

However, major factors contributing to individual variation in REE are anthropometric characteristics, such as age, gender and body size (29). If REE significantly influence estimated values, it is suggested that such variables should have improved EE estimation significantly, and been entered into Brandes´ estimation equation.

When using Brandes´ equation to estimate EE for more vigorous activities such as jogging and running, it overestimated both absolute and relative values. However, applying an equation based on walking trials to evaluate more vigorous activities may cause lower estimation accuracy since the slope and intercept of the regression line would be affected. Furthermore, research indicates that no single regression equation developed for use in children provides accurate estimations across a wide range of activities (22, 30-32). A lower back mounted accelerometer may measure vertical acceleration with a high degree of accuracy, but not identify horizontal acceleration such as arm movements with equal accuracy, which may be more present in children during jogging and running. It is therefore possible that activity specific equation may enhance accuracy of acceleration based EE estimation.

4.2 NTNU developed equations

In the present project we developed three new regression equations to estimate EE. One was based on walking activities only ($NTNU_{walking}$) one was based on jogging and running ($NTNU_{vigorous}$) and one was based on all activities conducted ($NTNU_{all\ intensities}$). Further, two equations included acceleration and weight ($NTNU_{walking}$ and $NTNU_{all\ int.}$), while one equation included height and accelerometer for absolute values and BMI and acceleration for relative values ($NTNU_{vigorous}$) as contributing factors.

Previous work has emphasized the high accuracy for measuring activities with an accelerometer attached as close as possible to the body's centre of mass, such as to the lower back, thigh or hip (33). In addition, adding anthropometrical characteristics seem to improve EE estimation (1, 22, 34) In particular, weight is known to explain a significant part of the variance in EE since heavier individuals expend more energy at a given speed than smaller individuals do (22).

When performing split sample validation we found that $NTNU_{walking}$ measured EE most accurate for walking activities both for absolute and relative units, while $NTNU_{all\ int.}$ and $NTNU_{walking}$ measured EE most accurate for vigorous intensities in absolute units. This is in contrast with previous findings, suggesting that activity-specific regression equations lead to more accurate EE results in children (34). In such, $NTNU_{vigorous}$ was expected to estimate EE more accurate than observed in this study. However, $NTNU_{vigorous}$ consisted of other contributing factors (BMI and height), which might explain some of the inadequate results. Additionally, our study used a limited set of structured activities, and it may be that activity-specific regression equations are needed in more complex free-living activities such as playing football, pushing and lifting objects.

Compared to Brandes´ equations, $NTNU_{walking}$ presented a higher accuracy for walking intensities while $NTNU_{all\ int.}$ and $NTNU_{walking}$ presented a higher accuracy for jogging and running in absolute units. For relative units, overall estimation accuracy was low for newly developed equations, and no good explanation was found. However, a possible explanation for the better estimation accuracy for absolute units was our study sample, only including children from 7-15 years. Previous research indicates that specific equations based on children should be applied when estimating EE in children (30) since it is more difficult to estimate EE in children compared to adults (22). This is mainly because of the difference in children´s metabolic rate, movement economy and activity pattern compared to older age groups (21, 22, 35). For example, when looking at the children running, the movement was more irregular compared to adult movement pattern. Hence, acceleration signal from child movement could provide a less rhythmic and repetitive signal with different vector magnitude than observed in the adult population (36).

Individual EE estimates are known to be more challenging than group estimates (22). This was coherent with our study results, showing a mean bias close to zero while the limits of agreements were considered to be broad. However, as previously mentioned, the limits should be interpreted with caution, since they are dependent of sample size. Consequently, our sample size is relatively small compared to Brandes et al.´s study. However, it should be mentioned that our study sample compared to Brandes et al. was smaller but still managed to narrow the limits, indicating that our regression equations succeeded to estimate EE more accurately for individual values.

When performing the stepwise regression, only regression equations based on all intensities (both absolute and relative units) and walking (in absolute units) entered vector magnitude output from the lower back into the equation. For the remaining equations, acceleration output (from the lower back) had to be entered manually, indicating that vector magnitude´s explained variance was too low for these equations. It may be that other factors in the acceleration signal influence EE with greater quantity, such as peak acceleration, total power, or root mean square. In addition, the accelerometer worn on the thigh did not improve

EE estimation for any equations, although it has shown high accuracy for measuring EE in ambulatory activities in the adult population (20). However, the current study only evaluated one-posture specific activities, suggesting that the ability to distinguish different orientations of body segments were not needed. For example, estimating EE for cycling or sitting may require multiple accelerometers for better estimation accuracy.

For some of the newly developed equations, velocity and heart rate output increased the explained variance with a reasonable amount. However, including such variables prevent these equations from being feasible for use in large surveillance or epidemiological studies. It complicates the regression equations and makes them less available for free-living measuring because of the demanding data retrieval. For example, when gathering heart rate information we need an additional sensor attached to the participants. Furthermore, it is not possible to calculate velocity precise enough from accelerometer output, and in such, it has to be gathered separately. In this way, variables not contributing in a sufficient manner would only be considered redundant and decrease robustness of an already decent and practicable regression equation.

The possibility to measure EE accurately using more accessible approaches, such as raw accelerometer data and additional anthropometrical characteristics in children calls for a better understanding. To date there is a lack of studies for EE estimations in children using raw accelerometer data. One study, conducted by Hildebrand and co-workers (2014) compared raw accelerometer output from wrist and hip worn monitors in children (ranging from 7-11 years) suggesting that acceleration output explained 71-78% of the variance in VO_2. Consequently, contribution of acceleration data were greater compared to our study results, despite both studies used children as study sample and vector magnitude as acceleration output. However, the accelerometer placements were different. In addition, the activity protocol consisted of treadmill walking and running conducting specific velocities, which result in a more standardised data material. Furthermore, it may be that gas exchange data have a greater relation to acceleration data, although this was not coherent with this study (results not shown).

Besides, it may be that other alternative methods of analysis manage to estimate EE more accurately. For example, artificial neural networks have appeared to be a promising approach (14, 19, 20). It is a nonlinear model that takes a set of inputs and uses them to estimate a certain output variable (e.g. energy expenditure). It can contain different input features (e.g. participant characteristics, time domain features) that allow high estimation accuracy. In addition, the technique seems to be appropriate when the ideal solution of the estimating outcome is unknown (19). However, future studies are needed to investigate which statistical approaches that improve precision and individual EE estimation in children.

4.3 Strengths and limitations

There are several strengths of the current study that should be highlighted. First and foremost, a study sample of children, including both genders, wide range of age and BMI levels was evaluated. Such heterogeneous participant groups ensure variance, which is considered to be important when conducting validation studies. Secondly, a semistructured, simulated free-living setting gave the participants some extent of freedom in regard of movement pattern and intensity, while the researchers could maintain control over activities conducted. As previously mentioned, this could be even more important when studying children because of the tendency of sporadic movements and rarely achievements of steady-state during free-living physical activity settings. Finally, our study compared estimated equations to indirect calorimetry, which is considered to be gold standard for EE measurements.

In addition, some limitations should be addressed. The study sample only included healthy children and our results may therefore not generalize to certain patient groups. Furthermore, although the experimental setting included free-living activities, it is questionable whether the activity pattern of children might differ from daily life behaviour. For practical reasons, only common daily life activities such as walking and running were evaluated. However, for children it could be even as common to jump, throw or crawl. In addition, it cannot be known whether the children behaved as they usually do. For example, some of the participants were observed moving a bit stiff, which may be due to all the attached equipment or the data collection situation. Finally, our newly developed equations were only tested on a small sample of children, and should be further examined in other children to ensure the equations external validity.

5. CONCLUSION

The current study indicates that Brandes´ equations manage to estimate EE in children most accurately for absolute values when walking moderately. However, stepwise regression equations developed in the present study were more accurate for both walking and vigorous intensities, supporting child-specific regression equations for estimating EE in children. Thus, stepwise regression equations may work reasonably well for estimating group estimates.

However, further development of the stepwise regression equations is needed to provide a more accurate individual EE estimation. In addition, future research should evolve toward a methodological consensus for accelerometry-based EE estimation in children.

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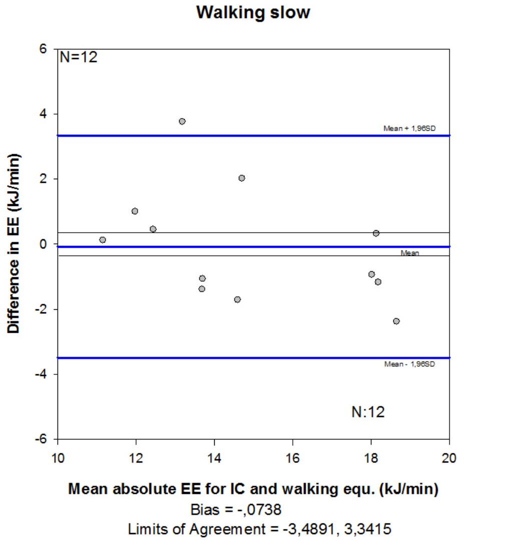
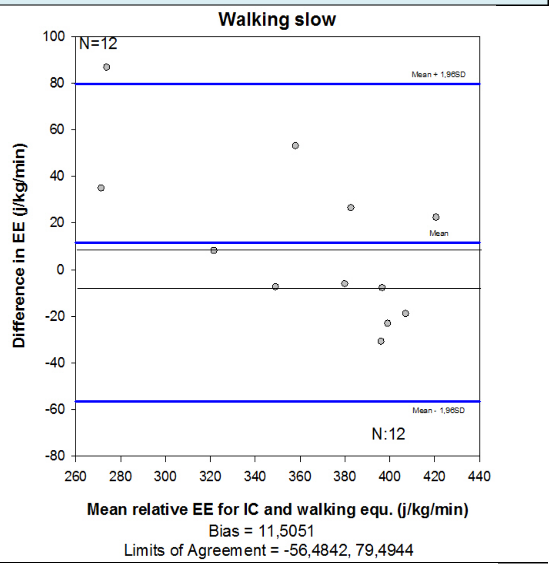
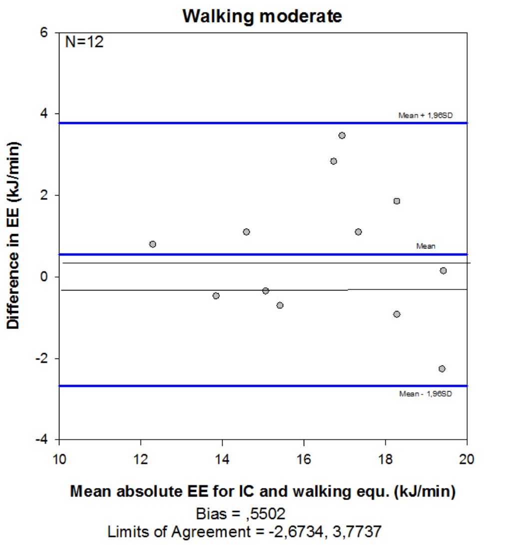
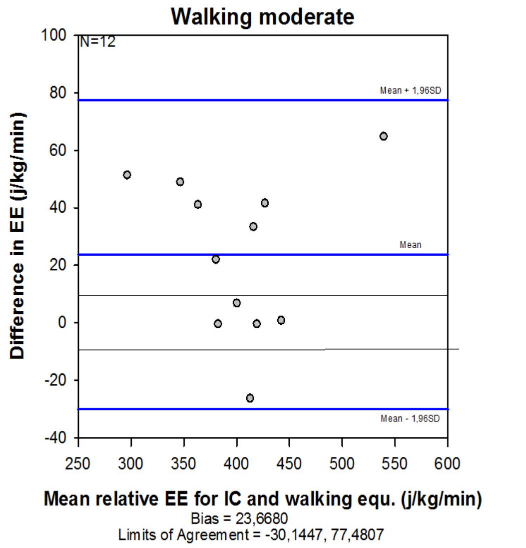
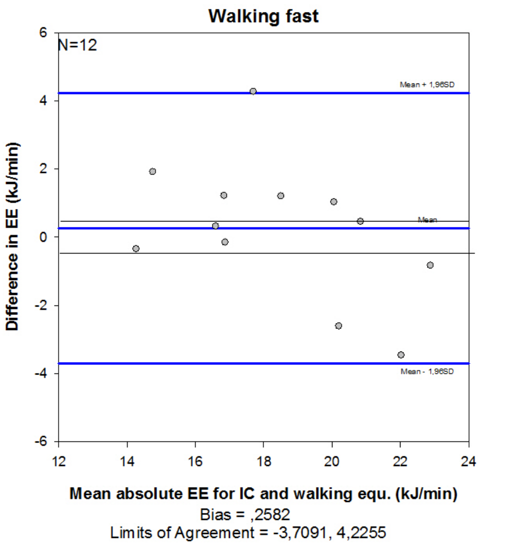
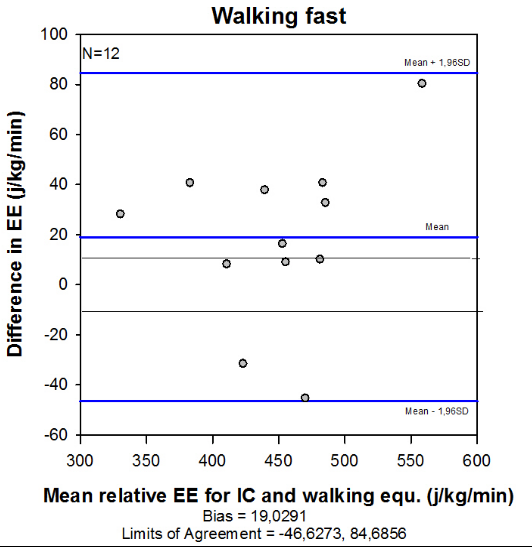
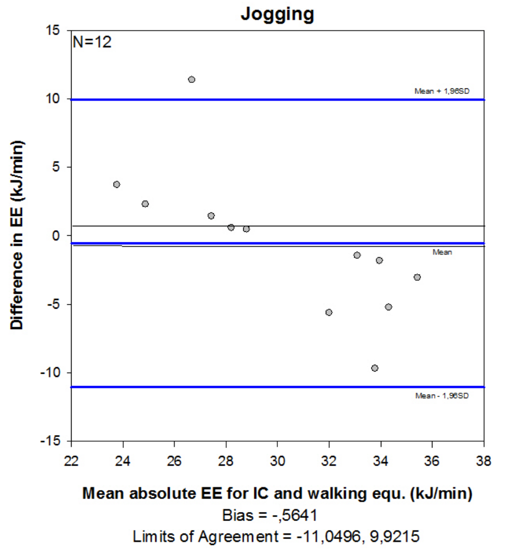
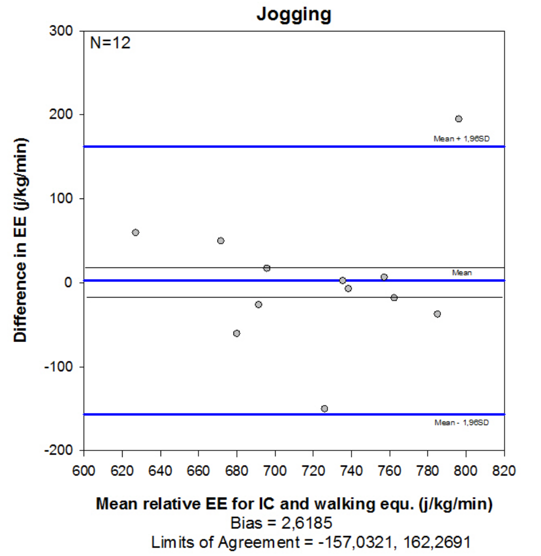
APPENDIX 1

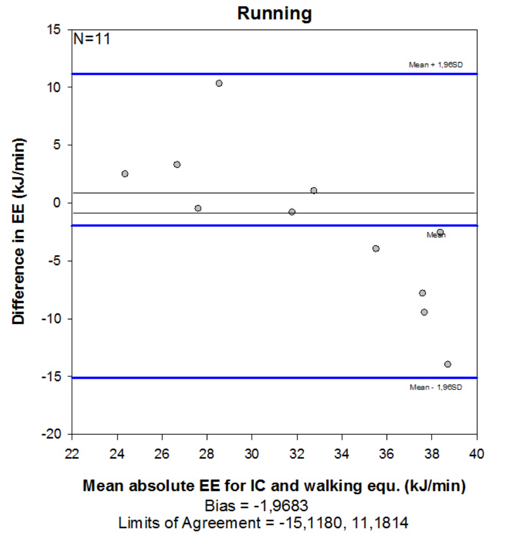
	NTNU$_{walking}$	
	Absolute	Relative
Walking slow		
Walking moderate		
Walking fast		

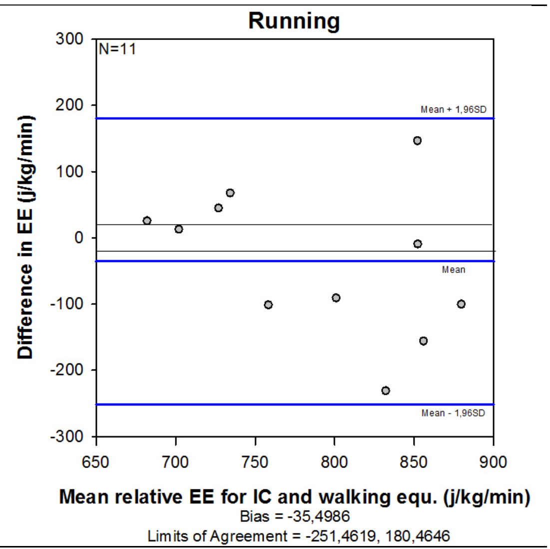
Jogging





Running



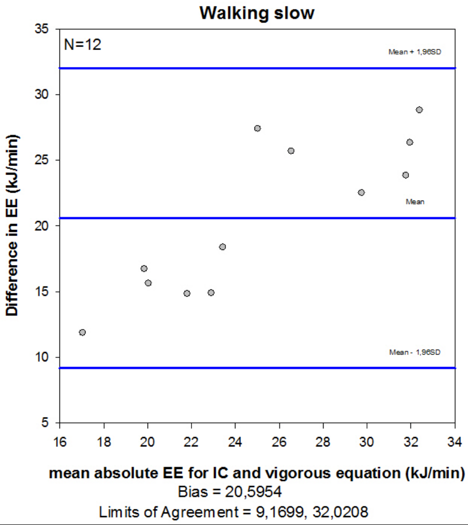


APPENDIX 2

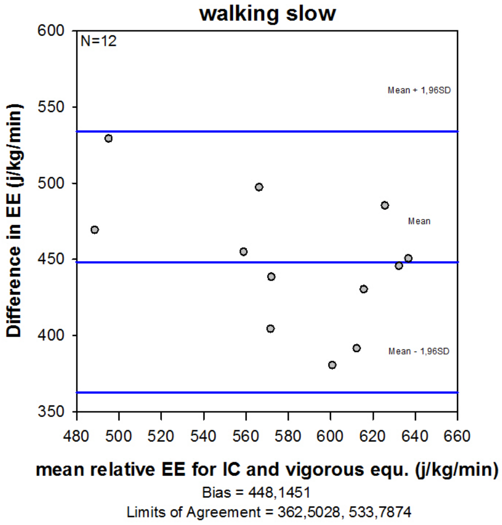
NTNU$_{vigorous}$

Walking slow

Absolute

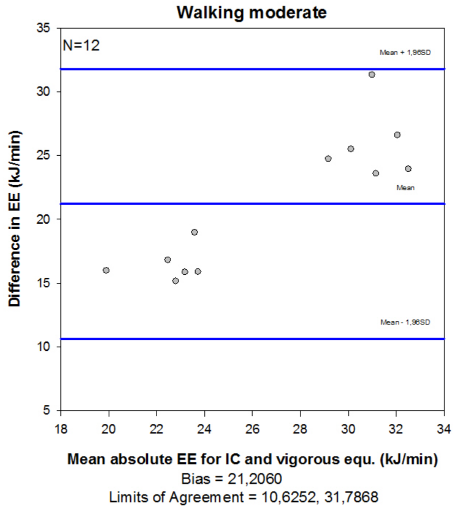


Relative

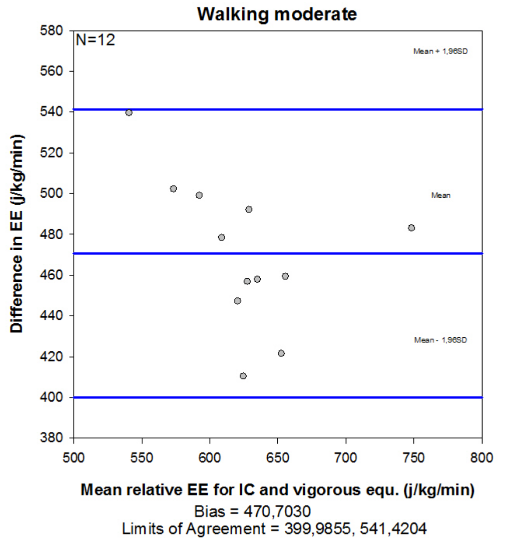


Walking moderate

Absolute

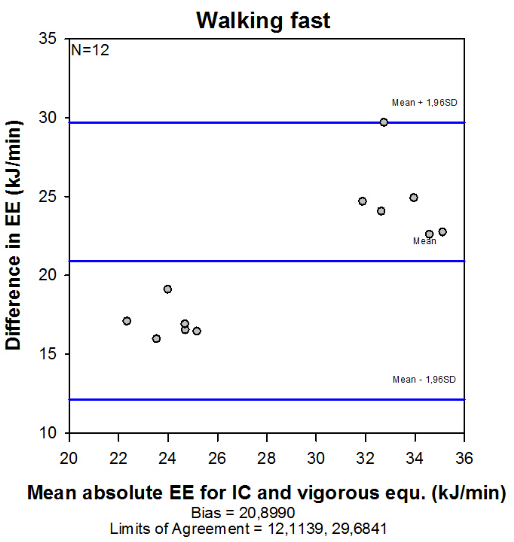


Relative

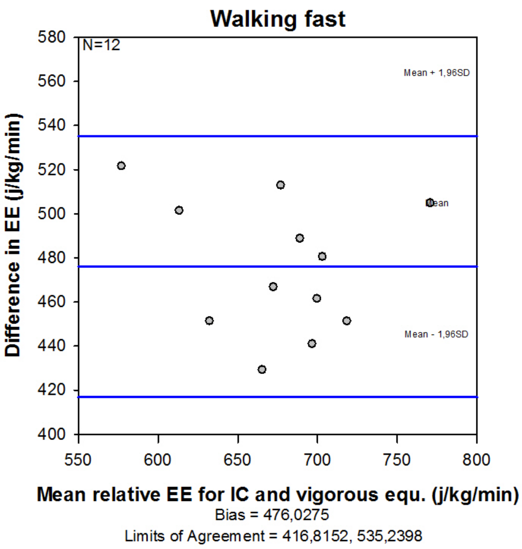


Walking fast

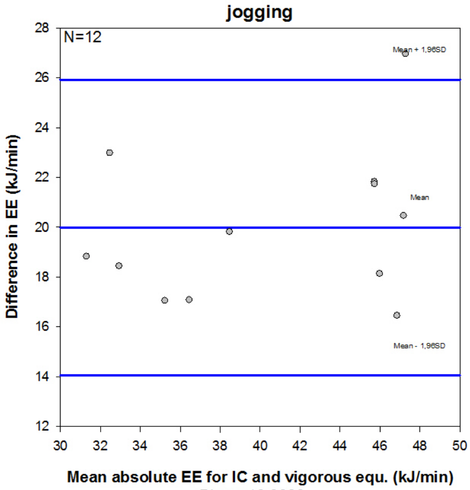
Absolute



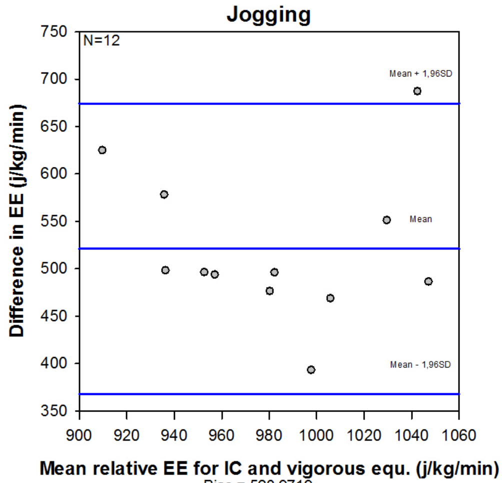
Relative



Jogging

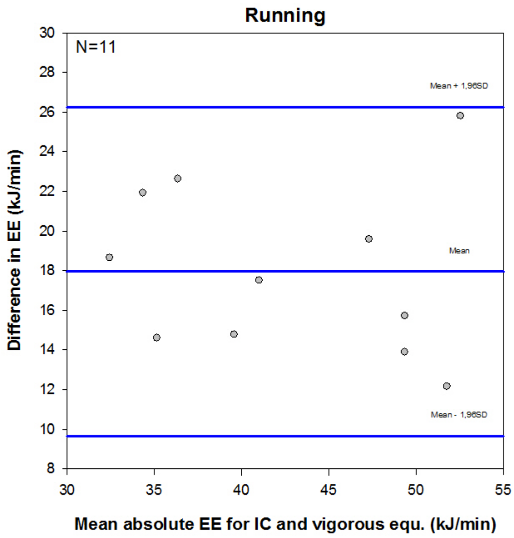


Bias = 19,9868
Limits of Agreement = 14,0494, 25,9242

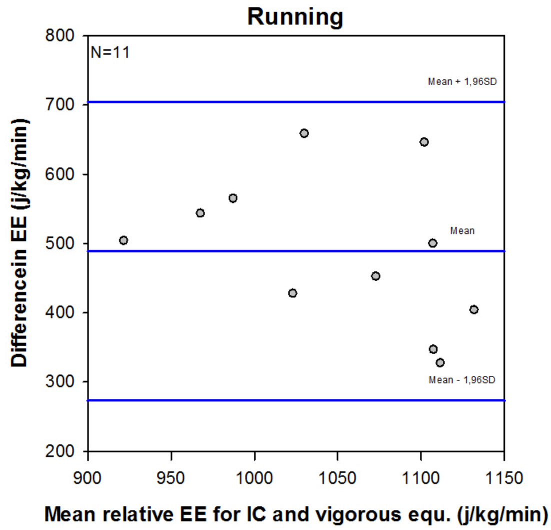


Bias = 520,9719
Limits of Agreement = 367,5988, 674,3450

Running



Bias = 17,9445
Limits of Agreement = 9,6525, 26,2364



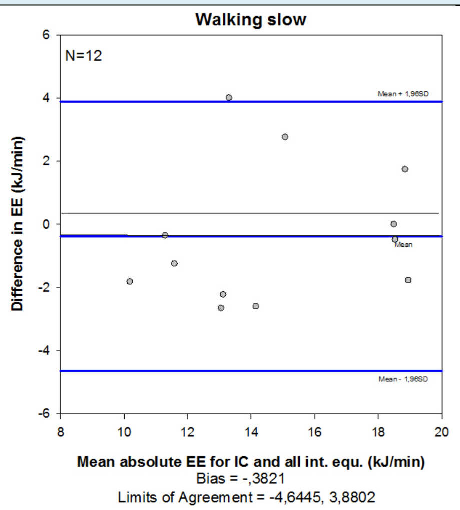
Bias = 488,9932
Limits of Agreement = 273,1711, 704,8152

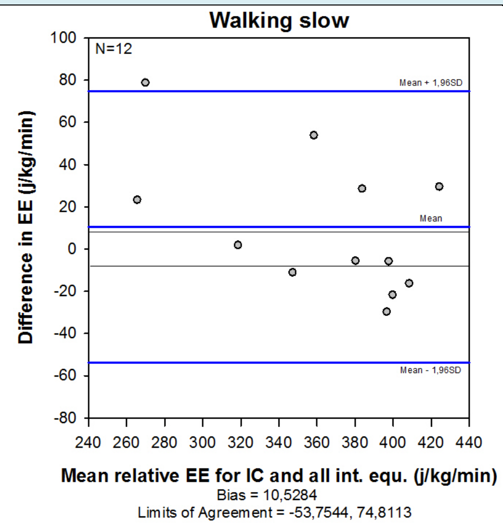
APPENDIX 3

NTNU$_{all. Int.}$

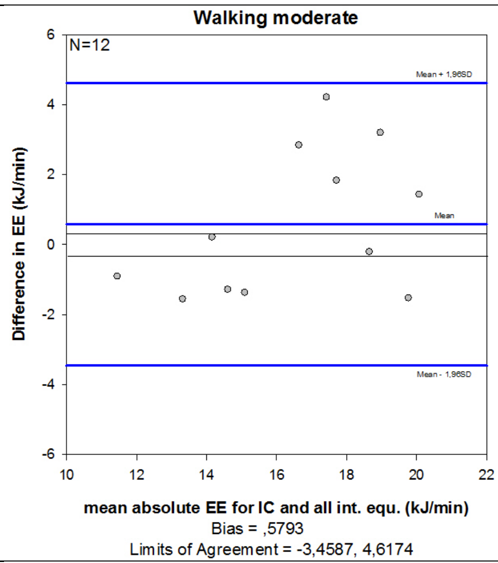
Absolute | Relative

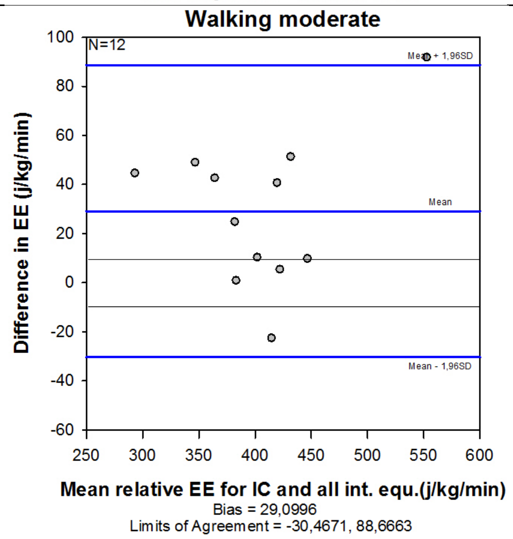
Walking slow



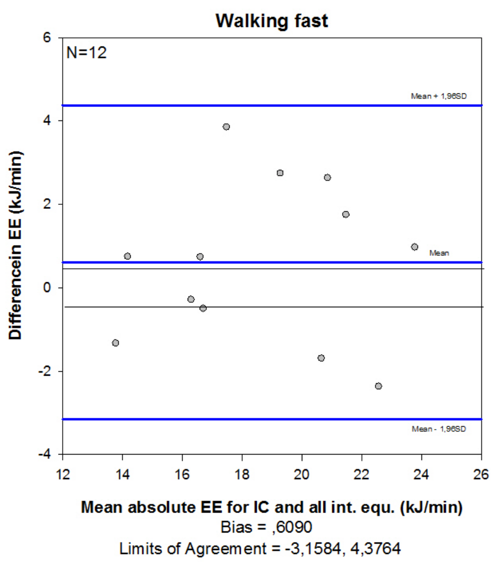


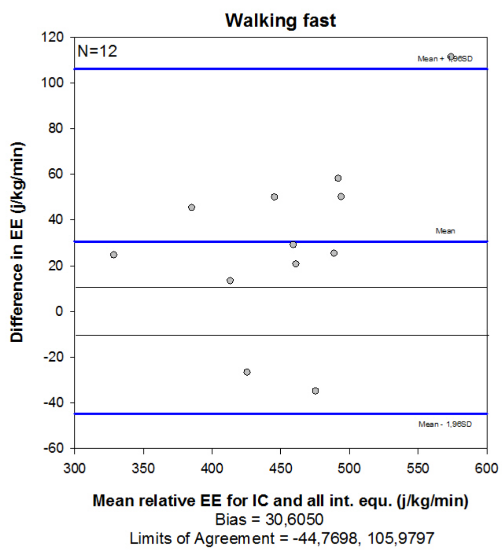
Walking moderate



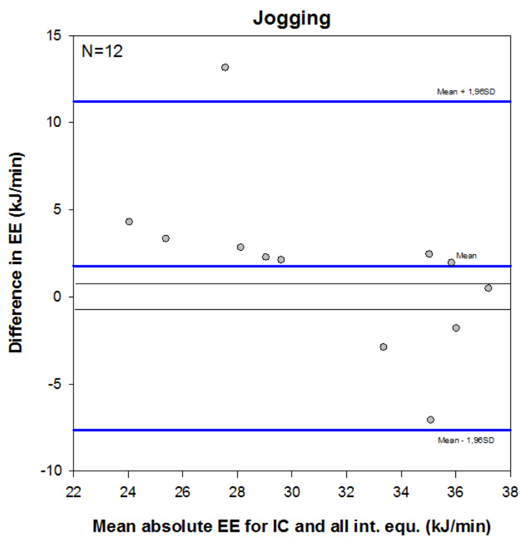


Walking fast

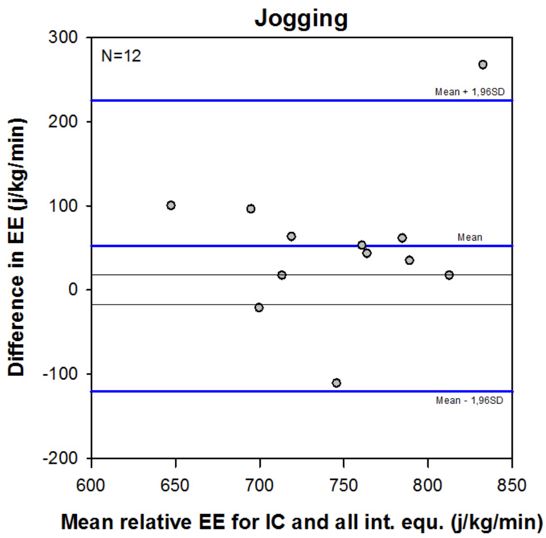




Jogging

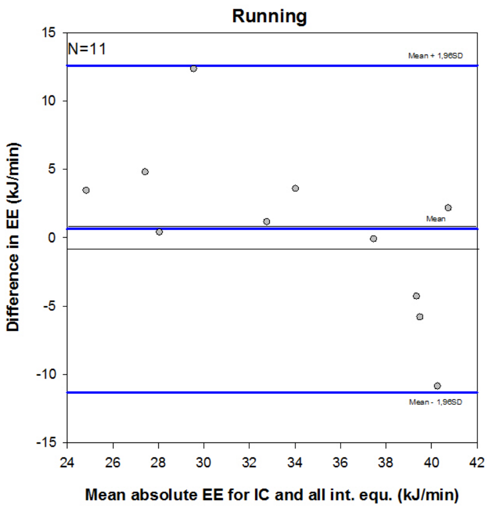


Bias = 1,7718
Limits of Agreement = -7,6620, 11,2056

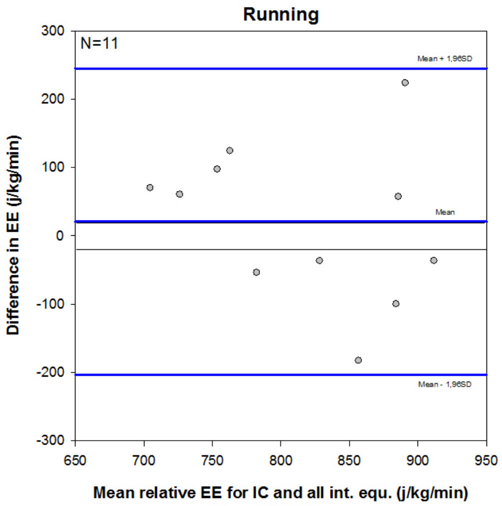


Bias = 52,0185
Limits of Agreement = -120,9100, 224,9471

Running



Bias = ,6373
Limits of Agreement = -11,3226, 12,5971



Bias = 20,6159
Limits of Agreement = -203,8177, 245,0495