ORIGINAL ARTICLE

Predicting Energy Expenditure of Manual Wheelchair Users With Spinal Cord Injury Using a Multisensor-Based Activity Monitor

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ABSTRACT. Hiremath SV, Ding D, Farringdon J, Cooper RA. Predicting energy expenditure of manual wheelchair users with spinal cord injury using a multisensor-based activity monitor. Arch Phys Med Rehabil 2012;93:1937-43.

Objective: To develop and evaluate new energy expenditure (EE) prediction models for manual wheelchair users (MWUs) with spinal cord injury (SCI) based on a commercially available multisensor-based activity monitor.

Design: Cross-sectional.

Setting: Laboratory.

Participants: Volunteer sample of MWUs with SCI (N=45).

Intervention: Subjects were asked to perform 4 activities including resting, wheelchair propulsion, arm-ergometer exercise, and deskwork. Criterion EE using a metabolic cart and raw sensor data from a multisensor activity monitor was collected during each of these activities.

Main Outcome Measures: Two new EE prediction models including a general model and an activity-specific model were developed using enhanced all-possible regressions on 36 MWUs and tested on the remaining 9 MWUs.

Results: The activity-specific and general EE prediction models estimated the EE significantly better than the manufacturer's model. The average EE estimation error using the manufacturer's model and the new general and activity-specific models for all activities combined was –55.31% (overestimation), 2.30% (underestimation), and 4.85%, respectively. The average EE estimation error using the manufacturer's model, the new general model, and activity-specific models for various activities varied from –19.10% to –89.85%, –18.13% to 25.13%, and –4.31% to 9.93%, respectively.

Conclusions: The predictors for the new models were based on accelerometer and demographic variables, indicating that movement and subject parameters were necessary in estimating the EE. The results indicate that the multisensor activity monitor with new prediction models can be used to estimate EE in MWUs with SCI during wheelchair-related activities mentioned in this study.

Key Words: Arm ergometry test; Energy expenditure; Physical activity; Rehabilitation; Spinal cord injuries; Wheelchairs.

REGULAR PHYSICAL ACTIVITY (PA) in persons with spinal cord injury (SCI) is associated with positive health benefits, such as increased muscular strength and cardiopulmonary fitness, and decreased deconditioning and pain.[1] However, previous research by Washburn and Hedrick[2] and Fernhall et al[3] showed that only 13% to 16% of persons with SCI reported regular PA. Reduction of PA levels in this population may be due to physiologic changes after SCI, as well as environmental barriers and mobility limitations associated with wheelchair use.[4,5] One of the prerequisites as well as strategies for promoting regular PA is to provide people with an accurate estimate of everyday PA and energy expenditure (EE).[2,3,6] However, persons with SCI, especially those who use manual wheelchairs for mobility, currently do not have an objective means to self-assess their PA participation and free-living EE. Such information can potentially assist manual wheelchair users (MWUs) with SCI to control and regulate their body weight and health.[1,2,7]

With the advancements in miniature sensing technology, there are a number of accelerometry-based activity monitors designed to estimate free-living EE in the ambulatory population.[8,9] St-Onge et al[8] evaluated the validity of a multisensor activity monitor in 45 adults without disabilities under free-living conditions. The mean signed EE estimated daily from the multisensor activity monitor was 117kcal/d (4.7%) lower than the criterion EE measured with doubly labeled water, with an intraclass correlation of .81 ($P<.01$). Berntsen et al[9] evaluated 4 accelerometry-based activity monitors including a multisensor, a single-sensor, and 2 dual-sensor activity monitors against a metabolic cart in 20 adults without disabilities during various activities and found that they underestimated total EE per minute by 9%, 15%, 5%, and 21%, respectively.

To our knowledge, none of the commercially available accelerometry-based activity monitors can accurately estimate EE in MWUs with SCI, as they typically do not consider the types of physical movement MWUs usually perform. Our

List of Abbreviations

EE	energy expenditure
MAE	mean absolute error
MSE	mean signed error
MWU	manual wheelchair user
PA	physical activity
SCI	spinal cord injury

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group has evaluated the performance of a multisensor activity monitor worn on the upper arm and a triaxial accelerometer worn around the waist in 24 MWUs with SCI during resting, wheelchair propulsion, arm-ergometry exercise, and deskwork.[6] Davis et al[10] evaluated the performance of a multisensor activity monitor in 10 MWUs with SCI during wheelchair propulsion on a treadmill at different velocities and gradients.

Despite the fact that current activity monitors cannot accurately estimate EE in MWUs with SCI, researchers have used activity monitors to quantify PA in MWUs with SCI.[11,12] Warms and Belza[11] evaluated the validity of a wrist-worn dual-axial accelerometer to measure community living PA in MWUs with SCI by correlating activity counts from the accelerometer with self-reported activity levels, and the Pearson correlation coefficients varied from .33 to .77. In another study, Washburn and Copay[12] assessed a wrist-worn uniaxial accelerometer in estimating the EE during wheelchair propulsion at 3 different speeds. Significant correlations (r=.52–.66, P<.01) were reported between the activity counts from both wrists and EE over the 3 pushing speeds. Studies by Warms and Belza[11] and Washburn and Copay[12] indicated correlations between activity counts from the activity monitors and PA intensity, but did not provide EE estimation.

The goal of this study was to develop EE prediction models for MWUs with SCI based on a commercially available multisensor activity monitor and evaluate the validity of the new models against criterion EE by a metabolic cart.

METHODS

This study took place at a university-based research facility. The institutional review board at the university approved the study.

Participants

A total of 45 MWUs with SCI volunteered and provided informed consent before their participation in the study. Subjects were included if they were between 18 and 60 years of age, used a manual wheelchair as a primary means of mobility, had an SCI, were at least 6 months postinjury, and were able to use an arm ergometer for exercise. Subjects were excluded if they were unable to tolerate sitting continuously for 4 hours, had active pelvic or thigh wounds, and failed to obtain their primary care physician's consent to participate in the study.

Procedures

The study protocol was described in detail elsewhere.[6] Subjects first completed a basic demographic questionnaire and had their weight,[a] height, and skinfold[b] thickness at 4 body sites (biceps, triceps, subscapular, suprailiac) measured. They were then fitted with a SenseWear[c] on the right upper arm over the triceps, and a K4b2 portable metabolic cart.[d] The activity session started with a resting routine where subjects were instructed to sit still in their wheelchairs. The resting routine was followed by 3 activity routines: wheelchair propulsion, arm-ergometer exercise, and deskwork. The wheelchair propulsion routine included 2 trials of propulsion on a computer-controlled dynamometer with average speeds of .89m/s (2mph) and 1.34m/s (3mph), and 1 trial on a flat tiled surface with an average speed of 1.34m/s (3mph). The arm-ergometer exercise routine consisted of 3 trials at 20W resistance and 60 rotations per minute, 40W and 60 rotations per minute, and 40W and 90 rotations per minute, respectively, on an Angio arm ergometer.[e] During the deskwork routine, subjects performed 2 tasks: reading a book of their choice for 4 minutes and taking a typing test on a computer for 4 minutes. The 3 activity routines were counterbalanced and the trials within each routine were randomized to counter order and carryover effects. Each activity trial lasted for 8 minutes with a resting period of 5 to 10 minutes between each trial and a period of 30 minutes between each activity routine.

Instrumentation and Data Collection

The SenseWear used in this study consisted of a 2-axis accelerometer, a galvanic skin response sensor, a skin temperature sensor, and a near-body temperature sensor. InnerView Research software[c] (version 7.0) was used to retrieve the raw sensor data and estimate EE in kilocalories per minute based on the manufacturer's prediction model. The sensor data included the average, mean absolute deviation, and number of peaks in longitudinal and transverse accelerations at 16Hz; and the average skin temperature, galvanic skin response, and near-body temperature at each minute. The K4b2 was calibrated for each subject as per the manufacturer's instructions. It was synchronized with the SenseWear before use. Cosmed K4b2 software[d] (version 9.0) was used to retrieve the criterion EE data in kilocalories per minute.

Development of EE Prediction Models

Two EE prediction models were developed including a general model (ie, 1 equation for all PA) and an activity-specific model (ie, multiple equations with 1 equation for each type of PA). For both cases, the prediction models were developed based on the data from 80% of the total participants (training group, n=36) and evaluated on the remaining 20% of the total participants (validation group, n=9). A stratified approach based on injury level (paraplegia vs tetraplegia) was performed to select subjects into the training and validation groups. Data preparation involved identifying steady-state conditions for each activity trial based on K4b2.[5,6,13] Steady-state conditions were determined by averaging breath-by-breath EE data over 30-second periods, and EE values having coefficients of variation of less than 10% computed over windows of at least 1 minute were used in the later analysis. To predict the criterion EE, we used 3 types of variables including the sensor data from the SenseWear, demographic data, and customized data derived from the sensor and demographic data. First, the sensor data from the SenseWear provided us with movement and physiologic information of the participant during activities. Second, the demographics data such as sex, age, height, weight, and completeness of injury provided us with wheelchair user–specific characteristics. Third, a number of custom variables including the nonlinear forms of the sensor and demographic data and combinations of the sensor and demographic data were calculated based on the existing literature in the field of PA monitoring and EE estimation in humans. For example, body mass to the power of .75 is a nonlinear variable considered to be a better predictor of EE than the body mass based on Kleiber's law.[14] On similar lines, height divided by mean absolute deviation is a combination variable that normalizes the arm movement by limb length. The custom variables might not have an intuitive definition, but empirically have a better linear relationship than the sensor and demographic data with the criterion EE. The model development process was data driven, which involves selecting the best variables from a pool of sensor, demographic, and custom variables to predict the criterion EE.[15]

A custom "all-possible-regressions" procedure was written in MATLAB software[f] (R2008a) to develop new general and activity-specific EE prediction models. This procedure was exhaustive, but integrated several approaches to avoid overfitting. First, correlations between any 2 predictors in the potential predictor set were calculated. For highly correlated pairs (Pearson correlation: $r>0.9$), 1 of the predictors was removed or 2 predictors were combined to minimize multicollinearity. If the 2 variables were obtained from the same sensor (eg, average acceleration vs mean absolute deviation in longitudinal direction), the variable that had a higher correlation with the criterion EE was retained; otherwise the variables were combined by multiplying one with the other. The variables retained varied from 20 to 24 predictor variables for the new general and activity-specific models. Every combination of 3-predictor variables was grouped together, thus resulting in 1140 to 2024 3-predictor sets for the new general and activity-specific models. Multiple regression models using each predictor set were constructed to estimate criterion EE. We chose to include only 3 predictors per set in order to reduce overfitting and ensure computational simplicity. Implicit in the modeling process for each predictor set was the use of a cross-validation technique instead of model fit statistics (eg, R^2) as a guard against overfitting the data.[15] Each time, a different set of 6 subjects' data was removed from the total, and the remaining data were used to determine the model's parameters (6-fold cross-validation with 6 subjects per fold). The model was then applied to the held out data and the EE prediction error calculated. All the errors were collated to indicate the predictive quality of the predictor set. The predictor set that yielded the smallest EE prediction error was selected to build the final EE prediction model from the whole training group.

Table 1: Demographic Characteristics of the Subjects

Variables	Values
Overall group	45
Sex	
Male	37
Female	8
Age (y)	40.2±11.0
Height (cm)	178.2±8.6
Weight (kg)	78.5±21.9
Total skinfold from 4 sites (mm)	57.3±23.4
Manual wheelchair usage (y)	13.8±9.1
Injury level (range)	C4 to L4
Paraplegia (T4 and below)	38
Tetraplegia (T3 and above)	7
Injury completeness	
Complete	21
Incomplete	24
Self-reported PA	
Regular	23
Occasional	13
No regular PA	9
Training group	36
Sex	
Male	30
Female	6
Age (y)	39.8±11.6
Weight (kg)	78.6±22.3 (44.2–141.1)
Height (cm)	178.7±8.2 (157.5–200.7)
Validation group	9
Sex	
Male	7
Female	2
Age (y)	42.3±8.9
Weight (kg)	78.1±21.9 (55.4–129.5)
Height (cm)	176.1±10.3 (165.0–190.5)

NOTE. Values are n, mean ± SD, or mean ± SD (range).

Table 2: Description of Variables Used in General and Activity-Specific EE Estimation Models

Variables	Description of Variables
EE_MET	EE measured using the K4b2 metabolic cart
LMAD	Mean absolute deviation in longitudinal acceleration
LPEAKS	Average number of peaks per minute in longitudinal acceleration
MASS_E_point75	Body mass raised to the power of .75
HTDivLMAD	Height divided by the mean absolute deviation in longitudinal acceleration
TLMAD	Product of mean absolute deviation in transverse and longitudinal acceleration
TAVE	Average transverse acceleration
SQRT_LMAD	Square root of mean absolute deviation in longitudinal acceleration

Data Analysis

The new general and activity-specific prediction models were evaluated separately using the validation group (n=9). The estimated EE for the validation group using the manufacturer's model and the 2 new models was compared with the criterion EE. The comparisons involved calculating the minute-by-minute mean absolute error (MAE) and mean signed error (MSE). We also compared the estimated "per-session" EE by the manufacturer's model and the new models over all the activities for each subject with the criterion EE using per-session MSE. The per-session MSE provided us with the average EE error per subject over the whole session including all the activity trials. The EE for all activities combined was estimated by using activity-specific models for the corresponding activity type before calculating the overall MAE or MSE. In addition, Bland and Altman plots were used to visually assess the agreement between the criterion and estimated minute-by-minute EE.[16] Scatterplots of the criterion EE against the estimated minute-by-minute EE and per-session EE for the validation group were plotted to evaluate the association between these measures. The Pearson moment correlations and intraclass correlations for single measure using a 2-way mixed model with consistency were also calculated between the criterion and estimated minute-by-minute EE for the validation group. Statistical significance was set at an α level of .05.

RESULTS

Demographic characteristics of the subjects are described in table 1. All the subjects completed the 8 activity trials. Because of device malfunction of the K4b2, 3 trials from 3 subjects had to be discarded. In addition, 5 trials from 4 subjects that did not yield steady-state conditions were also discarded.

The general model shown in equation 1 takes all the 4 activities into consideration. The activity-specific models are shown in equations 2 through 5. Table 2 lists the predictors selected for the new models. Table 3 shows the minute-by-minute MAE and mean absolute percentage difference between the criterion and estimated EE for the validation group. Table 4 shows the minute-by-minute MSE and mean percentage difference between the criterion and estimated EE. Table 5 shows the per-session MSE and percentage difference.

Table 3: MAE and Mean Absolute Percentage Difference of Minute-by-Minute EE Using the Manufacturer's Model, the New General Model, and the New Activity-Specific Model for the Validation Group

	MAE (kcal/min)			Mean Absolute Percentage Difference (%)		
Activities	Manufacturer's Model	General Model	Activity-Specific Model	Manufacturer's Model	General Model	Activity-Specific Model
Resting	0.3	0.4	0.2	28.0	28.4	18.2
Propulsion	2.9	0.7	0.6	90.6	22.3	16.5
Arm ergometry	2.0	1.3	0.9	45.4	25.7	17.6
Deskwork	0.5	0.3	0.2	41.3	25.3	13.4
All activities	2.0	0.9	0.6	59.2	24.7	16.8

NOTE. The 95% confidence interval MAE values for the manufacturer's, and new general and activity-specific models were 52.6% to 65.8%, 22.1% to 27.2%, and 15.2% to 18.5%, respectively, for all activities combined.

General Model (see table 2 for explanation)

$$\begin{aligned} EE\_MET = &-1.274203 \\ &+ 0.004104224 * LPEAKS + 0.3326474 * LMAD \\ &+ 0.08780239 * MASS\_E\_point75 \end{aligned} \quad (1)$$

Activity-Specific Model

Resting.

$$\begin{aligned} EE\_MET = &-0.009751037 \\ &- 0.00001228313 * HTDivLMAD \\ &+ 1.176567 * LMAD + 0.03884351 * MASS\_E\_point75 \end{aligned} \quad (2)$$

Wheelchair propulsion.

$$\begin{aligned} EE\_MET = &-2.450952 + 0.005949753 * LPEAKS \\ &+ 0.01841253 * TLMAD \\ &+ 0.1251561 * MASS\_E\_point75 \end{aligned} \quad (3)$$

Arm ergometry.

$$\begin{aligned} EE\_MET = &-0.5633703 + 0.005884454 * LPEAKS \\ &+ 0.03319644 * TLMAD \\ &+ 0.08795310 * MASS\_E\_point75 \end{aligned} \quad (4)$$

Deskwork.

$$\begin{aligned} EE\_MET = &-0.07291671 + 0.3559690 * TAVE \\ &+ 0.9740335 * SQRT\_LMAD \\ &+ 0.04039672 * MASS\_E\_point75 \end{aligned} \quad (5)$$

Figures 1 and 2 show the Bland-Altman plots and figures 3 and 4 show the scatterplots for the manufacturer's model and the new general and activity-specific models. All the data presented in figures 1 through 4 are from the validation group. The Pearson correlations between the criterion and estimated EE for the validation group using the manufacturer's model and the new general and activity-specific models for all activities combined were significant ($P<.001$) with values of .75, .74, and .88, respectively. The intraclass correlations were significant ($P<.001$) between the criterion and estimated EE for the validation group using the manufacturer's model, and the new general and activity-specific models for all activities combined were significant ($P<.001$) with values of .64 (95% confidence interval, .57–.70), .72 (95% confidence interval, .66–.77), and .86 (95% confidence interval, .82–.88), respectively.

DISCUSSION

Research has shown that off-the-shelf activity monitors cannot accurately predict EE in MWUs with SCI.[6,10] Our previous study[6] using SenseWear has found large EE estimation errors ranging from 24.4% to 125.8% among 24 MWUs with SCI. Davis[10] showed that the mean signed EE by SenseWear (14.3±6.0kJ/min) was much higher than the EE from a metabolic cart (11.4±4.0kJ/min) during wheelchair propulsion on a treadmill. This study with a larger cohort also showed a consistent trend of large EE estimation errors and has led to the development of new EE prediction models.

The new activity-specific and general models developed in this study integrated all-possible-regression and cross-validation techniques to leverage the benefits of exhaustive model search, avoid overfitting, and increase the robustness of the model's performance on unseen data. Our validation results

Table 4: MSE and Mean Percentage Difference of Minute-by-Minute EE Using the Manufacturer's Model, the New General Model, and the New Activity-Specific Model for the Validation Group

	MSE (kcal/min)			Mean Percentage Difference (%)		
Activities	Manufacturer's Model	General Model	Activity-Specific Model	Manufacturer's Model	General Model	Activity-Specific Model
Resting	−0.2±0.3	−0.1±0.5	0.0±0.3	−19.1±27.5	−8.3±34.9	−4.3±21.4
Propulsion	−3.0±2.0	−0.4±0.8	0.2±0.7	−89.8±64.5	−16.8±28.0	2.8±22.3
Arm ergometry	−1.7±2.0	1.3±1.0	0.6±1.0	−40.3±42.1	25.1±16.5	9.9±19.0
Deskwork	−0.4±0.5	−0.2±0.4	0.0±0.2	−34.6±34.4	−18.1±26.8	−0.4±16.1
All activities	−1.9±2.0	0.4±1.1	0.4±0.8	−55.3±56.1	2.3±31.7	4.9±20.7

NOTE. Values are mean ± SD. The 95% confidence interval MSE values for the manufacturer's, and new general and activity-specific models were −48.1% to −62.5%, 6.3% to −1.7%, and 7.5% to 2.2%, respectively, for all activities combined.

Table 5: MSE and Mean Percentage Difference of Per-Session EE Using the Manufacturer's Model, the New General Model, and the New Activity-Specific Models for the Validation Group

	MSE (kcal)			Mean Percentage Difference (%)		
Activities	Manufacturer's Model	General Model	Activity-Specific Model	Manufacturer's Model	General Model	Activity-Specific Model
All activities	–67.9±48.2	13.3±15.9	12.6±14.6	–51.5±31.6	10.4±11.8	9.6±10.9

NOTE. Values are mean ± SD. The average steady-state calories for performing all the activities over about 36 minutes were 128.60kcal using the portable metabolic cart.

showed high intraclass correlation coefficients between the predicted EE by the new models and the criterion EE, indicating that there is a good agreement between the estimated EE by the new models and the criterion EE.[17] We also compared the 2 new prediction models and the manufacturer's model with the criterion EE and found that the 2 new models significantly improved the EE prediction accuracy over the manufacturer's model. We used 4 measures for the comparison including minute-by-minute MAE and MSE that assess the model's ability to predict EE of performing a single activity for each minute, and per-session MSE that assesses the model's ability to predict EE of performing multiple activities over a period of time. The MAE provides information regarding the magnitude of the prediction error, and the MSE indicates whether the predictions are biased—that is, whether they tend to be disproportionately positive or negative. The minute-by-minute prediction error for the manufacturer's model was much higher than that for the generalized and activity-specific models (see tables 3 and 4). We also found that the manufacturer's model tended to overestimate EE, while the generalized and activity-specific models underestimated EE with smaller biases (see tables 4 and 5).

When further examining the 2 new models, we found the activity-specific model outperformed the general model, with a smaller absolute minute-by-minute EE prediction error for each individual activity and for all the activities combined (see table 3). The activity-specific model also performed better than the general model, with a smaller bias for each individual activity (see table 4). The general model selected the predictors that are sensitive to all activities as a whole, which compromises EE estimation for individual activities. However, we noticed that the general model had a smaller overall bias than the activity-specific model. This could be because the overestimations and underestimations from different activities tend to cancel each other out. For example, the general model tended to overestimate EE for wheelchair propulsion but underestimate EE for arm ergometry. For the same reason, the general model performed similarly as the activity-specific model for the per-session evaluation where the EE was estimated for multiple activities combined. These results suggested that the activity-specific model is more suitable for predicting minute-by-minute EE of individual activities, while the general model could be used when predicting the total EE over a group of activities together.

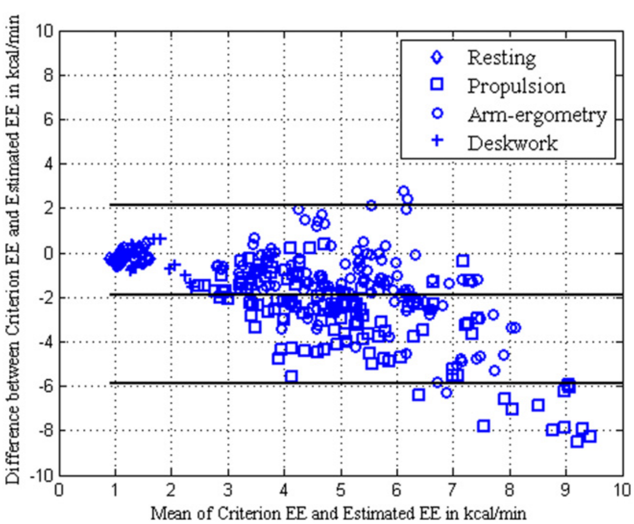

Fig 1. Bland-Altman plot for the criterion and estimated EE using the manufacturer's model for the validation group with a mean ± SD value of –1.87±2.04kcal/min.

As for the predictors of the general and activity-specific models, of all the demographic variables, the body mass to the power of .75 (MASS_E_point75) was selected as a predictor by all the models. This is consistent with Kleiber's law, which states that any mammal's metabolic rate is proportional to the mammal's mass raised to the power of .75.[14] The upper limb movements captured by the accelerometer in the SenseWear also played important roles in the EE estimation. The mean absolute deviation variables (LMAD, SQRT_LMAD, TLMAD) captured the variability of the upper limb movements in different directions. The number of peaks (LPEAKS) captured the change of direction in the arm movements. The height divided by mean absolute deviation (HTDivLMAD) was chosen for the resting activity possibly because subjects were not sitting completely still and small arm movements as well as fidgeting were picked up by the accelerometer. Taller individuals tend to have longer arms, and their arm movements are more easily detected by the accelerometer during resting. The predictors chosen in the models are specific for wheelchair-related activities, including the average number of peaks in longitudinal acceleration (LPEAKS) and the product of mean absolute deviation in transverse and longitudinal acceleration (TLMAD) for wheelchair propulsion and arm-ergometry activities. Because the predictors included in the models were not SCI specific (eg, injury level), the models can be used to estimate EE for all MWUs with SCI during the activities discussed in this study.

Study Limitations

Although the EE prediction accuracy was significantly improved with the new predictions models, it was relatively low when compared with the performance of the SenseWear among the ambulatory populations. Johannsen et al[18] evaluated the validity of the SenseWear in estimating total EE for 14 consecutive days among 30 healthy adults aged 24 to 60 years and found that the absolute prediction error rate when compared with the criterion measure using doubly labeled water was 8.1%±6.8%. Berntsen[9] found that the SenseWear underestimated total EE with a minute-by-minute MAE of 9% compared with an indirect calorimeter in 20 adults for a period of 120

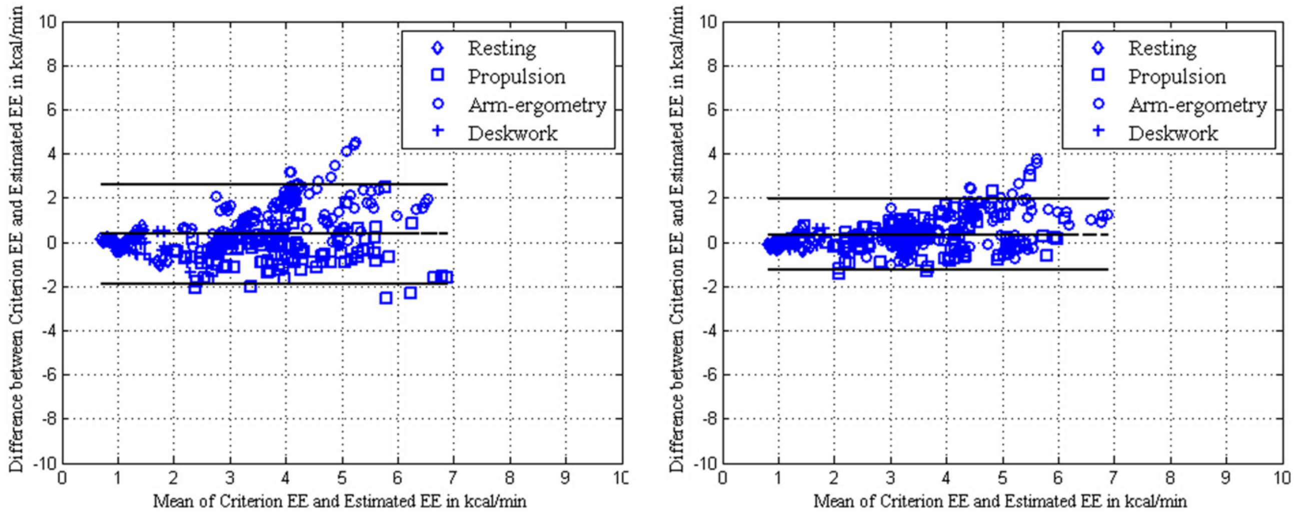

Fig 2. Bland-Altman plots for the criterion and estimated EE using the new general and activity-specific models for the validation group with a mean ± SD value of .37±1.14kcal/min and .35±.82kcal/min, respectively.

minutes during various types of activities and intensities. One possible reason for the relatively low prediction accuracy of the new models could be the small sample size for both the training and validation groups. The small sample size in the training group further limited our ability to achieve a balanced distribution of subjects with different ranges of weight. Subjects in certain ranges may be underrepresented compared with those in other ranges, possibly leading to relatively large prediction errors for validation subjects who fell under the underrepresented ranges. Other limitations include collecting resting EE while the subjects were seated still in their wheelchairs, limited number of PAs, PA trials tested in a structured laboratory setting, and other demographic factors related to the inclusion criteria. It is not yet clear whether the new models can be used to predict EE for free-living activities, and how the models will perform under various conditions (velocities, resistances, and environments). We hope our research will stimulate interest and efforts of other researchers to validate and refine the EE prediction models for MWUs with SCI. We recommend that researchers evaluate our models in their subject groups before use. Recommendations for future studies include testing more subjects with carefully planned recruitment strategies and experimental protocols containing free-living activities, testing the SenseWear among MWUs with other types of disabilities, and possibly developing PA monitors particularly suitable for MWUs.

CONCLUSIONS

In this study, we have developed and evaluated new EE prediction models for MWUs with SCI based on a popular commercially available activity monitor. To our knowledge, this is the first study to develop new EE prediction models for this population based on the SenseWear activity monitor. The new models developed here can be used in clinical

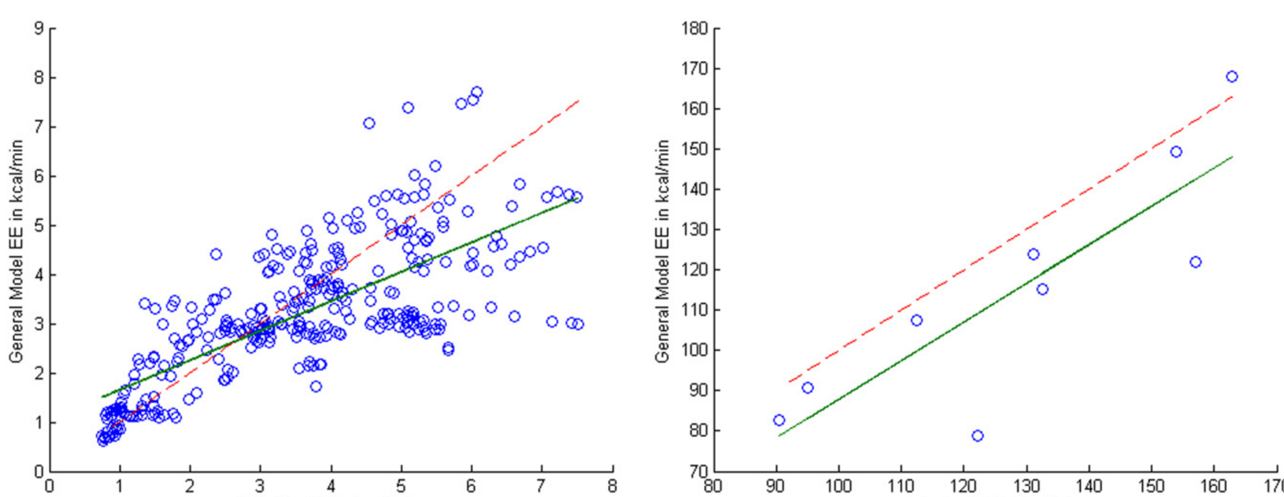

Fig 3. Scatterplots of the criterion and estimated minute-by-minute and per-session EE using the new general model for the validation group. The plots show the EE values for all activities combined. The straight line indicates the model's best fit, and the dotted line indicates the perfect agreement.

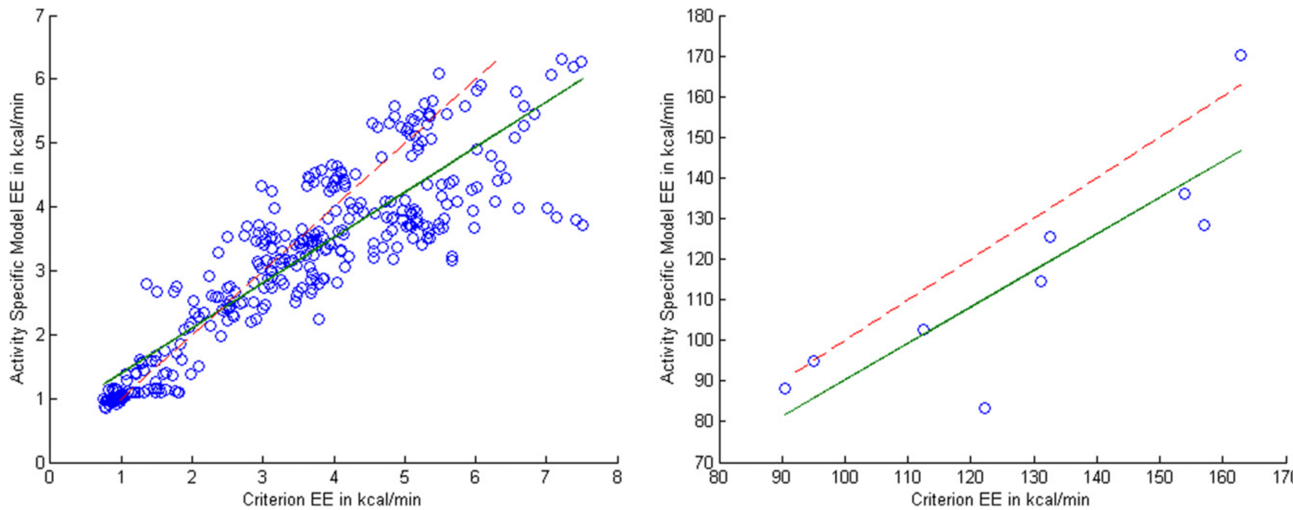

Fig 4. Scatterplot of the criterion and estimated minute-by-minute and per-session EE using the new activity-specific model for the validation group. The plots show the EE values for all activities combined. The straight line indicates the model's best fit, and the dotted line indicates the perfect agreement.

applications of using SenseWear activity monitors to estimate EE for MWUs with SCI during the wheelchair-related activities discussed in this study. We expect that the availability of the new models will encourage more research in this area, potentially leading to an accurate PA assessment tool for estimating free-living EE and time spent in light, moderate, and vigorous PA for MWUs with SCI. The availability of PA monitors that accurately estimate EE in MWUs with SCI could potentially facilitate better personal and clinical decisions on PA, energy balance, and healthier lifestyles in MWUs with SCI.

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Suppliers

a. Befour MX490D extra wide wheelchair scale; Befour, Inc, 102 Progress Dr, Saukville, WI 53080.
b. Lange skinfold caliper; Beta Technology, 2841 Mission St, Santa Cruz, CA 95060.
c. BodyMedia Inc, 420 Fort Duquesne Blvd, Ste 1900, Pittsburgh, PA 15222.
d. COSMED srl, Via dei Piani di Mt. Savello 37, Pavona di Albano, Rome 0004, Italy.
e. Angio arm ergometer; Lode B.V., Zernikepark 16, Groningen 9747AN, The Netherlands.
f. MATLAB software; The Mathworks Inc, 3 Apple Hill Dr, Natick, MA 01760-2098.