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Evaluation of custom energy expenditure models for SenseWear armband in manual wheelchair users

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Abstract—Physical activity monitors are increasingly used to help the general population lead a healthy lifestyle by keeping track of their daily physical activity (PA) and energy expenditure (EE). However, none of the commercially available activity monitors can accurately estimate PA and EE in people who use wheelchairs as their primary means of mobility. Researchers have recently developed custom EE prediction models for manual wheelchair users (MWUs) with spinal cord injuries (SCIs) based on a commercial activity monitor—the SenseWear armband. This study evaluated the performance of two custom EE prediction models, including a general model and a set of activity-specific models among 45 MWUs with SCI. The estimated EE was obtained by using the two custom models and the default manufacturer's model, and it was compared with the gold standard measured by the K4b2 portable metabolic cart. The general, activity-specific, and default models had a mean signed percent error (mean +/– standard deviation) of –2.8 +/– 26.1%, –4.8 +/– 25.4%, and –39.6 +/– 37.8%, respectively. The intraclass correlation coefficient was 0.86 (95% confidence interval [CI] = 0.82 to 0.89) for the general model, 0.83 (95% CI = 0.79 to 0.87) for the activity-specific model, and 0.62 (95% CI = 0.16 to 0.81) for the default model. The custom models for the SenseWear armband significantly improved the EE estimation accuracy for MWUs with SCI.

Key words: activities of daily living, activity monitors, energy expenditure, evaluation, exercise, manual wheelchair users, mobility, physical activity, prediction models, spinal cord injury.

INTRODUCTION

Physical inactivity is the fourth leading cause of death worldwide [1]. Approximately 3.2 million deaths each year are related to insufficient physical activity [2]. Due to mobility limitations and physiological constraints such as reduced circulation in the lower limbs and limited voluntary muscle control and reflexes [3], manual wheelchair users (MWUs) with spinal cord injury (SCI) tend to participate less in habitual or leisure physical activities (PAs) [4]. Lack of regular PA in turn increases their risk of developing secondary health problems such as obesity, high blood pressure, cancers, cardiovascular diseases, and loss of muscle strength [2,5]. Rimmer showed that regular exercise on most days of the week significantly reduces an individual's chances of developing stroke,

Abbreviations: CI = confidence interval, EE = energy expenditure, HERL = Human Engineering Research Laboratories, ICC = intraclass correlation coefficient, MAE = mean absolute percent error, MSE = mean signed percent error, MWU = manual wheelchair user, NVWG = National Veterans Wheelchair Games, PA = physical activity, SCI = spinal cord injury, SW = SenseWear, VA = Department of Veterans Affairs.

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diabetes, and overall mortality and helps maintain a healthy cholesterol level and body weight [6]. In addition, regular PA can help MWUs improve cardiovascular fitness and endurance; improve the ability to perform activities of daily living; develop and maintain joint flexibility, muscle strength, and balance; improve bone density; promote a sense of control over physical functioning; and enhance the feeling of well-being [7]. As stated in the Healthy People 2020 objectives, adults should engage in aerobic PA for at least 150 min/wk of moderate intensity, or 75 min/wk of rigorous intensity [8]. Healthy People 2020 further reported that adults with disabilities were 82 percent more likely to be physically active if their doctor recommended it [8]. However, it is difficult for MWUs with SCI to track their PA participation when the current technology is unable to accurately quantify whether they have reached their target PA goal as recommended by the Centers for Disease Control and Prevention and American College of Sports Medicine [9]. Additionally, the lack of PA monitoring tools for MWUs with SCI hinders the ability of health professionals to prescribe PA assignments and/or treatments to these individuals to maintain their fitness.

The use of micro-electromechanical systems in the form of activity monitors to track daily PA levels has become very popular in the last decade. Studies have proven that these systems are accurate in monitoring PA and have the potential to encourage users to develop a healthier lifestyle [10] for the general population. Activity monitors can provide objective real-time feedback on PA and energy expenditure (EE), and thus can be more convenient and reliable than subjective PA questionnaires or activity logs that rely on individuals' memories [11]. The real-time feedback also could increase individuals' awareness of the time spent being active and the intensity level of the PA and potentially help them develop a more active lifestyle. However, the existing activity monitors on the market remain ineffective in estimating PA and EE in MWUs [3,12–16]. The activity monitors on the market were designed to track activities that involve lower-limb movements of ambulatory populations, such as walking and running. However, MWUs mainly rely on their upper limbs for mobility, and therefore, these monitors need to be adapted for this population.

Our research team has recently developed custom models, including a general model and a set of activity-specific models for estimating EE of MWUs with SCI using the commercial monitor SenseWear (SW) (BodyMedia Inc, Pittsburgh, Pennsylvania) [17]. The models were developed based on the data collected from 45 MWUs with SCI while they performed four types of activities: resting while seated, deskwork, wheelchair propulsion, and arm ergometry. The activity-specific models included four equations for each of the four activities, while the general model used one equation for all activities and could be used when the type of activity performed by the users was not recorded. The aim of this study was to evaluate the validity of these custom models in estimating the EE of a separate cohort of MWUs with SCI when they performed a wide range of lifestyle-based PA and exercises. We hypothesized that the custom models will be more accurate than the default manufacturer's model used by the SW.

METHODS

A cross-sectional validation study design was used in this study.

Subjects

A total of 45 subjects with SCI participated in the study. Subjects were between 18 and 65 yr old, used manual wheelchairs as a primary mean of mobility, had an SCI, were at least 6 mo postinjury, and were able to use an arm ergometer for exercise. Subjects were excluded if they were unable to tolerate sitting for 3 h, had active pelvic or thigh wounds (pressure ulcers), had a history of cardiovascular disease, or were pregnant (based on self-report).

Instrumentation

The K4b2 portable metabolic cart (COSMED srl; Rome, Italy) was calibrated for each subject following the manufacturer's instructions. The EE measured by the K4b2 served as a criterion measure for the analysis [18–19]. The SW is an off-the-shelf activity monitor that consists of a two-axis accelerometer, a galvanic skin response sensor, a skin temperature sensor, and a near-body temperature sensor. The SW and K4b2 were time-synchronized to the clock of a single computer and worn by subjects while performing the activities. Each subject wore the SW over his or her triceps of the right arm, carried the K4b2 device at the chest area, and put on a facial mask while performing activities.

Procedure

The study was approved by the institutional review boards of the University of Pittsburgh, U.S. Army Medical Research & Materiel Command's Human Research Protection Office, and the Department of Veterans Affairs (VA) Pittsburgh Healthcare System.

The study was carried out at three locations: the Human Engineering Research Laboratories (HERL), the National Veterans Wheelchair Games (NVWG) 2012 in Richmond, Virginia, and subjects' homes. The NVWG is an annual event that encourages Veterans who use wheelchairs to participate in different activities by providing accessible transportation, planned social events, and competitive wheelchair sports events. These three locations represented three types of environments: structured, semistructured, and unstructured.

Human Engineering Research Laboratories and National Veterans Wheelchair Games

Prior to participating in the study, the researchers explained the purpose to each subject and obtained written consent. Each subject was asked to complete a basic demographic questionnaire that included personal information such as age, sex, level of SCI, and frequency of wheelchair use. Subjects' weight was measured to the nearest 0.5 kg using a Befour MX480D extra-wide wheelchair scale (Befour Inc; Sakukville, Wisconsin). Their height was either self-reported or measured to the nearest 0.1 cm by summing the sitting height, sitting depth, and lower leg length [20] using a tape rule (Stanley Black & Decker; New Britain, Connecticut). Subjects were equipped with the K4b2 metabolic cart and the SW. The protocol started with a resting routine during which we asked the subjects to sit still in their own wheelchairs. Then, subjects performed at least 10 other PAs of their choice from the following list: (1) propelling the wheelchair on a tile surface at a self-selected medium pace or (2) fast pace; (3) propelling the wheelchair on a medium pile carpet at a self-selected medium or (4) slow pace; (5) propelling the wheelchair up and down a ramp at a self-selected pace; (6) being pushed in a wheelchair on a tile surface, (7) on a medium pile carpet, or (8) up and down a ramp; (9) playing wheelchair basketball; (10) playing darts; (11) folding laundry; (12) performing deskwork involving reading and using a computer; (13) using a resistance band (Thera-band; Akron, Ohio); and (14) exercising on an arm ergometer at a self-selected pace and resistance. We asked subjects to perform each activity for at least 6 min (submaximal range) and to take a 5 to 10 min break between two activity trials. This arrangement allowed subjects to attain a comfortable pace during activity trials while finishing all trials in about 2 h. Time stamps were used to annotate the start and the end of each activity trial on both devices. After each trial, subjects rated the activity based on Borg's modified rate of perceived exertion scale (possible range of 6–20).

Home

Subjects from the Pittsburgh area were invited to participate in the follow-up session at their residences. The follow-up session was scheduled within 6 mo of their testing at HERL. Similar to the HERL and NVWG trials, subjects wore both the K4b2 and SW and started with a resting trial, and then they were asked to perform 10 activities for 6 min per activity continuously in 1 h. Activities included (1) propelling in the home on a tile or carpet surface; (2) propelling in the community on an asphalt, grass, or ramp surface; (3) watching television; (4) simulated eating; (5) sweeping the floor; (6) preparing food/cooking; (7) making the bed; (8) using dumbbells; (9) using a handgrip; (10) washing dishes; (11) doing wheelchair pushups (lifting the buttocks off the chair by pushing on the armrests or wheels); (12) filing papers; (13) checking the mail; (14) arranging groceries; (15) vacuuming; (16) doing laundry; (17) cleaning a table; and (18) playing video games systems such as the Wii.

Custom Energy Expenditure Prediction Models

Our group recently developed a custom general model and a set of activity-specific models [17] for estimating EE using the data collected by the SW and the body weight and height of 45 MWUs with SCI. The models were developed based on the data collected when these individuals performed four types of activities: resting while seated, deskwork, wheelchair propulsion, and arm ergometry in a laboratory setting. Details of the development of the custom EE models can be found in Hiremath et al. [17]. In this study, we used these custom EE models to estimate the EE of another group of 45 MWUs with SCI while they performed a wide range of lifestyle-based PAs and exercises in three different settings. **Table 1** highlights the different testing conditions used in the model development study and this validation study.

Statistical Analysis

All data from the K4b2 and SW were analyzed using MATLAB (R2013a, MathWorks Inc; Natick, Massachusetts). To evaluate the performance of the general model,

Table 1.
Testing conditions used in model development and model validation studies.

Variable	Model Development	Model Validation
Subjects	45 MWUs with SCI	45 MWUs with SCI (18 of them participated in Model Development study, 27 were new).
Testing Environment	HERL	HERL, NVWG, home.
Types of PAs	Resting, deskwork, wheelchair propulsion, arm ergometry	Resting, doing deskwork, propelling wheelchair, performing arm ergometry, watching television, eating, folding clothes, preparing food, washing dishes, filing papers, arranging groceries, doing laundry, playing Wii, cleaning table, using dumbbell, using handgrip, playing darts, using resistance, playing basketball, sweeping floor, making bed, cleaning room, vacuuming, checking mail, cleaning car, wheelchair push-up.
Speed and Intensity*	Propel wheelchair on computer-controlled dynamometer with average speeds of 0.89 m/s (2 mph) and 1.34 m/s (3 mph) and on flat tiled surface with average speed of 1.34 m/s (3 mph).	Propelling wheelchair at self-selected normal, high, and low speed on flat tiled surface.
	Perform arm ergometry at 20 W resistance and 60 rpm, 40 W and 60 rpm, and 40 W and 90 rpm.	Performing arm ergometry at self-selected normal, high, and low speed and resistance.

*Wheelchair propulsion and arm ergometry only.
HERL = Human Engineering Research Laboratories, MWU = manual wheelchair user, NVWG = National Veterans Wheelchair Games, SCI = spinal cord injury.

we applied it to all activities performed by the participants. To evaluate the performance of the activity-specific models, we first classified all activities into four groups, i.e., resting, deskwork, wheelchair propulsion, and arm ergometry based on the nature and the frequency of the motions involved (**Table 2**), and then applied each activity-specific model to the corresponding group of activities. For example, "watching television" was classified as resting because it involves almost no movement, and "basketball" was classified as wheelchair propulsion because it involves many wheelchair manipulations. We compared the estimated EE using the general model, the activity-specific model, and the default manufacturer's model with the criterion EE by the K4b2. The mean signed percent error (MSE) and mean absolute percent error (MAE) were calculated between the estimated and criterion EE in kilocalorie/minute per subject for each group of activities (**Equations 1–2**).

$$\text{MSE (\%)} = \frac{\text{EE}_{\text{k4br2}} - \text{EE}_{\text{estimation}}}{\text{EE}_{\text{k4br2}}} \times 100\% \ , \qquad \textbf{(1)}$$

$$\text{MAE (\%)} = \frac{\text{EE}_{\text{k4br2}} - \text{EE}_{\text{estimation}}}{\text{EE}_{\text{k4br2}}} \times 100\% \ . \qquad \textbf{(2)}$$

The MSE indicates whether the estimated EE is biased and whether it is disproportionately positive or negative when compared with the criterion, while the MAE shows the magnitude of the error. The intraclass correlation coefficient (ICC) of two-way mixed single measures (ICC(3,1)) with absolute agreement was computed using a statistical software package (SPSS Statistics 21.0, IBM Corporation; Armonk, New York) to investigate the agreement between the estimated and criterion EE. In addition, we constructed Bland-Altman plots with the estimated bias and 95 percent limits of agreement of the estimated and criterion EE.

RESULTS

Validity of Custom Models in Manual Wheelchair Users

A total of 45 subjects with SCI participated in this study. Their demographic information can be found in **Table 3**. Of the 45 subjects, 20 participated at the NVWG and 25 participated at HERL. Of the 25 subjects who participated at HERL, 20 also took part in the home trial.

Table 2.
Classification of variety of lifestyle-based activities in four major groups.

Group	Activities
Resting	Resting, watching television, eating.
Deskwork	Deskwork, folding clothes, preparing food, washing dishes, filing papers, arranging groceries, doing laundry, playing Wii, cleaning table, using dumbbell, using handgrip, playing darts, resistance.
Wheelchair Propulsion	Propelling on carpet, propelling at self-selected fast pace, propelling on ramp, playing basketball, sweeping floor, making bed, propelling in community, cleaning room, vacuuming, checking mail, propelling on grass, cleaning car, wheelchair push-up.
Arm Ergometry	Arm ergometry at medium speed and medium resistance, at slow speed and low resistance, at fast speed and low resistance, at medium speed and low resistance, at slow speed and medium resistance.

Out of 45 subjects, 18 had previously participated in the study of developing the custom EE prediction models.

The MSE between the estimated EE by the general, activity-specific, and default models and the criterion EE are shown in **Table 4**. Overall, both the general (MSE = –2.8 ± 26.1%) and activity-specific models (MSE = –4.8 ± 25.4%) performed better than the default models used by the SW (MSE = –39.6 ± 37.8%). The MAE between the estimated and criterion EE is reported in **Table 4**. Both the general (MAE = 20.6 ± 16.2%) and activity-specific models (MAE = 19.6 ± 16.8%) had similar performance, and their errors were about 20 percent lower than the default models used by the SW (MAE = 43.3 ± 33.5%). The general model tended to have a higher accuracy in estimating EE for activities in wheelchair propulsion and arm ergometry categories, while the activity-specific models had a higher accuracy in estimating EE for activities with relatively low intensity levels (**Tables 4–5**).

The ICC with absolute agreement was also computed to examine the agreement between the estimated and criterion EE. The general model had the strongest agreement (ICC(3,1) = 0.86, 95% confidence interval [CI] = 0.82 to 0.89) when compared with the K4b2, and was followed closely by the activity-specific models (ICC(3,1) = 0.83, 95% CI = 0.79 to 0.87). The default models used by the SW only showed an intermediate agreement (ICC (3,1) = 0.62, 95% CI = 0.16 to 0.81). This suggested that the differences between the estimated EE by both the general and the activity-specific and the criterion EE were consistent across subjects, while the differences between the estimated EE by the SW and the criterion were not.

A set of Bland-Altman plots also illustrated the agreement between the estimated and criterion EE. Both custom models had very strong agreement with the K4b2.

Table 3.
Subject demographics. Data presented as *n* unless otherwise noted.

Demographic	Value
Total Number of Subjects	45
Sex	
Male	39
Female	6
Age (yr)*	41.0 ± 12.6
Height (m)*	1.8 ± 0.1
Weight (kg)*	78.1 ± 18.1
Injury Level	
Above T3	14
Below T4	31
Completeness of Injury	
Complete	22
Incomplete	23
Experience Using Manual Wheelchair (yr)*	12.6 ± 8.6
PA Habit	
Some Form of Regular PA	36
Occasional PA	5
No PA	4

*Reported as mean ± standard deviation.
PA = physical activity, T = thoracic.

The estimated bias between the estimated and criterion EE was 0.00 kcal/min (95% CI = –0.06 to 0.07), with the 95 percent limits of agreement ranging from –1.05 kcal/min (95% CI = –1.12 to –0.99) to 1.06 kcal/min (95% CI = 0.99 to 1.12) for the general model. The estimated bias for the activity-specific models was 0.00 kcal/min (95% CI = –0.08 to 0.07), with the 95 percent limits of agreement ranging from –1.17 kcal/min (95% CI = –1.24 to –1.10) to 1.16 kcal/min (95% CI = 1.09 to 1.24). Both custom models tended to underestimate the EE, but the differences between the criterion and the estimated EE

Table 4.
Mean signed percent error between estimated energy expenditure by general, activity-specific, and manufacturer (SenseWear) models and criterion energy expenditure.

Activity	General Model	Activity-Specific Model	SenseWear
Overall	–2.8 ± 26.1	–4.8 ± 25.4	–39.6 ± 37.8
Resting	0.4 ± 32.6	–6.4 ± 21.5	–19.3 ± 25.0
Deskwork	–5.2 ± 21.6	–4.6 ± 18.1	–35.0 ± 26.5
Wheelchair Propulsion	–9.8 ± 22.5	5.7 ± 24.9	–61.2 ± 31.2
Arm Ergometry	6.1 ± 23.8	–18.4 ± 33.3	–44.4 ± 55.8

Table 5.
Mean absolute percent error of energy expenditure predicted by general, activity-specific, and manufacturer (SenseWear) models compared with criterion energy expenditure.

Activity	General Model	Activity-Specific Model	SenseWear
Overall	20.6 ± 16.2	19.6 ± 16.8	43.3 ± 33.5
Resting	27.1 ± 17.7	17.3 ± 14.1	24.4 ± 19.7
Deskwork	17.0 ± 14.1	14.1 ± 12.1	36.5 ± 24.5
Wheelchair Propulsion	18.4 ± 16.1	21.2 ± 13.9	61.4 ± 30.7
Arm Ergometry	19.4 ± 14.7	28.8 ± 24.6	54.3 ± 45.9

were consistent even when the intensity of activity increased (**Figures 1–2**). The estimated EE by default models of the SW did not agree with the criterion EE, and the estimated bias was –0.94 kcal/min (95% CI = –1.08 to –0.80), with the 95 percent limits of agreement ranging from –3.08 kcal/min (95% CI = –3.22 to –2.95) to 1.20 kcal/min (95% CI = 1.07 to 1.34). Additionally, the default models tended to overestimate the EE, and this difference became bigger as the level of activity intensity increased (**Figure 3**).

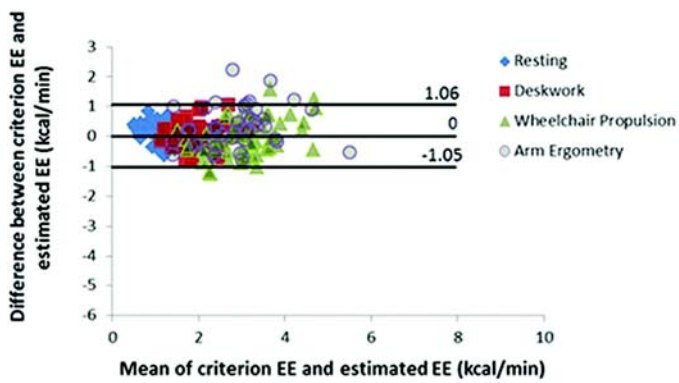

Figure 1.
Bland-Altman plot showed estimated energy expenditure (EE) by general prediction model agreed with criterion EE well. Custom general model tended to underestimate EE for activities at high level of intensities. Estimated bias between estimated and criterion EE was 0.00 kcal/min (95% confidence interval [CI] = –0.06 to 0.07) with 95% limits of agreement ranging from –1.05 kcal/min (95% CI = –1.12 to –0.99) to 1.06 kcal/min (95% CI = 0.99 to 1.12).

Performances of Custom Models in Different Conditions

Since the custom models were developed based on activities performed in a structured manner in a laboratory setting, we further broke down the activities based on the locations, i.e., HERL, NVWG, and home, to see whether there was a setting effect (**Table 6**). Only wheelchair propulsion and arm ergometry trials were performed differently across locations (**Table 1**). For wheelchair propulsion, the activity-specific models had the smallest error at NVWG (MSE = 5.2 ± 30.0%), whereas the general model had the smallest error at home (MSE = –8.8 ± 17.4%). For arm ergometry, the general model performed slightly better at NVWG (MSE = –10.5 ± 20.1%) than at HERL (MSE = 18.0 ± 18.6%), but the activity-specific models performed much better at HERL (MSE = –3.1 ± 27.6%) than at NVWG (MSE = –39.8 ± 28.8%).

We then compared the performance of the custom models between the 18 subjects who participated in the previous study of developing the custom models (group I) and the rest subjects who did not (group II). This could give us an idea of whether or not the custom models were too dependent on the testing conditions used in model

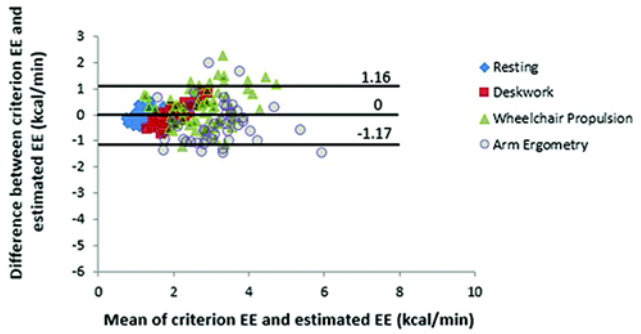

Figure 2.
Bland-Altman plot showed strong agreement between criterion energy exposure (EE) and estimated EE by activity-specific models. Estimated bias was 0.00 kcal/min (95% confidence interval [CI] = –0.08 to 0.07) with 95% limits of agreement ranging from –1.17 kcal/min (95% CI = –1.24 to –1.10) to 1.16 kcal/min (95% CI = 1.09 to 1.24).

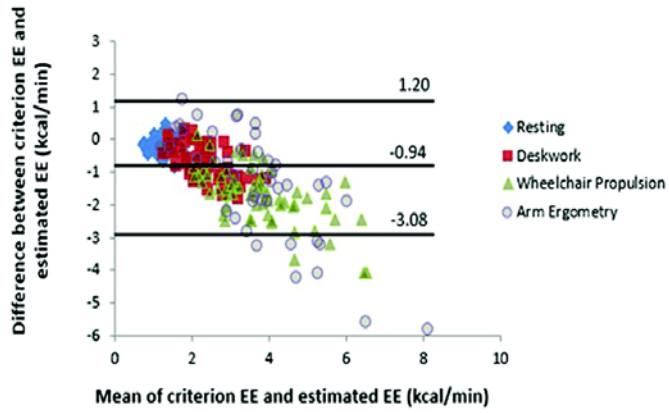

Figure 3.
Bland-Altman plot showed default models used by SenseWear tended to overestimate energy expenditure (EE). Difference between criterion and estimated EE increased as level of intensity of activities increased. Estimated bias was –0.94 kcal/min (95% CI = –1.08 to –0.80) with 95% limits of agreement ranging from –3.08 kcal/min (95% CI = –3.22 to –2.95) to 1.20 kcal/min (95% CI = 1.07 to 1.34).

development. The activity-specific models had smaller errors and standard deviations across all PAs for group I than for group II (**Table 7**). For wheelchair propulsion and arm ergometry particularly, the activity-specific models had MSE of 10 percent and 30 percent lower, respectively, in group I than in group II. On the other hand, only small differences were observed between group I and group II when the general model was used (**Table 7**).

Finally, we computed the total EE (kilocalories) of all activities over 1 h during the home trial for each subject, which would more closely resemble using the monitor over a period of time during the day. We compared the estimated EE with the criterion, and calculated both MSE and MAE among all subjects. The activity-specific models performed the best (MSE = 1.9 ± 13.2%, MAE = 10.5 ± 7.8%), followed by the general model (MSE = –2.5 ± 18.2%, MAE = 15.2 ± 9.8%) and the default SW model (MSE = –37.4 ± 22.5%, MAE = 37.7 ± 22.0%). The result showed that the custom prediction models could be used to monitor PA of MWUs over a period of time with high accuracy.

DISCUSSION

Validity of Custom Models in Manual Wheelchair Users with Spinal Cord Injury

This study showed that custom EE estimation models for MWUs with SCI could be a potential solution to the aforementioned problem. Both custom models yielded good accuracy and agreement when compared with the criterion EE. The activity-specific models developed, however, may be too specific to the conditions that they were based on. The activity-specific model for arm ergometry was developed based on the data collected during trials at HERL using an Angio Arm Ergometer (Lode B.V.; Groningen, the Netherlands); therefore, this model did not perform as expected when estimating the EE for activities collected at the NVWG, where a different brand of arm ergometer was used, and resulted in larger errors (MSE = –39.8 ± 28.8%) compared with the general model (MSE = –10.5 ± 20.1%), as shown in **Table 6**. Furthermore, when we looked at the performance of the custom models between group I and group II, the activity-specific models were generally more accurate in group I than in group II (**Table 7**), while the general model yielded similar results for both groups. This suggested that the performance of the activity-specific models was more dependent on the characteristics of the individuals whose data were used in constructing the models. Overall, it seems that the general model encompassed more variation across activities because it was developed from all data sets, making it less specific to activities but more applicable over a range of PA.

The SW was originally designed to track PA and EE in the general population, and studies have shown that it

Table 6.
Mean signed percent error between estimated energy expenditure by general, activity-specific, and default models compared with criterion energy expenditure during wheelchair propulsion and arm ergometry at Human Engineering Research Laboratories (HERL), National Veterans Wheelchair Games (NVWG), and home.

Activity	General Model	Activity-Specific Models	SenseWear
Wheelchair Propulsion	–9.84 ± 22.5	5.72 ± 24.9	–61.2 ± 31.2
HERL	–10.5 ± 21.4	6.12 ± 22.7	–58.0 ± 25.4
NVWG	–10.1 ± 29.3	5.15 ± 30.0	–79.9 ± 33.5
Home	–8.78 ± 17.4	5.72 ± 23.5	–48.4 ± 28.9
Arm Ergometry	6.10 ± 23.8	–18.4 ± 33.3	–44.4 ± 55.8
HERL	18.0 ± 18.6	–3.10 ± 27.6	–25.6 ± 32.3
NVWG	–10.5 ± 20.1	–39.8 ± 28.8	–70.6 ± 70.4

Table 7.
Mean signed percent error (MSE) and mean absolute percent error (MAE) of predicted energy expenditure (kcal/min) compared with criterion energy expenditure (kcal/min) among those who participated in previous study on developing custom models (group I) and those who did not (group II).

Measure	Activity	General		Activity-Specific	
		Group I (*n* = 18)	Group II (*n* = 27)	Group I (*n* = 18)	Group II (*n* = 27)
MSE (%)	Resting	–3.29 ± 29.6	–1.86 ± 33.8	–8.80 ± 18.9	–7.72 ± 22.6
	Deskwork	–9.36 ± 17.8	–6.54 ± 25.4	–5.98 ± 17.7	–6.60 ± 21.3
	Wheelchair Propulsion	–12.7 ± 23.3	–8.64 ± 26.0	1.00 ± 21.3	9.11 ± 28.4
	Arm Ergometry	21.2 ± 18.2	–4.78 ± 21.4	1.11 ± 25.2	–32.5 ± 31.5
MAE (%)	Resting	25.9 ± 13.3	28.1 ± 18.0	15.9 ± 13.1	18.3 ± 15.1
	Deskwork	16.2 ± 11.4	18.7 ± 17.9	14.2 ± 11.7	16.7 ± 14.4
	Wheelchair Propulsion	19.5 ± 17.5	18.8 ± 19.6	17.2 ± 11.8	25.2 ± 15.3
	Arm Ergometry	23.4 ± 15.1	16.6 ± 14.0	19.6 ± 15.1	35.4 ± 28.1

was accurate in estimating the total EE of the ambulatory population [12,21]. Jackicic et al. showed the MSE between the estimated EE by the SW and the criterion EE by indirect open-circuit calorimetry among 40 subjects was 2.8 ± 9.4 percent for walking, 0.9 ± 10.7 percent for cycle ergometry, 0.9 ± 11.9 percent for taking steps, and 3.8 ± 9.9 percent for arm ergometry [12]. Liden et al. showed the SW predicted the total EE well for a 2.5 h activity session that included a variety of activities such as resting, walking at different speeds, biking, and standing. The MAE between the estimated EE by the SW and the criterion EE by a MedGraphics CPX Express Metabolic Cart was 5.56 ± 5.69 percent among a total of 40 subjects [21]. Berntsen et al. and Wetten et al. further reported that the SW only underestimated total EE by about 9 percent with an ICC of 0.73 (95% CI = 0.44 to 0.88) when ambulatory subjects performed free-living activities [22] and light-intensity exercise and sedentary activities [23]. Although the SW performed well in tracking different types of PA and overall EE in the ambulatory population, our results show that the SW overestimated the EE by about 40 percent (MSE = –39.6%, MAE = 43.3%) in MWUs with SCI. This result is consistent with previous studies on evaluating SW in MWUs [4,15,24], indicating that its default models were not suitable for our intended population. Despite the relatively small estimation errors yielded by both custom models, there were relatively large standard deviations for all four categories of activities. This could be due to the individual variation, the level and completeness of injury, the experience of using a manual wheelchair, the existence of other health problems or secondary complications, the intensities and ways of moving, and the current lifestyle, or a combination of any of these could affect the physical abilities of subjects and contribute to the large variations we observed. We specifically picked those who had high errors and observed any common characteristics among them. The high level (C-level) and incompleteness of injury and relatively short experience of using a manual wheelchair (<10 yr) seemed to make some contribution to the high errors, though they were

not selected as the predictors when the custom models were constructed, possibly due to the small sample size.

Limitations and Future Work

One limitation of this study is the information bias when we categorized the activities into the four groups. The study investigators classified each lifestyle or sporting activity into one of four categories (i.e., resting while seated, deskwork, wheelchair propulsion, and arm ergometry). The classification of those activities that were not originally included in constructing the custom models into one of the four categories could influence the choice of the activity-specific models applied to these activities and hence might alter both MSE and MAE for the activity-specific models. Besides, the custom models did not account for participants' power output during PA, which might contribute to large variations among MWUs with SCI while estimating EE. Although the SW was able to collect physiological data such as near-body temperature and galvanic skin response to reflect a participant's power output during PA, none of these factors were selected by the algorithm as predictors for EE when the custom models were developed. This could be due to the short duration of the activity trials in the model development phase and/or slow responses from the physiological sensors. Another limitation of the study is the generalizability of the results. This study only included MWUs with SCI and evaluated a single commercial monitor. It is not clear if the custom models can be applied to MWUs with different diagnoses. Also, the custom models may not be valid for other accelerometer-based activity monitors. Finally, given the relatively large variability among individuals with disabilities, the sample size used to construct the custom models was small. Future work should refine the custom models by including a larger and diverse group of subjects, such as MWUs with various diagnoses and female MWUs, and extend the duration of each activity trial to obtain more meaningful data during the model development phase. Additionally, other factors that could potentially improve the accuracy of estimates, such as heart rate and levels of SCI, should be taken into account in future model development. Although activity monitors have potential in tracking both the quantity and quality of bodily motions, we only focused on the ability of using them to track the amount of PA in MWUs in this study. Using monitors to qualify motions will provide additional information on performance and promote physical health in MWUs. Despite the study limitations and relatively large standard deviations in the estimated EE by our custom models, we have created a web application that encapsulates the two custom models and can convert the raw data collected by the SW into more accurate measures for MWUs with SCI (www.rectech.org).

CONCLUSIONS

In this study, we evaluated the performance of two custom models, a general model and a set of activity-specific models for the SW activity monitor in estimating EE in MWUs with SCI. The general and activity-specific models significantly improved the EE estimation accuracy (<5% MSE) when compared with the default model used by the SW (~40% MSE). We plan to further improve the accuracy of the custom models for the SW by testing more MWUs with various diagnoses on various types of activities. More accurate and generalizable models will increase the applicability of the activity monitors in MWUs and help promote a healthier lifestyle among this population.

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