EVALUATION OF ACCELEROMETER-BASED ACTIVITY MONITORS TO ASSESS ENERGY EXPENDITURE OF MANUAL WHEELCHAIR USERS WITH SPINAL CORD INJURY

by

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A primary objective of the study was to determine the validity of a SenseWear (SW) activity monitor (AM) in assessing Energy Expenditure (EE) of manual wheelchair users with spinal cord Injury (SCI) while resting and performing three types of physical activities including wheelchair propulsion, arm-ergometer exercise, and deskwork. A secondary objective of the study was to build and validate a new EE prediction model for a SW AM for the physical activities performed in the study. A tertiary objective was to examine the relationship between the criterion EE and three activity monitors including the ActiGraph, the RT3 on arm, and RT3 on waist. Ten manual wheelchair users with SCI were recruited to participate in this pilot study.

The results indicate that EE estimated by SenseWear AM with the default EE equation for resting was close (0.2%) to the criterion EE in manual wheelchair users with SCI. However, the SW AM overestimated EE during deskwork, wheelchair propulsion and arm-ergometry exercise by 6.5%, 105% and 32%, respectively.

From the investigation, we found that the EE estimated by SW AM using the new regression equation model significantly improved its performance in manual wheelchair users with SCI. The Intraclass Correlation Coefficient of EE estimated by SW using new prediction equation and the criterion EE were excellent (0.90) and moderate (0.74) with percent errors reduced to 17.4% and 7.0% for wheelchair propulsion and arm-ergometry exercise, respectively. The new prediction equation for SW AM was able to differentiate and discriminate (sensitive)

EE estimation in physical activities like wheelchair propulsion and arm-ergometer exercises in manual wheelchair users with SCI indicating that it has a potential to be used in manual wheelchair users with SCI.

In addition, the variance explained by RT3 ($R^2 = 0.68$, $p<0.001$) on arm and the ActiGraph ($R^2 = 0.59$, $p<0.001$) on the wrist wrist indicate that AMs placed on an arm or wrist may be able to better predict EE compared to the AM on the waist.

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1.0 INTRODUCTION

The lack of participation in regular physical activity is one of the top public health concerns for the general population [1], but it appears more acute among people with disabilities [2, 3]. Despite proven health benefits associated with regular physical activity, such as reduced risk of cardiovascular disease and other chronic conditions, and improved psychological well-being, people with disabilities remain one of the most physically inactive groups in society. *Healthy People* 2010 outlines the levels of physical activity among various subpopulations in the United States based on cross-sectional surveys; it indicated that individuals with disabilities are much less active than their non-disabled counterparts and participate in less regular and vigorous physical activity[4]. There is also a prevalence of secondary conditions among people with disabilities such as pain, fatigue, weight gain, and deconditioning [5], many of which are considered preventable by physical activity and exercise interventions [6].

People with spinal cord injury [7] who rely on manual wheelchairs as their primary means of mobility face special challenges in engaging in regular physical activity. These individuals use their upper extremities for locomotion and other activities of daily living [8] as well as for exercise and recreational activities. Several physiological factors, including the relatively small muscle mass that is under voluntary control, deficient cardiovascular reflex responses, and decreased blood circulation in the legs, can markedly reduce their capacity for arm activity [9]. Such physiological changes along with mobility limitations contribute to a large extent of the sedentary lifestyles in this population [10]. This lack of physical activity is further aggravated by alterations in body composition and metabolism after SCI, resulting in significant decrements in physical fitness and increased risk of secondary conditions such as weight gain, cardiovascular disease, and diabetes mellitus.

The positive effects of physical activity on reducing or mitigating secondary conditions such as deconditioning and pain, increasing cardiorespiratory fitness and muscular strength, and improving quality of life is well documented in persons with SCI [9, 11-18]. However, such interventions generally occur in laboratory settings and physical activity participation in free-living conditions is frequently assessed through self-report [19]. There is no validated objective tool, to our knowledge, that allow these individuals to gauge their physical activity levels in free-living conditions and enable professionals to evaluate interventions that aim to promote physical activity participation in this population.

Extensive studies have been done to investigate the technical reliability and methodological usefulness of pedometers and activity monitors in measuring physical activities and predicting activity-related energy expenditures for an ambulatory population without disabilities [20, 21]. Quantified information about day-to-day physical activity levels have been used to motivate users to continue or alter their physical activity behaviors [22]. However, these pedometers or activity monitors cannot be simply applied to manual wheelchair users with SCI who often have volitional movements only in the upper extremities. In this research, we examined the validity of three off-the-shelf activity monitors with different complexities in assessing energy expenditure in manual wheelchair users with SCI. We also developed and evaluated new energy expenditure prediction model based on one of the activity monitors to provide manual wheelchair users with SCI an accurate means to gauge their physical activity participation on a daily basis.

1.1 PHYSICAL ACTIVITY AFTER SPINAL CORD INJURY

Spinal Cord Injury is a disorder that can result in paraplegia or tetraplegia due to lesions that hinder the transmission of nerve signals between the brain and periphery [9]. Persons with tetraplegia have SCI to the cervical region of the spinal cord, while people with paraplegia have lesions in the thoracic, lumbar, or sacral regions of the spinal cord. There are two types of SCI: complete (lack of sensor and motor function below the level of injury) and incomplete (some motor or sensory function below the level of injury). It has been estimated that there were between 227,080 and 300,938 persons with SCI in 2007 with 41.5% of that population with paraplegia and 58.5% with tetraplegia [23]. There are approximately 12,000 new cases of SCI each year [23]. Life expectancy for persons with SCI continues to increase with individuals with paraplegia having a near normal life expectancy, whereas those with tetraplegia having a 10 percent lower life expectancy than nondisabled individuals [23]. Currently, the prevalent causes of death with long-term SCI appear to be related to a variety of cardiovascular and respiratory disorders [24].

Physical activity is defined as bodily movement produced by skeletal muscles that results in energy expenditure ranging from light leisure-time activity to vigorous exercise [25]. People with SCI face considerable challenges in pursuing regular physical activity due to both intrinsic and extrinsic factors. The wasting of skeletal muscle mass in lower extremities of people with SCI due to disuse of the venous pump reduces the cardiovascular reflex during exercise. The exercise capacity of persons with SCI may further be decreased due to dysfunction of the sympathetic nervous system. Paralysis of chest and abdominal muscles in persons with high SCI results in reduced lung capacity and volume affecting exercise endurance and capacity. As a result of paralysis there is a decrease in blood and nerve supply to the skeletal bones (reduced nutrients) resulting in less bone mass density [9]. Additionally persons with SCI usually use relatively small muscles (upper arm) for physical activity such as wheelchair propulsion and other activities of daily living. This is further compounded by deficient cardiovascular reflex responses to physical activity, causing early fatigue of active arm muscles, discomfort, pain or injury [9, 14, 17, 26]. Persons with SCI are more insulin resistant than the ambulatory population[27]. Immunity to insulin adversely affects sugar metabolism resulting in multiple metabolic and blood pressure abnormalities such as non-insulin dependent diabetes mellitus, impaired glucose tolerance, high blood pressure (hypertension), and high blood fat [27]. These metabolic abnormalities along with loss of skeletal muscle mass adversely affect the exercise capacity of a person with SCI. The physiological changes after SCI along with their mobility impairments and environmental barriers discourage these individuals from engaging in regular physical activity.

Many people with SCI adopt sedentary lifestyle due to lack of accessible gymnasiums, reduction of recreation therapy in rehabilitation centers, requirement of specialized exercise equipment which may not be covered by the insurance companies and absence of group activity opportunities like the National Veterans Wheelchair Games. Only 13-16% of persons with SCI reported consistent physical activity [28] and the majority of people with SCI report virtually no regular physical activity [26, 28-31]. The physical activity level (PAL), expressed as daily EE due to basal metabolic rate, in persons with paraplegia were found to be low compared to the

World Health Organization (WHO) recommendation of 1.75 times of daily EE due to basal metabolic rate [10, 32]. The study found that PAL in persons with paraplegia measured using doubly labeled water over a duration of three days was low compared to the World Health Organization (WHO) recommendations, and the total daily EE was 24.6% lower in persons with complete SCI than those with incomplete SCI [10]. The literature review performed by Fernhall found that the levels of physical activity in persons with SCI were lower than the ambulatory population and demonstrated early onset of cardiovascular and other chronic diseases [26].

A sedentary lifestyle can further contribute to the decrement of cardiovascular and functional fitness, and secondary conditions such as weight gain, cardiopulmonary, and diabetes. Physical activity has been found to be an important factor influencing the physical capacity of manual wheelchairs users. Muraki et al. performed a multivariate analysis and found level of physical activity, age, smoking, occupation, level of SCI and time period since SCI were factors influencing physical work capacity in persons with paraplegia. The two most important factors in determining physical work capacity in persons with paraplegia were the level of SCI ($r = 0.651$) and the physical activity level ($r = 0.583$) [33]. In a similar study, Janssen et al., attempted to define normative values and determinants of physical capacity for fitness status and therapeutic interventions in individuals with tetraplegia and paraplegia. Using multiple regressions, they found that 48-80% of the variance in physical capacity can be explained by physical activity level, body mass, gender, age, time since injury, lesion level and completeness [34].

Researchers have shown that moderate intensity handbiking, wheelchair racing, wheelchair basketball, and wheelchair tennis are sufficient to maintain fitness and prevent cardiovascular diseases [35, 36]. Maki et al. showed that persons with SCI are able to utilize hand bikes and row cycles at an intensity high enough to improve and maintain cardiorespiratory fitness without leading to undue fatigue [37]. Previous studies have found that the cardiorespiratory fitness of active or trained persons with SCI is higher than those who are inactive. Davis et al. compared cardiorespiratory fitness between active and inactive persons with paraplegia using arm crank [38]. The active group showed significantly higher cardiorespiratory fitness with the average VO_2 peak of 2.24 l/min compared to the inactive group with an average VO_2 peak of 1.56 l/min. In another study by Bougenot and colleagues [39], wheelchair ergometer training program showed significant improvements in maximal tolerated power (+19.6%), peak oxygen consumption (+16%) and oxygen uptake per heart beat (+18.7%) in persons with SCI. Jacobs et al. found that circuit training three times a week in persons with paraplegia for a duration of 12 weeks improved their cardiorespiratory endurance by 30% and their upper extremity muscle strength from 12% to 30% [40]. Hicks et al. conducted a randomized controlled trial to evaluate the impact of a long-term exercise training program (nine months, two times a week) on persons with SCI [17]. The results showed that the experimental group achieved significant improvements in submaximal arm ergometry power output and upper body muscle strength, whereas the control group presented no significant changes. In addition, the experimental group reported significantly less pain, stress and depression after training, and scored higher than the control group with respect to indices of satisfaction with physical function, level of perceived health and overall quality of life.

1.2 CRITERION MEASURE OF ENERGY EXPENDITURE

Total Energy expenditure (EE) in calories is an important and actionable parameter for weight control, cardiorespiratory fitness, performance in sports, and body composition changes [41].

The EE is comprised of resting energy expenditure (REE), the thermic effect of food (TEF), and energy expenditure from physical activity [42]. REE refers to the energy expenditure from normal cellular and organ function during resting conditions and contributes 65-75% of the EE. REE can be found by using either the Harris-Benedict equations or indirect calorimetry [43-45]. The Harris-Benedict equations take into account gender, age, height and weight and can explain about 50% to 75% of the variability in REE [45]. The REE estimated by indirect calorimetry uses VO_2 and VCO_2 in the abbreviated Weir Equation [44]. Commonly used REE prediction equations based on physical attributes often overestimate REE in SCI population by 5–32% [46]. REE in people with SCI measured by indirect calorimetry was 14–27% less than those without injury due to decreased fat-free mass and sympathetic nervous system activity. The thermic effect of food refers to energy expenditure associated with the increase in metabolism due to digestion, assimilation of nutrients in food and contributes 5-10% of EE. It was found that metabolic activity and thermic effect of food in persons with SCI were low compared to persons without SCI [46]. Energy expenditure from physical activity is a result of volitional mechanical work, such as exercise and daily activities, and non-volitional activity, such as fidgeting, spontaneous muscle contractions, and maintaining posture, which accounts for 15%-30% of EE. Energy expenditure from physical activity is the most variable component in the EE and depends on the intensity and duration of activities. Three methods used to measure EE include direct calorimetry, indirect calorimetry, and doubly labeled water, all of which can serve as a criterion measure of EE [47-50].

1.2.1 Direct Calorimetry

Direct calorimetry measures the total heat loss dissipated by evaporation, radiation, conduction and convection from the study participant who is placed in a thermally-isolated chamber [48, 49]. Direct calorimetry is rarely used for clinical data collection due to the technical challenges and costs involved.

1.2.2 Indirect Calorimetry

Indirect calorimetry measures the oxygen consumption (VO_2) and the carbon dioxide production (VCO_2) by the participant when performing an activity and computes the total EE from these respiratory gases using standard equations [35]. Indirect calorimetry can be classified as a closed-circuit system, which measures changes in the amount of gases in a reservoir over time, or an open-circuit system, which measures the difference between inspired and expired gas concentrations. Open-circuit systems are more appropriate for measuring EE from physical activity.

Respiratory metabolic carts based on open-circuit indirect calorimetry are widely used and accepted in the research community as a criterion measure of EE [50]. Portable respiratory metabolic carts are devices that require participants to wear an analyzer module in a harness either on the chest or the back, and breathe through a mouthpiece or a mask over the nose and mouth. They are able to measure EE from physical activity in the field, but are limited by battery power and memory capacity, and cannot be used to measure EE in a free-living environment for extensive periods of time. The stationary and portable metabolic carts may differ from one another by 5-10% and their values on repeated measurements of the same activity may vary by around 5-10% [41, 51, 52]. Studies have used both stationary and portable metabolic carts as a criterion measure to measure EE from different types of physical activity in persons with SCI such as arm cranking, rowcycle, circuit training, wheelchair racing, wheelchair tennis, wheelchair basketball and wheelchair rugby [11, 12, 17, 35-37].

Respiratory chambers are another open-circuit system that can measure EE from a wide variety of activities over long period of time (e.g., 24 hours) without the discomfort of a mask or mouthpiece [53-55]. These chambers regulate the temperature at $24.0 \pm 0.5^{o}C$ and continuously monitor both the oxygen consumption (VO_2) and carbon dioxide production (VCO_2) of a participant in the chamber. Monroe et al. have used a respiratory chamber to compare the daily EE in persons with SCI and without SCI. The study results indicated that the 24-hour EE and the 24-hour EE adjusted for fat-free mass, fat mass and age were both lower in persons with SCI than without SCI [54]. The disadvantages of using respiratory chambers are its high cost of construction and maintenance.

1.2.3 Doubly Labeled Water

The Doubly Labeled Water (DLW) method is considered the most accurate way to measure EE in free-living individuals [41]. Participants are asked to take an oral dose of water containing a known amount of two stable isotopes: Deuterium and Oxygen-18. Urine or saliva concentration of the isotopes is measured both before and several days after consumption of the labeled water, and the differential clearance rate of the isotopes is used to assess the CO_2 production, which can be used to calculate total EE. Unlike indirect calorimetry that estimates EE breath-by-breath, DLW only gives information about total EE over the study periods, usually 4-20 days. DLW is also expensive due to the high cost of the isotopes (~1500USD per person) and the specialized expertise required for isotope analysis. DLW has been used to measure EE in ambulatory population [56, 57], but no DLW studies were encountered in the literature review in persons with SCI.

1.3 METHODS OF EE ESTIMATION

Although the measures in the previous section can provide accurate EE estimation, there are many factors that may limit their use in assessing EE in free-living conditions such as high investment in the equipment, need of laboratory resources, controlled environments and trained personnel. Alternative methods with varying sensitivity and accuracy have been developed to estimate EE in free-living conditions which include self-report, heart rate monitoring, wheel rotation datalogger, motion based monitors and multi-sensor activity monitors. Currently there are a number of these methods that have been validated to assess physical activity and estimate EE in ambulatory population and manual wheelchair users. The method used for EE estimation in a research study is based on factors such as the number of participants to be monitored, the time period of measurements and the finances available [47]. Alternative methods to estimate EE may be affected by variations in physiological factors between people, performance of the physical activity and environment. In the majority of cases alternative methods have been validated against a criterion measure for only few specific physical activities, which may affect the accuracy of EE estimation when the method is used for a non-validated physical activity [51, 58-64].

1.3.1 Self-Report

One of the most widely used and least expensive ways of measuring physical activity are questionnaires [65]. However this method relies on self-report which may suffer from participant bias, inaccuracy from recall activities, and choice of consistent low or high score on the surveys leading to floor effects and social acceptability bias [65-69]. Physical activity questionnaires for people with disabilities need to assess low-intensity and low-frequency activity as well as capture the activity performed by movement of arms. Three such instruments which have been specifically constructed for people with disabilities are the Physical Activity and Disability Survey (PADS), the Physical Activity Scale for Individuals with Physical Disabilities (PASIPD) and the Human Activity Profile (HAP) [65, 70-72]. Washburn et al. evaluated the construct validity of the 13-item Physical Activity Scale for Individuals with Physical Disabilities (PASIPD) [70]. The PASIPD requests participants to record the number of days a week and hours daily of participation in recreational, household, and occupational activities over the last 7 days. Total scores are calculated as the average hours (daily) times a metabolic equivalent value summed over all items. Those who reported excellent health had higher total, vigorous sport and recreation, and occupation and transportation subcategory scores compared with those who rated their health fair or poor ($p<0.05$) [70].

Physical activity is also measured by asking participants to regularly record their physical activities and the duration of performance for a fixed time interval during the study [73]. Based on the self-report, activities are categorized into specific physical activities like running, walking, deskwork, sleeping and others [74]. For the categorized activities, EE per activity is estimated using activity specific equations validated by large samples, which takes into account demographic variables like age, height, weight and BMI [74]. The total EE is calculated by integrating the activity specific EE estimated over the duration of time. Warms and Belza evaluated validity of an accelerometer to measure community living physical activity in wheelchair users with SCI with respect to self-reported activity [73]. The Pearson correlation coefficients between the activity counts and self-reported activity intensity varied from 0.30 to 0.77 for individual participants.

1.3.2 Heart Rate Monitoring

Researchers have utilized the method of heart rate (HR) monitoring to estimate EE in persons performing physical activity. Studies have shown that the HR and VO_2 have a fairly close linear ($r>0.802$) relationship during exercises involving large muscle groups [8, 75]. Records of HR and VO_2 in an individual can be used to construct calibration curves for EE estimations [8, 76]. In the FLEX HR method of EE estimation [75], each individual is monitored simultaneously for HR and VO_2 while resting, lying down, sitting, standing, and performing exercises at a variety of intensities to construct EE estimation equations. The total daily estimates of EE from HR may contain errors of up to 30% in individuals, although the average for a group of individuals is likely to be within 10% of the true value [47].

Hayes et al. evaluated the accuracy of calibrated HR from a maximum exercise test for predicting EE during five activities of daily living (ADL) in participants with tetraplegia and paraplegia. They showed that the HR measured and the HR derived, from individualized regression equations, explained 8.3% and 55% of the variance in measured EE, respectively. The calibrated HR consistently overestimated by 25% the actual EE and can be used as a gross estimate of EE during higher-intensity ADL [77]. Mukherjee et al. found that quadratic functional relationships exist between manual wheelchair propulsion by persons with paraplegia at different speeds and physiological factors [78]. The variance in the propulsion speed (m/min) explained by HR, oxygen consumption (ml/kg/min), Physiological Cost Index (beats/meter) and oxygen cost (ml/kg/meter) were found to be 0.90, 0.65, 0.60 and 0.81, respectively. Additionally HR and oxygen consumption increased progressively with increasing propulsion speed.

HR monitors are commonly used to estimate EE due to the ease of HR acquisition; HR monitors are portable and can be used to collect data in free-living conditions. However, HR monitors need individual calibration, and are influenced by many factors other than physical activity like gender, BMI, fitness level, high ambient temperature, high humidity, hydration level, posture and illness, emotional stress, and caffeinated drinks. Variations in HR may also be hard to detect during low-intensity activity. Additionally participant calibration process is usually impractical because of the time and expense [79]. In persons with SCI use of HR monitoring has unique challenges. Due to sympathetic nervous system dysfunction the change in HR during an exercise in persons with SCI is diminished to varying degrees [9]. Persons with complete tetraplegia usually have a peak exercise HR (100-120 beats/min) that is well below age-predicted maximal due to withdrawal of parasympathetic vagal tone to the sinoatrial node [9].

1.3.3 Wheel Rotation Datalogger

The Human Engineering Research Laboratories (HERL) has developed a wheel rotation datalogger (datalogger) that can be mounted on a wheelchair to detect the mobility aspects (distance travelled and speed) of wheelchair users in a free-living environment. Tolerico et al. have used the datalogger to collect gross mobility characteristics of manual wheelchair users in the National Veterans Wheelchair Games (NVWG) and in community settings [80]. MWC users were found to use their wheelchairs for about 116.23±50.30 min/day and 42.60±34.13

min/day in the NVWG and community, respectively. Although the datalogger is portable, easy to use and can collect gross activity for up to three months in free living conditions, the major limitation is that it cannot measure or estimate EE. The other limitations that hinder datalogger usage are its inability to differentiate between self propulsion of the wheelchair or being pushed by a caregiver, and inability to assess activities such as deskwork or arm-ergometry.

1.3.4 Motion Based Monitors

Motion based monitors have been developed in an attempt to objectively monitor physical activity in the day-to-day activities [81]. These monitors range from simple mechanical pedometers to complex activity monitors that have multiple sensors and use complex algorithms to record physical activity with varying degrees of sensitivity. The advantages of these motion based monitors include the small size, non-obtrusiveness, commercial availability and the ability to store data continuously over long periods of time. Many motion-based monitors have been tested in ambulatory population to investigate its validity with respect to motion, physical activity, steps and EE [50, 53, 64, 67, 68, 82-96]. Very few studies have researched motion based monitors among to assess physical activity in wheelchair users with SCI [73, 80, 97]. To our knowledge only Washburn et al. investigated the validity of motion based monitors with respect to EE in manual wheelchairs users during wheelchair propulsion [97].

Pedometers are devices worn by ambulatory individuals on their waist to estimate number of steps, pace and EE. Electronic pedometers usually consist of sensors and microprocessor that detect steps by sensing the vertical movement at the waist or the biomechanical bounce created during walking [88]. In mechanical pedometers the vertical movement at the waist triggers a lever arm to move vertically and rotate a ratchet to record steps

[47]. Pedometers worn on the waist tend to be less sensitive to the upper extremity movement and may underestimate EE in persons using wheelchairs. Step counts detected by pedometers are a major contributor of EE estimation in ambulatory population [86, 88, 93]. The absence of step counts in manual wheelchair users may considerably underestimate EE in this population.

An accelerometer is a sensing element that measures acceleration in single or multiple axes. Based on the type of sensing element and the principle of operation, accelerometers are classified as capacitive, piezoelectric, piezoresistive, hall effect, and Micro-Electro-Mechanical Systems [98]. Most common types of accelerometers are based on piezoelectric or piezoresistive principles. ActiGraph (ActiGraph, Inc.) uses piezoelectric accelerometer to collect uni-axial acceleration data[99]. Accelerometry based AMs have been developed and validated to measure activities and predict EE in ambulatory populations [50, 53, 64, 67, 68, 82-92, 94-96, 100-105]. Activity monitors using uni-axial accelerometers like Caltrac (Hemokentics, Inc.), CSA (Computer Science Applications, Inc.) and ActiGraph [67, 81, 95, 105] and tri-axial accelerometers like Tritrac R3D (Hemokentics, Inc.) [81, 102] have been validated to assess physical activities like walking, running, outdoor activities with respect to criterion EE in adults, children and young adults. Large inconsistencies have also between found by researchers between AMs and criterion EE [50, 53, 81, 102]. Studies have found that CSA, Biotrainer Pro (Individual Monitoring Systems, Inc.), Tritrac-R3D, and Actical (Mini-Mitter Co., Inc.) AMs are reliable and feasible in elderly, youth and children [85, 90, 96, 102, 106, 107].

Studies have shown that ActiGraph provides a method to estimate EE and participation in moderate and vigorous activity in adults, children, and wheelchair users with SCI [73, 82, 89]. Rothney et al. evaluated the validity of ActiGraph to predict physical activity intensity by comparing the EE estimation by regression equation and the EE measured by room calorimeter[82]. METS estimated by ActiGraph was not significantly different from the METS measured by the criterion for the whole duration, however the RT3 significantly underestimated METS when the visit was divided into sedentary, light, moderate, and vigorous activities ($P < 0.001$) [82]. Crouter et al. developed a new two-regression model using activity counts from ActiGraph to estimate EE over a wide range of physical activities [89]. The mean estimates using the new algorithm (2-regression model with an inactivity threshold) were within 0.75 metabolic equivalents (METs) of measured METs for each of the activities performed ($P>=0.05$), which was a substantial improvement over the single-regression models [89].

Previous studies have also shown that RT3 provides a valid estimate of inactivity, walking, running and objectively measures physical activity levels in children, adults and overweight adults [62, 64, 82, 84]. Rothney et al. evaluated the validity of RT3 to predict physical activity intensity by comparing the EE estimation by regression equations and the EE measured by room calorimeter[82]. METS estimated by RT3 was not significantly different from the METS measured by the criterion for the whole duration, however the RT3 significantly underestimated METS when the visit was divided into sedentary, light, moderate, and vigorous activities ($P < 0.001$) [82]. Jacobi et al performed two experiments to evaluate RT3 estimation of physical activity EE in overweight adults [84]. In the first experiment overweight/obese participants were monitored over 2 weeks in everyday life, and no significant difference was found between EE measured by DLW (704+/-223kcal/d) and EE estimated by RT3(656+/-140kcal/d) [84]. In the second experiment, 8 overweight/obese participants and 10 normal-weight participants were monitored during a treadmill walking protocol, and it was found that RT3 accelerometer was sensitive to the changes in treadmill speed, with no significant difference between EE measured by indirect calorimetry and EE estimated by RT3 in overweight/obese participants [84]. Rowlands et al. evaluated and compared the validity of the RT3 accelerometer for the assessment of physical activity in boys and men performing running on a treadmill, kicking a ball, playing hopscotch and sitting quietly [64]. RT3 counts correlated significantly with SVO_2 in boys (r = 0.87, P < 0.01) and men (r = 0.85, P < 0.01). However RT3 counts were significantly higher for boys (P < 0.05) during treadmill activities. In another study, Hussey et al. assessed the validity of the RT3 accelerometer in measuring inactivity, walking and running in children [62]. EE from RT3 significantly correlated with that obtained by indirect calorimetry for each activity independently (r=0.56–0.84, all P<0.01) [62].

Different algorithms have been developed to estimate EE by comparing the activity counts from activity monitors and the oxygen consumption from a criterion measure. Linear regression equations are commonly used to predict EE from accelerometer counts [87]. Crouter et al. have presented a two regression equation approach to estimate EE, where the choice of the regression equation is based on the observed coefficient of variation (accelerometer counts) over a period of 10 seconds [89]. Some of the linear regression equations also use parameters such as age, gender, height and mass to estimate EE [101]. Researchers have also proposed Artificial Neural Network (ANN) algorithms to estimate EE based on an extracted number of acceleration features and participant demographics that correlated well with the minute-by-minute EE [108]. Parrka et al. used a modified integral method, which takes absolutes of the three-dimensional acceleration signals to generate one signal. The metabolic estimates for some of the everyday tasks were obtained by fitting a line on the data set (ingenerated signal vs. measured metabolic equivalent) [109].

Few studies have been conducted to evaluate the validity of activity monitors among wheelchair users. Washburn and Copay assessed the validity of ActiGraph worn on the wrists to measure the EE during wheelchair propulsion at three different speeds [97]. Significant correlation (0.52-0.66, $p < 0.01$) were reported between the activity counts from both wrists and EE over the three pushing speeds. Warms et al. assessed the suitability and validity of ActiGraph as a measure of free-living physical activity for wheelchairs users with SCI [73]. The Pearson correlation coefficients between the activity counts and self-reported activity intensity varied from 0.30 to 0.77 for individual participants. Mean activity counts by actigraphy during active tasks were significantly different from the counts during inactive tasks ($p = .003$) [73]. Studies involving multi-axial accelerometer to estimate EE in persons with SCI are missing.

1.3.5 Multi-Sensor Monitors

Researchers have also explored the use of more than one sensor to estimate EE. One of the common methods is to combine motion-based sensors with heart rate to estimate EE [110-112]. The basic idea in this approach was to use an accelerometer as a secondary measurement instrument to verify that elevations in heart rate are relevant responses to physical activity thereby reducing the variability of HR as a single primary predictive measure [112]. The estimation of the EE was performed by using a regression equation with HR and combined activity as variables[112]. Another example is the SenseWear Pro (SW) AM (Bodymedia, Inc.) which combines an accelerometer, skin temperature sensor, Galvanic Skin Resistor (GSR) sensor, Heat Flux (HF) sensor and near body temperature sensor to provide information regarding the physical activity and in estimating EE [58]. The machine learning algorithms present in the SW AM use multiple sensors to accurately monitor the physiological state of the wearer to classify the physical activity. Based on the activity detected, the algorithm uses specific regression equations to predict the measure of physical activity or EE.

The SW has been studied and validated in estimating EE while performing resting, rowing, arm-ergometry, walking, cycle-ergometry, stepping exercise and running in a variety of populations including, adults, children, morbidly obese and chronic obstructive pulmonary disorder [41, 59, 60, 63, 113-115]. Malavolti et al. reported no significant difference was found in mean REE between SenseWear (1540±280kcal/day) and Sensor Medics Vmax (1700±330kcal/day) (p=ns) and the correlation between REE measured by SenseWear and Sensor Medics Vmax was high ($r=0.86$, $p<0.0001$) [114]. In another study, the correlations between indirect calorimetry and EE estimated by SenseWear for arm and rowing ergometry, the treadmill and recumbent stepper were r=0.90, r=0.67, r=0 .80 and r=0.74, respectively [60]. Bland and Altman plots revealed the greatest spread of scores for the rower and the treadmill [60]. Cole et al. also indicated that EE estimated by SenseWear appears to be exercise dependent in those with heart disease and needs to be cautiously interpreted[60]. No significant differences were found between energy expenditure estimates from indirect calorimetry (144±5 MET-min) and the SenseWear (139±6 MET-min; –4%) [63]. Fruin et al found that the the SenseWear significantly overestimated the EE for walking with no grade (27.4% for 3 mph, $p<0.001$; 12.6% for 4 mph, $p<0.02$) and significantly underestimated EE for walking on a 5% grade (21.9%, $p<0.002$) indicating that the SenseWear was sensitive to change in speed and not in resistance [115]. Jackicic et al. found that the SenseWear Pro Armband significantly underestimated EE by 14.9+/-17.5 kcal (6.9+/-8.5%) during walking exercise, 32.4+/-18.8 kcal (28.9+/-13.5%) during cycle ergometry, 28.2+/-20.3 kcal (17.7+/-11.8%) during stepping exercise, and overestimated EE by 21.7+/-8.7 kcal (29.3+/-13.8%) during arm-ergometer exercise ($P <= 0.001$)[113]. However, there is no research involving wheelchair users utilizing multi-sensor based activity monitors to estimate EE.

2.0 SPECIFIC AIMS & HYPOTHESIS

The goal of the study is to examine the validity of three types of activity monitors including SW, ActiGraph, and RT3 to assess EE of manual wheelchair users with SCI during varying modes and intensities of physical activity. This was conducted by comparing outputs of these devices with the criterion EE from a portable metabolic cart on the targeted physical activities. We also aim to explore building EE predictive equations to improve the accuracy of activity monitors for this population. We expect this research will lead to a convenient and effective tool for manual wheelchair users with SCI to estimate energy expenditure associated with physical activity level and aid clinical professionals to monitor interventions that promote physical activity among this population.

The thesis focused on a complete analysis of the SenseWear armband and a preliminary analysis of the ActiGraph worn on the wrist, the RT3 worn on the upper arm (RT3A), and the RT3 worn on the waist (RT3W).

Aim 1: Determine the validity of SenseWear armband in assessing EE of manual wheelchair users with SCI while resting and performing three types of physical activities including wheelchair propulsion, arm-ergometer exercise, and deskwork.

Hypothesis 1.1: *EE estimated by SW using its default EE prediction equation will be significantly different from the criterion EE for each activity.*

Hypothesis 1.2: *EE estimated by SW using its default EE prediction equation will NOT be able to differentiate between different intensities of wheelchair propulsion and arm-ergometry exercise.*

Aim 2: Build and validate a new EE prediction model for SenseWear armband for the activities mentioned in Aim 1.

Hypothesis 2.1: *EE estimated by SW using the new EE prediction equation will NOT be significantly different from the criterion EE for each activity.*

Hypothesis 2.2: *EE estimated by SW using the new EE prediction equation will be able to differentiate between different intensities of wheelchair propulsion and arm-ergometry exercise.*

Aim 3: Examine the relationship between the criterion EE and three activity monitors including the ActiGraph, the RT3 on arm, and RT3 on waist.

Hypothesis 3.1: *Raw accelerometer data (i.e., activity counts) from each activity monitor will at least moderately correlate (r>0.6) with the criterion EE across all the activities.*

3.0 METHODS

3.1 RECRUITMENT PROCEDURES

Participants were identified through Institutional Review Board (IRB) approved registries at the Human Engineering Research Laboratories (HERL), the Center for Assistive Technology at the University of Pittsburgh Medical Center (UPMC), and UPMC Department of Physical Medicine and Rehabilitation. Participants in these registries have provided informed consent to be contacted for research studies. In addition, we recruited participants via flyers and advertisements in print media such as magazines and newsletters, and web-based postings. Flyers were also posted in local rehabilitation facilities, outpatient facilities, and disability organizations.

People who expressed interest in the study first went through a screening procedure via telephone when they answered questions regarding the inclusion/exclusion criteria and completed the Physical Activity Readiness Questionnaire (PAR-Q) recommended by the American College of Sports Medicine as a self-screening tool for moderate intensity physical activity [116]. The inclusion/exclusion criteria for the study included participant to 1) use a manual wheelchair as primary means of mobility (>20 hrs/week), 2) be between the ages of 18 and 60, 3) have a diagnosis of SCI below T1, 4) be at least six months post-injury, 5) be able to use an arm-ergometer to exercise, 6) not have history of cardiovascular or cardiopulmonary disease with him/herself or an immediate family member (parents, grandparents and siblings), which was defined as death as a result of CVD prior to the age of 55.

Persons with SCI who satisfied the inclusion/exclusion criteria and answered No to all the PAR-Q questions were sent a physician release form for completion prior to participating in the study.

3.2 PROTOCOL

The study was approved by the IRB at the University of Pittsburgh and the VA Pittsburgh Healthcare System. Participants were asked to make one visit to the Human Engineering Research Laboratories (HERL), where the protocol was completed in no more than 3.5 hours. Participants were instructed to refrain from eating at least 2 hours and from exercising at least 12 hours prior to arriving at HERL. The protocol consisted of a pre-test session and an activity session.

3.2.1 Pre-test Session

The purpose and overall procedure of the study was explained to the participants. After signing the informed consent, participants were asked to complete a questionnaire including questions on demographics such as gender, ethnicity, age, injury level, and time of injury, wheelchair information such as brand and model, and health and physical activity history. General feeling about the nutritional habits and fitness level were also inquired about as part of the questionnaire (Appendix A). Body weight was then measured using a wheelchair scale to the nearest 0.5kg.

Participant's reported height was used or, it was measured using a measuring tape (PowerLock, The Stanley Works) to the nearest cm if the participants were not aware of their height. Skinfold measurements were performed at four sites (i.e., biceps, triceps, subscapular and suprailiac) using the Lange® skinfold caliper to a mm of accuracy [117]. Three measurements were taken at each site and averaged [118]. The triceps skinfold site measured was between tip of the olecranon process of the ulna (elbow) and the acromion process of the scapula (shoulder). The biceps skinfold site was measured at the midpoint of the muscle belly. The subscapular skinfold site was measured at the tip of inferior angle scapula, 45 degrees vertical to shoulder blade. The suprailiac skinfold site was measured above the ilac crest in mid-axillary line.

3.2.2 Activity Session

At the commencement of the protocol, resting EE from the participants was measured while they were quietly seated in their wheelchairs for a period of eight minutes. Following the resting, EE from participants was measured while they performed three types of physical activities including wheelchair propulsion, arm-ergometer exercise, and desk work. The wheelchair propulsion session included three trials of eight minutes each. Two trials were conducted on a stationary dynamometer (dyno) where participants propelled their own wheelchairs at low (2 mph) and medium (3 mph) speeds, respectively (Figure 1). Speed feedback was provided by a monitor in front of the participant. In the other trial, participants were asked to propel the wheelchair at a medium speed (3 mph) on a flat tile floor. They were asked to follow a power wheelchair travelling at 3 mph as closely as possible to maintain the target speed. The arm-ergometer session also included three trials of eight minutes each. Participants were seated in their own wheelchair to perform arm-ergometer exercise at 1) low speed (60 rpm) and low resistance (20

Watts), 2) low speed (60 rpm) and medium resistance (40 Watts), 3) medium speed (90 rpm) and medium resistance (40 Watts) (Figure 2). The deskwork session included only one trial where participants were asked to perform tasks of retrieving a set of books from the overhead shelf, reading a book for about four minutes and typing on a computer for four minutes.

Figure 1. Participant performing wheelchair propulsion

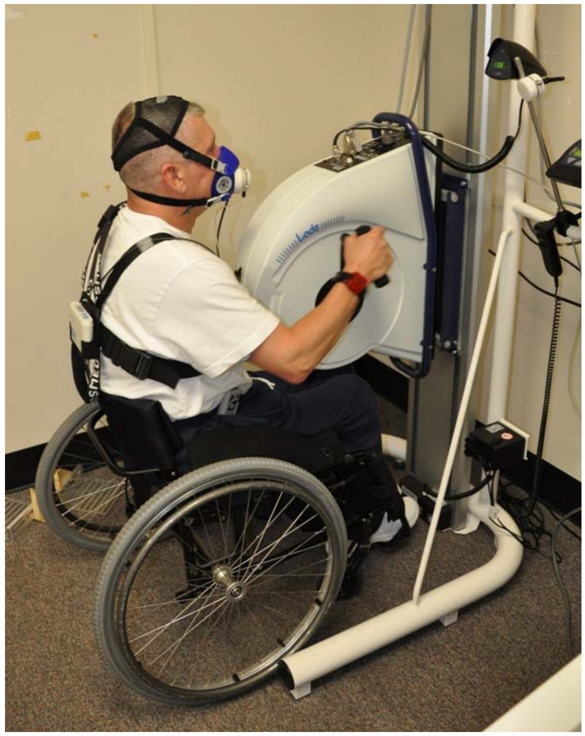

Figure 2. Participant performing arm-ergometry exercise

Participants were given a short period of time for practice and warm-up before each activity session. They were also allowed to rest for 5 to 10 minutes between each trial and up to 30 or 40 minutes between each activity session. Participants were asked to perform each trial for eight minutes which was intended to allow sufficient time to establish steady state physiological response. The activity sessions were counterbalanced and the trials in each activity session were randomized to counter order effects. Participants were asked to provide a rating on the Borg's CR10 scale [74] after each trial with 0-1 for nothing at all to very weak activity, 2-5 for weak to strong activity, and 7-11 for very strong to absolute maximum activity.

3.3 INSTRUMENTATION

Throughout the protocol, participants wore five instruments that provided concurrent estimates of the activity of each trial for a total of eight trials including resting, three wheelchair propulsion trials, three arm-ergometry trials, and deskwork. The instruments used in the study included a Cosmed K4b^2 portable metabolic cart (COSMED USA, Inc., Chicago, IL [www.cosmed.it]), and four commercially available activity monitors, i.e., one Bodymedia SenseWear® Pro Armband (Bodymedia Inc., Pittsburgh, PA [www.bodymedia.com]), two StayHealthy RT3 tri-axial accelerometers (Stayhealthy Inc., Monrovia, CA [www.stayhealthy.com]), and one ActiGraph uni-axial accelerometer (GT1M ActiGraph, ActiGraph LLC, Fort Walton Beach, FL [www.theactigraph.com]). All instruments were programmed using a single computer, during which the clock of the computer and the devices were synchronized.

3.3.1 Portable Metabolic Cart

The Cosmed K4b^2 shown in Figure 3 is a portable metabolic cart that measures the exhaled gas concentrations to estimate EE in kilocalories per minute (Kcal/min). The system has been shown to be both valid and reliable in the general population [119, 120]. It has been also used to measure oxygen consumption in published studies involving people with SCI [35, 121, 122], although it has not been specifically validated in these populations. The system comprises of an analyzer unit and a rubber face mask. The face mask covers the participant's mouth and nose to capture the expired air, and is held in place with a head nylon mesh harness. The exhaled air is channeled through a ventilation turbine into the analyzer unit where the contents of O_2 and CO_2 in the expired air are measured. The analyzer unit along with the battery weighs approximately

1.5 kg. Participants wore the analyzer unit on the chest and the battery on the back using a chest harness.

Prior to each test, the K4b^2 system was calibrated according to manufacturer's guidelines for turbine, gas and delay calibration. After the device calibration, information regarding the humidity of the test environment and demographics of the participant is updated in the metabolic cart. Prior to each activity trial, the metabolic cart performed a room air calibration and adjusted for the device temperature. At the start and end of each trial the metabolic cart was annotated. Cosmed 9.0 software was used to retrieve and analyze the metabolic data. The data collected from the metabolic cart included EE in kcal/ min, VO_2 and VCO_2 in mL/min/kg for each breath. The EE in kcal/min was used a criterion measure throughout the study. Data were also collected from a Polar heart rate monitor (Polar, USA [www.polarusa.com]), during the activity session.

Figure 3. K4b^2 Metabolic Cart

3.3.2 Activity Monitors

The SenseWear (SW) Armband (Figure 4) is a multi-sensor activity monitor that collects and analyzes physiological and lifestyle data to determine energy expenditure and activity levels. It consists of a unique array of biometric sensors including a two-axis accelerometer, skin temperature sensor, Galvanic Skin Resistor (GSR) sensor, Heat Flux (HF) sensor, and near body temperature sensor. The physiologic information collected by these sensors along with personal information including gender, age, height and weight are processed to provide estimation of EE for many different types of physical activity. The multi-sensor information is used by the algorithms in the device to detect a particular context or activity such as resting, running, walking, jogging, sleeping and biking. Based on the context and activity detected, the SW chooses a specific EE estimation equation. All the sensors in the SW are internally sampled at a frequency of 32 Hz and can be down sampled and stored at any user-defined sampling frequency. The SW can collect data for 3 hours at a frequency of 8Hz.

Figure 4. SenseWear Armband AM

Before commencement of each participant testing, the SenseWear was initialized according to manufacturer specifications. It was positioned on the right upper arm on the triceps. As data collection was planned for two and half to three hours, we chose to sample the acceleration signals at 8Hz. The annotation button on the SW device was used to note the start and end of each trial. The data collected from the SenseWear included transverse and longitudinal acceleration components sampled at 8Hz, EE in kcal/ min, and heat flux, galvanic skin response and skin temperatures sampled every minute. InnerView Research Software 4.2 and InnerView Research Software 7.0 was used to retrieve and analyze the SW data.

The RT3 (Figure 5) is a pager-size single sensor AM that is recommended by the manufacturer to place around the waist. The RT3 consists of a piezoelectric tri-axial accelerometer that senses acceleration in three dimensions at 1Hz and is able to collect data for three hours [123]. The RT3 ASSIST software uses raw data from the RT3 to convert it into activity counts using a proprietary formula based on the product of mass and integrated acceleration, which is used to estimate activity kilocalories. The software also computes resting kilocalories in adults using the participant's physiological statistics [124]. The total EE estimated by the RT3 ASSIST software is the sum of resting and activity kilocalories.

Prior to the commencement of each participant testing, the RT3s were initialized according to manufacturer specifications. The manufacturer of the RT3 recommends that the device be worn on the waist to accurately estimate EE in ambulatory population. In this research we chose to test two RT3s that were positioned on the triceps of the left upper arm (RT3A) and the waist (RT3W), respectively, to evaluate the acceleration values at different sites on the body. The data collected from the RT3 included total calories, activity calories, and activity counts at 1Hz in three orthogonal directions as well as the vector magnitude. The RT3 continuously collected data throughout the activity session and annotations from SW were taken as the reference annotations for RT3. StayHealthy RT3 ASSIST was used to retrieve and analyze and the RT3 data.

Figure 5. RT3 Tri-axial AM

The GT1M ActiGraph (Figure 6) is a compact uni-axial accelerometer that uses a cantilevered piezoelectric plate to sense acceleration in one direction. The accelerometer output is digitized by an analog to digital converter (ADC) at the rate of 30Hz and passed through a digital filter that band-limits the output data to the frequency range of 0.25 to 2.5 Hz corresponding to normal human motion [99]. The collected accelerometer data samples are summed over a user specified interval of time called an 'epoch'. Similar to RT3, ActiLife software analyzes the acceleration data from the device to report activity counts and steps taken. However, ActiGraph activity counts are not comparable to RT3 due to different sensitivity (AD converter) and filtering algorithms in the device. The software uses a Crouter 2 regression equation based on activity counts and steps to determine activity levels and EE [89, 100, 125].

The ActiGraph was initialized according to manufacturer specifications prior to the commencement of each participant testing. The ActiGraph was positioned on the right wrist of the participant. The ActiGraph continuously collected data throughout the activity session and annotations from SW were taken as the reference annotations for the ActiGraph. ActiLife software was used to retrieve and analyze the ActiGraph data to produce total calories and acceleration counts in 1Hz. Work energy theorem, the Freedson equation and the combination of work energy theorem and the Freedson equation are the three options available in the ActiLife software to estimate EE from the raw ActiGraph data.

Figure 6. ActiGraph AM

3.4 DATA ANALYSIS

Power analysis was performed to calculate the number of participants required to test these hypotheses [126]. Using a paired t-test, we calculated that with a total of 50 participants and effect size 0.5, it will provide a statistical power of 70% for a two-tailed hypothesis with an alpha level of 0.5. Currently data has been collected from ten participants, but ultimately this data will be used in conjunction with the data collected from the remaining participants. As such we will conduct the data analysis as though this is a pilot study at this time.

Descriptive statistics were performed on participant characteristics and experimental test responses. All experimental test responses were also checked for normality using Shapiro-Wilk's W test. Given the small number of participants (n=10) in the study, non-parametric statistical tests were used to test the hypotheses. Custom MATLAB programs (R2008a, The MathWorks, Inc.) were used to clean the data files from the metabolic cart and all the AMs for statistical analysis. An average of the last six minutes of data was utilized for data analysis. All analyses were performed using SPSS for windows (version 15.0, SPSS, Inc.). The significance level was set at $\alpha < 0.05$.

To test hypothesis 1.1, Wilcoxon signed rank sum tests were used to compare the EE estimated by the SW default equation with the criterion EE for each activity trial. To test Hypothesis 1.2, two one-way Friedman tests with *post hoc* pairwise comparisons were performed to evaluate differences in criterion EE in three intensities of wheelchair propulsion and three intensities of arm-ergometry exercise, respectively. The same procedure was also used to evaluate differences in the EE estimated by the SW default equation during these activities. The estimated EE by SW was also compared with the criterion measure using the Intraclass correlation coefficient (ICC), mean absolute error (MAE), mean squared error (MSE), and percent error for each activity, each participant, three propulsion trials, three arm-ergometry trials, and all the eight trials of the 10 participants pooled together. The ICC used for the comparison was single measures, two-way mixed model of type consistency with 95% confidence level. The MAE, MSE and percent error used the equations 1, 2 and 3, respectively.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |(EE(i)_{criterion} - EE(i)_{SW})| \quad (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (EE(i)_{criterion} - EE(i)_{SW})^2 \quad (2)$$

$$error(\%) = \frac{1}{n}\sum_{i=1}^{n} (EE(i)_{criterion} - EE(i)_{SW})/(EE(i)_{MET}) * 100 \quad (3)$$

Pace regression in Weka 3 (a data mining software package in Java) [127] was performed to construct a new EE prediction model. Pace regression was used to select the attributes for new EE prediction model, as it is known to pick as few attributes as possible [128]. A 10-fold cross validation was used to evaluate the model performance. The dependent variable was the criterion

EE by the portable metabolic cart, and the independent variables included the number of acceleration peaks in transverse direction (TPEAKS), the number of acceleration peaks in longitudinal direction (LPEAKS), average acceleration in transverse direction (TAVG), average acceleration in longitudinal direction (LAVG), mean absolute deviation in transverse direction (TMAD), mean absolute deviation in longitudinal direction (LMAD), average heat flux (HF), average skin temperature (STEMP), average near body temp (NBTEMP), average galvanic skin resistance (GSR), detection of physical activity (DETECTPA), weight, age, gender and completeness of injury. Data from all the activity trials were pooled and treated as independent observations.

To test hypothesis 2.1, Wilcoxon signed rank sum tests were used to compare the EE estimated by the new SW EE prediction equation with the criterion EE for each activity trial. To test Hypothesis 2.2, two one-way Friedman tests with *post hoc* pairwise comparisons were performed to evaluate differences in the EE estimated by the new SW EE prediction equation during these activities. The EE estimated by new SW EE prediction equation was also compared with the criterion measure using the ICC, MAE, MSE, and percent error for each activity, each participant, three propulsion trials, three arm-ergometry trials, and all the eight trials of the 10 participants pooled together. The ICC used for the comparison was single measures, two-way mixed model of type consistency with 95% confidence level. The MAE, MSE and percent error used the equations 1, 2 and 3, respectively.

To test hypothesis 3.1, the association between the criterion EE and activity counts was assessed with Spearman Rho tests for ActiGraph, RT3A and RT3W during wheelchair propulsion, arm-ergometry, and all eight activity trials as a whole. Data from the three propulsion trials, three arm-ergometry trials, and all the eight trials of the 10 participants were pooled and treated as independent observations.

4.0 RESULTS

4.1 DEMOGRAPHIC CHARACTERISTICS OF PARTICIPANTS

Ten participants (9 males and 1 female) with an average age of 43±11 years (ranging from 26 to 59 years) completed the study. Particpants had been using manual wheelchairs for 15.6±7.8 years (ranging from 9 months to 27.5 years). The level of SCI among the participants varied from T4-T12 with two T4 and T5, one T7, T8, and T11, and three T12. Half of the participants had a complete spinal cord lesion. Eight of the participants were Caucasian, with one African American and one of Arabic ethnicity. The average body weight and height of the participants were 81.4±18.3 kg and 182.8±7.4 cm, respectively. The average skinfold measurements for participants at triceps, bicep, subscapula, and suprailiac were 17.2±10.2 mm, 10.3±7.4 mm, 20.4±8.5 mm, 21.5±8.7 mm, respectively. The percentage body fat estimated based on the total skinfold measurement and age was 26.8±5.8% [117].

Four participants reported they were athletes, exercising at least twice a week. Among the six non-athlete participants, two did not exercise at all and four exercised regularly. The type of physical activity reported by the participants included wheelchair basketball, weight lifting, arm-ergometry, wheeling, and pushups etc. Only one participant reported to be a smoker (20 cigarettes a day). The perceived nutritional habit on a 5-point Likert scale (poor=1 to excellent=5) was 3.5±1.2. The perceived fitness level was 3.4±1.2.

4.2 EE MEASURED BY METABOLIC CART

Energy expenditure in kcal per minute for four types of physical activities measured by the portable metabolic cart is shown in Table 1. The Metabolic Equivalent of Task (MET), defined as the ratio of metabolic rate during a specific physical activity to a reference rate of metabolic rate at rest (set by convention to 3.5 ml(O_2)/kg/min), was also calculated for each type of physical activity (Table 1). The heart rate and rating of perceived exertion based on the Borg CR10 scale for each activity is also shown in Table 1.

Table 1. Energy expenditure for four types of physical activities in manual wheelchair users

Activity		METs (SD)	EE kcal/min (SD)	HR (SD)	RPE (SD)
Resting		0.9 (0.2)	1.5 (0.5)	62.3 (16.7)	0.0 (0.0)
Wheelchair propulsion	2mph on Dyno	3.0 (0.9)	4.5 (1.8)	97.8 (11.2)	3.3 (1.9)
	3mph on Dyno	4.1 (1.6)	5.9 (2.8)	117.1 (22.6)	5.0 (2.8)
	3mph on Tile	2.1 (0.6)	3.1 (1.2)	88.6 (19.1)	2.3 (1.6)
Arm-ergometry	20W at 60 rpm	2.5 (0.3)	3.6 (0.6)	94.6 (13.3)	2.0 (2.1)
	40W at 60 rpm	3.5 (0.8)	4.9 (0.5)	112.8 (14.8)	3.4 (2.0)
	40W at 90 rpm	4.2 (0.7)	5.9 (0.7)	131.0 (18.6)	5.6 (2.9)
Deskwork		1.1 (0.3)	1.5 (0.4)	78.7 (17.8)	0.5 (0.5)

4.3 EE ESTIMATED BY THE SENSEWEAR ARMBAND

Hypothesis 1.1: *EE estimated by SW using its default EE prediction equation will be significantly different from the criterion EE for each activity.*

Mean and standard deviation (SD) of the criterion EE from the portable metabolic cart and the estimated EE from the SW are shown in Table 2.

Table 2. Mean and SD for EE from metabolic cart and SW for four types of physical activities

Activity		**EE kcal/min (SD)**			**P-value**
		Metabolic Cart	**SenseWear**	**Error (%)**	
Resting		1.5 (0.5)	1.4 (0.3)	+0.2 (32.5)	0.386
Wheelchair propulsion	2mph on Dyno	4.5 (1.8)	9.1 (4.2)	-111.1 (79.8)	**0.005**
	3mph on Dyno	5.9 (2.8)	9.8 (5.3)	-75.4 (60.4)	**0.005**
	3mph on Tile	3.1 (1.2)	6.6 (1.9)	-128.6 (58.1)	**0.005**
Arm-ergometry	20W at 60 rpm	3.6 (0.6)	5.2 (1.3)	-44.3 (19.7)	**0.005**
	40W at 60 rpm	4.9 (0.5)	6.0 (0.8)	-22.0 (14.9)	**0.009**
	40W at 90 rpm	5.9 (0.7)	7.7 (2.0)	-29.7 (21.4)	**0.009**
Deskwork		1.5 (0.4)	1.6 (0.3)	-6.5 (20.3)	0.575

The Wilcoxon signed rank sum test showed that the EE estimated by SW was not significantly different from the criterion EE during resting ($Z = -0.866$, $p = 0.386$), and deskwork ($Z = -0.561$, $p = 0.575$). However, the same test showed the criterion EE and EE estimated by the SW was significantly different for three wheelchair propulsion trials ($z = -2.803$, $p = 0.005$ for 2mph on dyno; $z = -2.803$, $p = 0.005$ for 3mph on dyno and $z = -2.803$, $p = 0.005$ for 3mph on tile) and the three arm-ergometry trials ($z = -2.803$, $p=0.005$ for 20W at 60rpm; $z = -2.599$, $p=0.009$ for 40W at 60rpm and $z = -2.599$, $p=0.009$ for 40W at 90rpm).

The percent error between the SW and the criterion measure for each activity is shown in Table 2. The summary statistical measures including the Intraclass correlation (ICC), Mean Absolute Error (MAE), Mean Square Error (MSE), and percent error between the SW and the criterion measure for wheelchair propulsion, arm-ergometry, and all activities as a whole are shown in Table 3. The ICC, MAE, and percent error between the SW and the criterion measure were also computed for all the activities performed by each of the 10 participants and illustrated in Figure 7 to Figure 9, respectively.

Table 3. Comparison of EE between SW and metabolic cart

Activity	ICC	MAE (kcal/min)	MSE ($kcal^2/min^2$)	Error (%)
Wheelchair propulsion	0.55	4.00	25.71	-105.05
Arm-ergometry	0.74	1.54	3.36	-31.99
All activities	0.65	2.15	10.93	-52.18

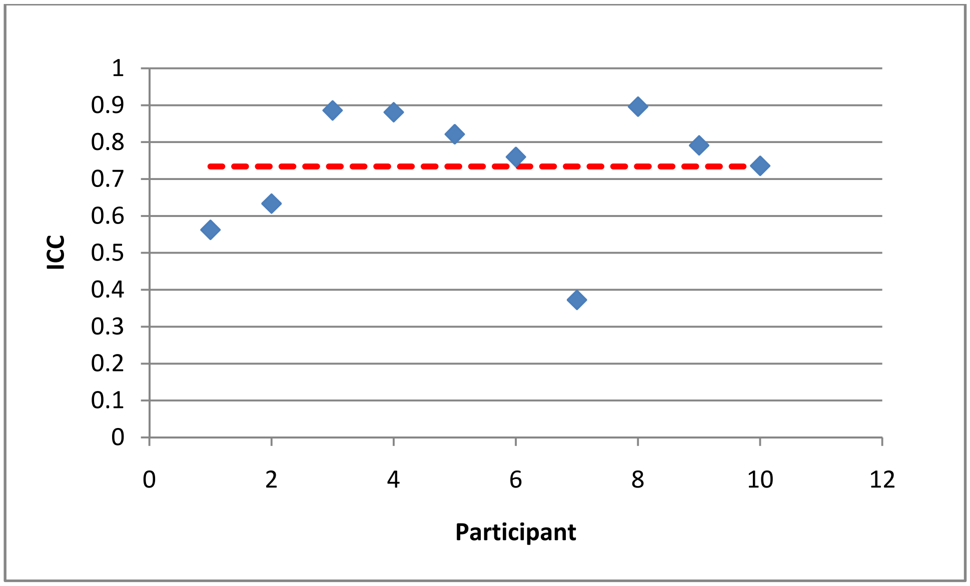

Figure 7. Plot of Intraclass correlation coefficient of SW for ten participants

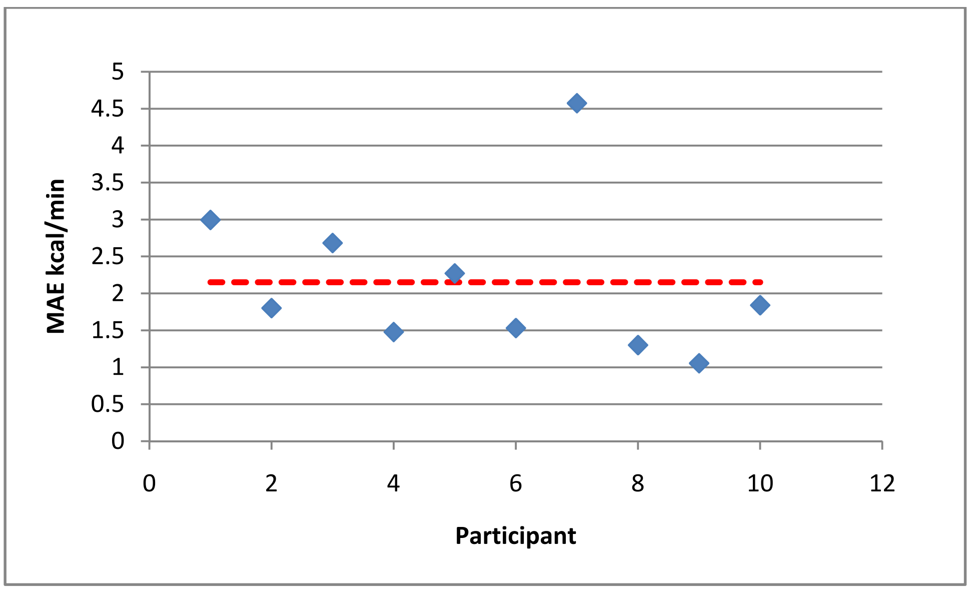

Figure 8. Plot of mean absolute error (MAE) of SW for ten participants

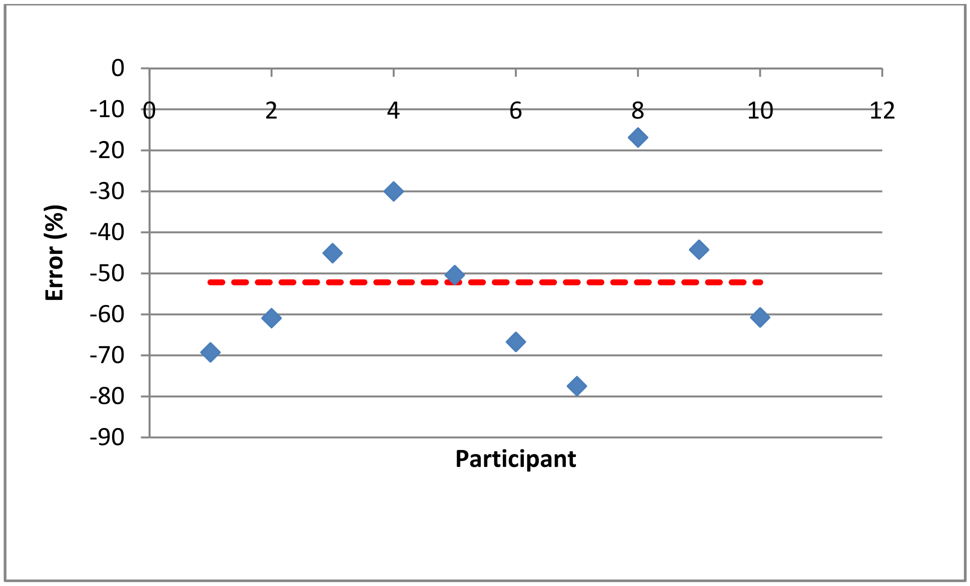

Figure 9. Plot of Percent Error of SW for ten participants

Hypothesis 1.2: *EE estimated by SW using its default EE prediction equation will NOT be able to differentiate between different intensities of wheelchair propulsion and arm-ergometry exercise.*

The Friedman test showed that the criterion EE was significantly different across the three propulsion trials ($p < 0.001$), and pairwise comparisons (with adjusted $\alpha = 0.017$) revealed that the criterion measure was significantly different between the 2mph dyno trial and 3mph over ground trial ($z = -2.803$, $p = 0.005$), and between the 3mph dyno trial and 3mph over ground trial and ($z = -2.803$, $p = 0.005$), but failed to discriminate between the 2mph and 3mph dyno trials ($z = -2.293$, $p = 0.022$). The same test showed that the EE estimated by the SW was also significantly different across the three propulsion trials ($p = 0.002$), and pairwise comparisons (with adjusted $\alpha = 0.017$) revealed a similar trend as the criterion EE that the SW output was able to discriminate between the 2mph dyno trial and 3mph over ground trial ($z = -2.803$, $p = 0.005$)

and the 3mph dyno trial and 3mph over ground trial (z = -2.599, p =0.009), but failed to find a significant difference between the 2mph dyno trial and 3mph dyno trial (z = -0.764, p = 0.445).

The Friedman test also showed that the criterion EE was significantly different across the three arm-ergometry trials ($p < 0.001$), and pairwise comparisons (with adjusted $\alpha = 0.017$) revealed that the criterion measure at the 60rpm 40W trial was significantly greater than at the 60rpm 20W trial (z = -2.803, p = 0.005), and that the criterion measure at the 90rpm 40W trial was significantly greater than at the 60rpm 40W trial (z = -2.803, p = 0.005). The same test showed that the EE output from SW was also significantly different across the three arm-ergometry trials (p = 0.001), and pairwise comparisons (with adjusted $\alpha = 0.017$) revealed that the SW output was only able to discriminate between the 60rpm 20W trial and 90rpm 40W trial (z = -2.803, p = 0.005), but failed to find a significant difference between the 60rpm 20W trial and 60rpm 40W trial (z = -2.293, p = 0.022), and the 60rpm 40W trial and 90rpm 40W trial (z = -2.293, p =0.022).

4.4 NEW EE PREDICTION MODELS

The new EE prediction model obtained by performing Pace regression on the SW data is shown in Equation 4. The most significant predictors of the new prediction equation are the number of acceleration peaks in transverse direction (TPEAKS), average longitudinal acceleration (LAVG), mean absolute deviation in longitudinal acceleration (LMAD) and weight of the participant. The R-squared for the prediction equation was 0.8 and the MAE was 0.76 kcal/min. Figure 10 shows the scatter plot of the new predicted EE and the default EE from the SW versus the criterion EE.

$$EE_{MET} = -0.475 + 0.0048 * TPEAKS - 2.3743 * LAVG + 0.384 * LMAD + 0.0391 * weight \quad (4)$$

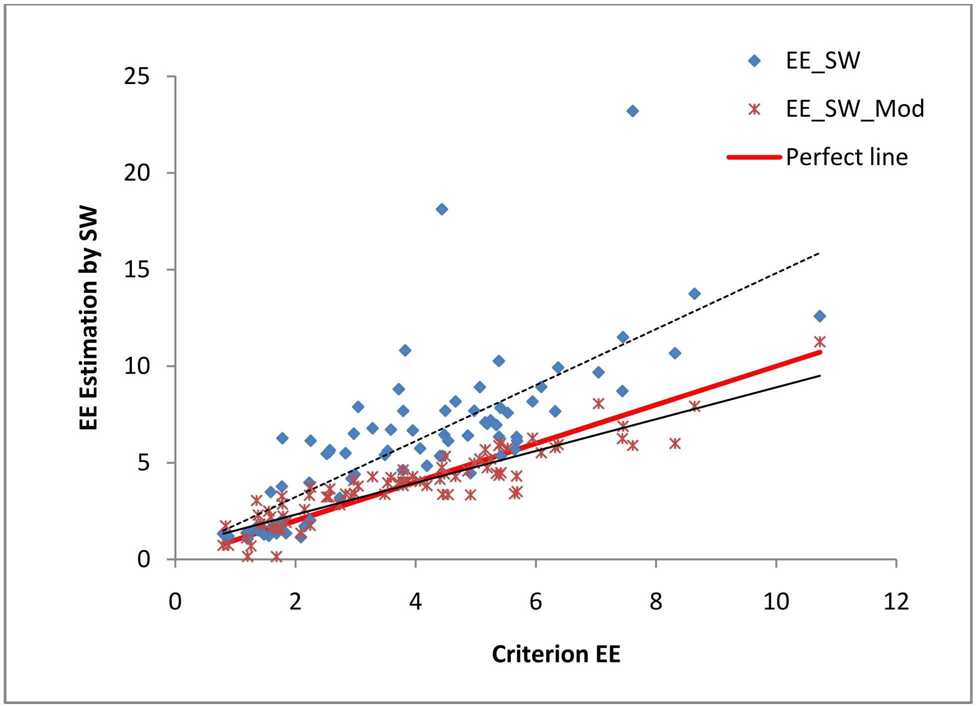

Figure 10. Scatter plot of EE from SW and EE from SW Model versus Criterion EE

Hypothesis 2.1: *EE estimated by SW using the new EE prediction equation, will NOT be significantly different from the criterion EE for each activity.*

Mean and standard deviation (SD) for the EE outputs from the portable metabolic cart and the SW prediction model are shown in Table 4. The Wilcoxon signed rank sum test showed that the EE estimated by the SW model was significantly different from the criterion EE during most of the activities except the resting trial and the 3mph over ground propulsion trial.

The percent error between the predicted EE from the new model and the criterion EE for each activity is shown in Table 4. The summary statistical measures including the ICC, MAE, MSE, and percent error between the predicted EE and criterion EE were shown in Table 5. The ICC, MAE, and percent error between the new predicted EE and the criterion EE, and between the default SW EE and the criterion EE for all the activities by each participant are illustrated in Figure 11 to Figure 13, respectively. Figure 14 shows the predicted EE and the default EE from the SW compared to the criterion EE.

Table 4. Mean and SD for EE from metabolic cart and SW model for four types of physical activities

Activity		EE kcal/min (SD)			P-value
		Metabolic Cart	**SW Model**	**Error (%)**	
Resting		1.5 (0.5)	1.1 (0.7)	+24.8 (45.4)	0.059
Wheelchair propulsion	2mph on Dyno	4.5 (1.8)	4.9 (1.3)	-14.7 (18.3)	**0.037**
	3mph on Dyno	5.9 (2.8)	5.9 (2.3)	-10.0 (33.7)	**0.009**
	3mph on Tile	3.1 (1.2)	3.7 (1.0)	-27.3 (22.7)	0.959
Arm-ergometry	20W at 60 rpm	3.6 (0.6)	3.8 (0.7)	-7.0 (7.2)	**0.028**
	40W at 60 rpm	4.9 (0.5)	4.1 (0.6)	+16.1 (12.2)	**0.005**
	40W at 90 rpm	5.9 (0.7)	5.2 (1.2)	+12.0 (15.3)	**0.022**
Deskwork		1.5 (0.4)	2.0 (0.6)	-37.6 (46.0)	**0.022**

Table 5. Comparison of EE between SW model and metabolic cart

Activity	ICC	MAE (kcal/min)	MSE ($kcal^2/min^2$)	Error (%)
Wheelchair propulsion	0.91	0.78	0.87	-17.35
Arm-ergometry	0.74	0.65	0.76	7.03
All activities	0.90	0.68	0.75	-5.46

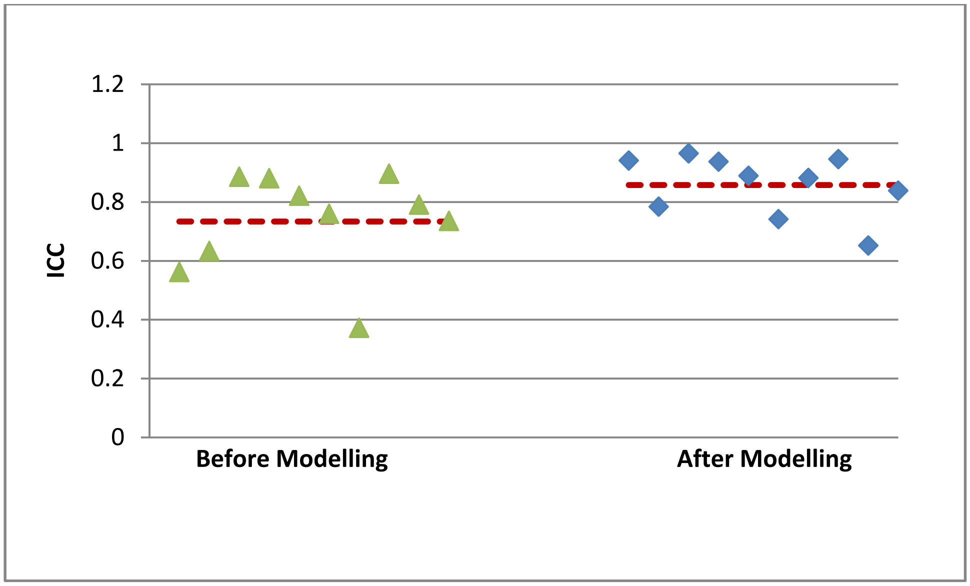

Figure 11. Plot of Intraclass correlation coefficient of SW model for ten participants

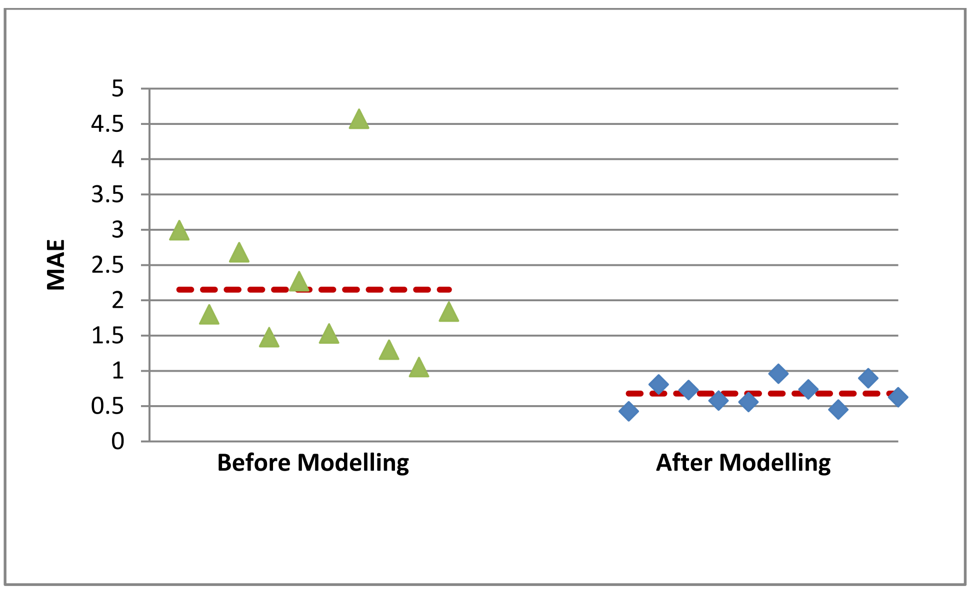

Figure 12. Plot of mean absolute error (MAE) of SW model for ten participants

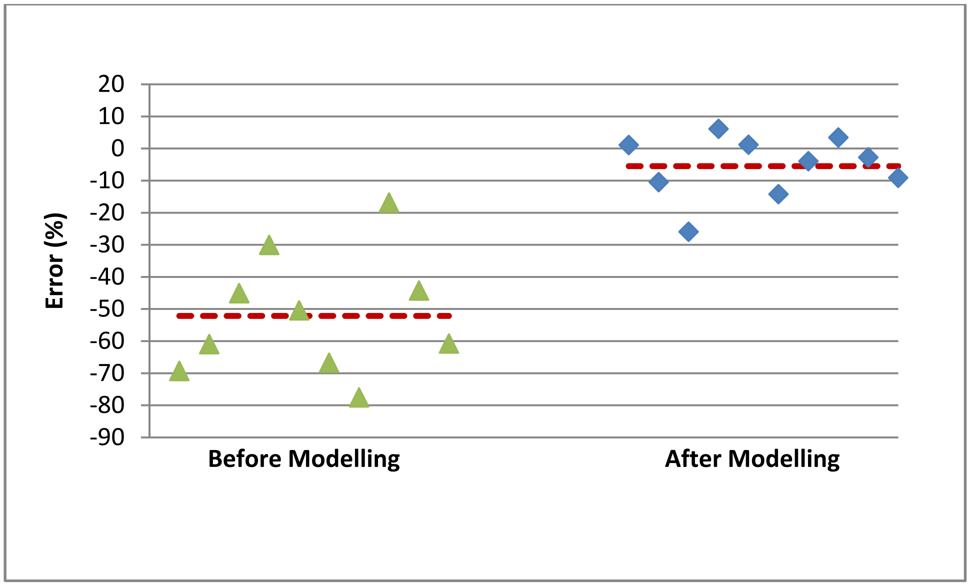

Figure 13. Plot of Error (%) of SW model for ten participants

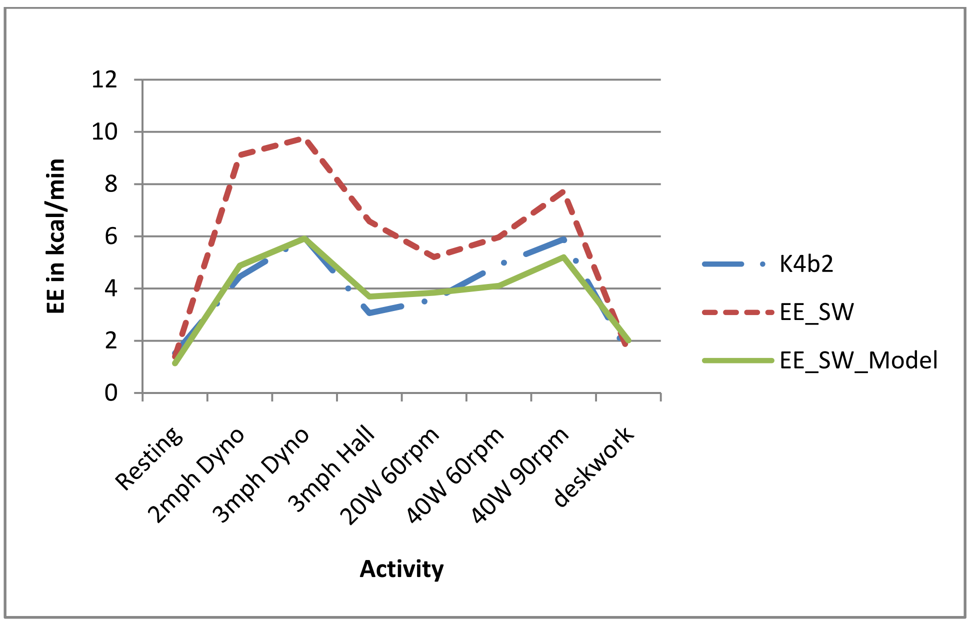

Figure 14. Plot of EE from metabolic cart, SW AM and SW Model versus activity

Hypothesis 2.2: *EE estimated by SW using the new EE prediction equation will be able to differentiate between different intensities of wheelchair propulsion and arm-ergometry exercise.*

The Friedman test showed that the predicted EE from the new model was significantly different across the three propulsion trials ($p < 0.001$), and pairwise comparisons (with adjusted

$\alpha = 0.017$) revealed that the predicted EE was able to discriminate between the 2mph dyno trial and 3mph over ground trial ($z = -2.803$, $p = 0.005$), and between the 3mph dyno trial and 3mph over ground trial and ($z = -2.803$, $p = 0.005$). There was a borderline significant difference between the 2mph and 3mph dyno trials ($z = -2.395$, $p = 0.017$).

The Friedman test showed that the predicted EE was significantly different across the three arm-ergometry trials ($p = 0.001$), and pairwise comparisons (with adjusted $\alpha = 0.017$) revealed that the EE from SW model at the 90rpm 40W trial was significantly greater than at the 60rpm 40W trial ($z = -2.701$, $p = 0.007$), and the 90rpm 40W trial was significantly greater than the 60rpm 20W trial ($z = -2.803$, $p = 0.005$). However, there was only a borderline significant difference between the 60rpm 20W trial and the 60rpms 40W trial ($z = -2.395$, $p = 0.017$).

4.5 ACTIVITY COUNTS IN ACTIGRAPH AND RT3

Hypothesis 3.1: *Raw accelerometer data (i.e., activity counts) from the ActiGraph, the RT3A, and RT3W will at least moderately correlate (r>0.6) with the criterion EE across all the activities.*

Table 6 shows the correlation coefficient (R) and variance (R^2) explained by the activity counts from ActiGraph, RT3A, and RT3W. Figure 15 shows the variance of EE explained by the ActiGraph, RT3A and RT3W for each participant. Data from the RT3W for one participant was lost and not included in the plot.

Table 6. Correlation coefficient (R) and variance (R^2) explained by the activity counts from ActiGraph, RT3A, and RT3W

Activity	ActiGraph			RT3 ARM			RT3 WAIST		
	R^2	R	P	R^2	R	P	R^2	R	P
Wheelchair propulsion	0.44	0.67	<0.001	0.56	0.75	<0.001	0.08	0.29	0.118
Arm-ergometry	0.13	0.36	0.050	0.38	0.61	<0.001	0.08	0.29	0.120
All activities	0.59	0.77	<0.0001	0.68	0.83	<0.001	0.22	0.47	<0.001

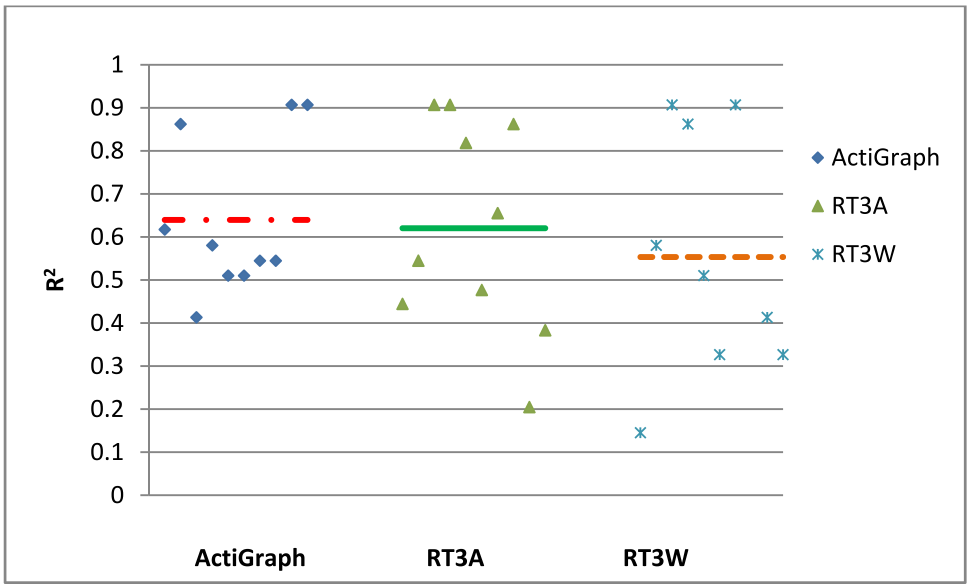

Figure 15. Plot of Variance of AMs for ten participants

5.0 DISCUSSION

Activity monitors have been extensively studied to measure physical activities and predict activity-related energy expenditure among the ambulatory population without disabilities [20, 21, 41, 61, 86, 103, 104]. Information provided by AMs regarding physical activity levels have been shown to motivate its users to continually alter their physical activity behaviors [22]. However, these AMs cannot be directly used by manual wheelchair users who often use upper extremities for performing all the physical activities [73]. Very few studies have been performed to evaluate activity monitors among wheelchair users [73, 77, 80, 97]. This is the first study to examine the validity of common activity monitors including SenseWear, RT3, and ActiGraph AMs to estimate EE in manual wheelchair users with SCI, and is an important step towards providing accurate self-monitoring tool for this population to gauge their activity levels on a daily basis.

Metabolic costs during resting

Eight of the ten participants in this pilot study performed some kind of regular physical activity which deviates from the norm of 13-16% [28]. Metabolic costs during resting are often expressed as a function of body weight using predictive equations, the majority of which have been validated in able-bodied participants [46]. The resting EE measured is proportional to the fat-free mass in the participant [46]. When these equations are used in the SCI population, they overestimate resting EE by 5–32% [129-132], with higher overestimations in persons with tetraplegia [130, 131]. The resting EE measured in the participants of this study was 1.5±0.5

kcal/min (MET =0.9±0.2) which deviates from the resting EE measured by Abel et al. in wheelchair tennis players 1.13±0.21 Kcal/min, wheelchair rugby players 1.06±0.21 kcal/min and wheelchair basketball players 1.04±0.25 kcal/min. The low resting EE measured by Abel et al. may be due to the lower body weights in their study participants (tennis players: 75.4± 11.4 kg, rugby players: 73.7±12.7 kg and basketball players: 73.9± 20.6 kg) compared to our study (81.4±18.3 kg). Research has shown that resting EE in people with SCI measured by indirect calorimetry was 14–27% less than those without injury due to decreased fat-free mass and sympathetic nervous system activity [46]. However the when adjusted for fat-free mass, the difference in resting EE between the persons with SCI and without SCI are less than 3% (P = 0.77) [133].

Metabolic costs of wheelchair related activities

According to Pate et al. light, moderate and vigorous-intensity activities are defined as those with MET scores below 3.0, between 3.0 and 6.0, and above 6.0, respectively [134]. According to the Healthy People 2010 adults should perform 2.5 hours of moderate-intensity activity per week for maintaining a healthy body, enhancing psychological well-being, and preventing premature death [4]. The MET data indicated that wheelchair propulsion on dyno at 3mph (MET=4.1±1.6) and arm-ergometery exercise at 60rpm 40W (MET=3.5±0.8) and 90rpm 40W (MET=4.2±0.7) were moderate, while the rest of the activity trial were light. Especially, propelling on tile floor at 3mph was a light-intensity activity (MET=2.1±0.6), similar to walking at 2mph. The lower values of MET for wheelchair propulsion on tile versus dyno could be due to less rolling resistance on tile and psychological feeling of staying stationary on dyno compared to following a powered wheelchair on tile. Similar to previous research [9, 26, 29, 35, 46], this result also indicates that daily propelling of wheelchair may not enough to maintain or elicit improvements in cardiorespiratory fitness. The rating of perceived exertion (RPE) was found to reflect the same trend as the MET and the HR values for wheelchair propulsion and arm-ergometry trials. However, 80% of participants reported to perform regular exercise, they rated the moderate-intensity activity trials including the arm-ergometry trial at 90rpm 40W and wheelchair propulsion at 3mph on dyno as strong (RPE=5.6 and 5.0, respectively). It was also observed that some participants could not maintain the target speed of propulsion at 3mph on dyno or arm-ergometry at 90rpm 40W for the eight-minute duration.

Validity of the SW in assessing EE

One of the primary findings of this study is that the SW consistently overestimated EE for all the activity trials except for resting where there was only 0.2% difference from the criterion EE. "The most quantitatively important component of total daily energy expenditure is resting metabolic rate, accounting for approximately 65% of the total [46]". The close EE estimation by SW in persons with SCI for resting may improve the daily EE estimation. Energy expenditure estimation for deskwork, consisting of reading magazines and using a computer, was slightly overestimated by 6.5%. However, the SW moderately overestimated EE for arm-ergometry exercise by 32% with a moderate ICC value (0.74) and an average MAE of about 1.5 kcal/min, and greatly overestimated EE for wheelchair propulsion by 105% with a poor ICC value (0.55) and an average MAE of 4.0 kcal/min. Energy expenditure estimation for wheelchair propulsion at 3mph on tile floor was found to have the largest discrepancy from the criterion EE (128.6%). The hypothesis that EE estimated by SW using its default EE prediction equation would significantly differ from the criterion EE was partially supported for all wheelchair propulsion and arm-ergometry exercise trials, but not for resting and deskwork. Considering wheelchair propulsion is a major daily activity in this population, similar to walking among the ambulatory population, the level of inaccuracy in EE estimation by SW can limit its applicability in manual wheelchair users.

There are several possible explanations for the overestimation of EE by SW for wheelchair propulsion. The primary reason is that the SW uses algorithms specifically developed for ambulatory population [41]. Unlike other activity monitors that use one regression equation for all types of activities, the SW first classifies the activity into a predefined category and then uses activity-specific equations to estimate EE [41, 68, 86, 102, 104, 107]. As the classification algorithms were evaluated and refined based exclusively on the ambulatory population, wheelchair propulsion cannot be among the predefined activity categories, and thus was possibly misclassified into a strenuous type of activity such as jogging, leading to greater EE estimation. As for resting and deskwork, they represent common activities among all population and therefore the SW was able to accurately estimate EE and did not significantly differ from the criterion measure. Secondly, the SW used in this study utilizes two-axis accelerometer, which may not be sufficient to pick up arm movements in all directions during wheelchair propulsion. The high standard deviation (SD) in criterion EE and EE estimated by the SW during wheelchair propulsion also indicates arm movements during wheelchair propulsion are not as uniform as during arm ergometry and participants were likely use different propulsion patterns [135]. This may cause the greater EE overestimation by SW during wheelchair propulsion than during arm-ergometry exercise.

It was also noticed from Figures 7-9 that the variability between individual participants was relatively high, indicating the SW was not appropriate to estimate EE in individuals. Participant 7 seemed to be an outlier with a low ICC and MAE values, and high percent error. The review of the demographics of this participant showed this participant was the only female among the 10 participants. On closer analysis we found that the EE estimated by SW for participant seven was significantly overestimated for wheelchair propulsion (308.2% for 2mph on dyno, 204.7% for 3mph dyno and 116.5% for 3mph on tile). These results may indicate that the participant may have an energy efficient (low EE measured by metabolic cart) propulsion pattern while regulating the speed (high acceleration recorded by SW AM) on the dyno.

We also hypothesized that EE estimated by SW using their default EE prediction equation will not be as sensitive as the criterion measure to be able to discriminate different intensities of wheelchair propulsion and arm-ergometry trials. However, the SW showed a similar trend of sensitivity as the criterion measure during wheelchair propulsion. The criterion EE for 3mph on tile was significantly smaller than 2mph on dyno ($p=0.005$) and 3mph on dyno ($p=0.005$), and this was also reflected in EE estimated by SW, which is significantly higher for 2mph on dyno than 3mph on tile ($p=0.005$), and 3mph on dyno than 3mph on tile ($p=0.009$). However, both the criterion EE and the SW EE failed to detect the difference between 2mph on dyno and 3mph on dyno ($p=0.022$ for criterion measure, and $p=0.445$ for SW). The insensitivity of the criterion measure to the propulsion speed change on dyno may be due to the inability of some participants to maintain the 3mph on dyno.

The SW did not follow the same trend of sensitivity as the criterion measure during arm-ergometry trials. The criterion measure was able to discriminate the three intensities of arm-ergometry exercise. The criterion EE for the 90rpm 40W trial was greater than for the 60rpm 40W trial ($p=0.005$), and the latter was greater than the 60rpm 20W trial ($p=0.005$), while the EE estimated by SW was only be able to discriminate the highest intensity (90rpm at 40W) from the lowest intensity (60rpm at 20W) ($p=0.005$). This result indicates that the SW may not be sensitive to change in resistance at same speeds or change in speed at same resistance, unless the change is relatively large. Nonetheless, the validity analysis of the SW indicates the device cannot be directly used for manual wheelchair users with SCI due to the large discrepancy in EE estimation for wheelchair propulsion, and the inaccuracy and insensitivity of discriminating different intensities of arm-ergometry exercise.

Development and evaluation of new EE prediction model for SW

Given the inaccuracy of EE estimation in SW, a linear regression model using pace regression was constructed based on the pooled data from the ten participants. Pace regression was used due to its ability to evaluate the effect of each variable and using a clustering analysis to improve the statistical basis for estimating their contribution to the overall regression, leading to reduced model dimensionality [128]. The selected attributes were three acceleration-based features and body weight (Equation 4). From the scatter plots in Figure 10, we can observe that the EE estimated with the new model were less dispersed and the regression line was moving towards a complete agreement line (i.e., “perfect line” in Figure 10).

We hypothesized that the EE estimated by the new SW model and the criterion measure would not differ significantly for each activity. However, the results failed to support this hypothesis. The EE estimated by the new SW model was not significantly different compared to criterion EE for resting and wheelchair propulsion trial of 3mph on dyno, but was significantly different for deskwork, all the arm-ergometry trials and wheelchair propulsion trials of 2mph on dyno and 3mph on tile surface. The probable reasons for the EE estimated by SW using the new EE prediction equation being significantly different compared to the criterion EE are small sample size and a single EE estimation equation that was developed for all activities.

When examining the model closely, we noticed that new EE prediction equation underestimated the criterion EE by 24.8% for resting and overestimated the criterion EE by

37.6% for deskwork, which was worse than the default EE from the SW (0.2% for resting, and 6.5% for deskwork). However, the EE prediction equation produced better results for wheelchair propulsion and arm-ergometry trials. The percent error for wheelchair propulsion dropped from 105.0% using the default SW EE to 17.4% using the new prediction equation (111.1% to 14.7% for 2mph on dyno, 75.4% to 10.0% for 3mph on dyno and 128.6% to 27.3% for 3mph on tile). The percent error for arm-ergometry dropped from 32.0% using the default SW EE to 7.0% using the new prediction equation (44.3% to 7.0% for 60rpm at 20watts, 22.0% to 16.1% for 60rpm at 40watts and 29.7% to 12.0% for 90rpm at 40watts). The ICC value for (Table 5) wheelchair propulsion was excellent (0.91) with low MAE (0.78kcal/min) and percent error (17.35%). The ICC value for arm-ergometry exercise was moderate (0.74) with less than 0.65kcal/min MAE and a comparatively lower percent error (7.03%).The ICC values for EE estimated by SW using default and new prediction equation remain the same for arm-ergometry trials. The ICC value for the EE estimated by SW using new prediction equation for all activities and participants together was excellent (0.90) and the MAE was 0.68kcal/min with very low percent error overestimation (5.46%). ICC values (Figure 11) for all activities together after modeling has significantly improved compared to before modeling. The mean MAE and percent error (Figure 12 and Figure 13) for ten participants performing all activities together have significantly reduced to 0.68kcal/min and 5.46%, respectively indicating that the EE estimated by SW using prediction equation is much closer to the criterion EE compared to the EE estimated.

We also hypothesized that EE estimated by SW using the new EE prediction equation will be sensitive to the different intensities of wheelchair propulsion and arm-ergometry trials. For wheelchair propulsion the results showed the EE estimated by SW using the new equation, is significantly higher for 2mph on dyno than 3mph on tile (p=0.005) and 3mph on dyno than 3mph on tile (p=0.005). However, the SW EE using new equation produced a borderline significant difference between the 2mph and 3mph dyno trials (p=0.017). The new model reflects the same pattern as the criterion EE with a borderline significance which may improve with more participants in the study. Arm-ergometry trial results showed that the EE estimated by SW using new prediction equation for 90rpm at 40watts was greater than for 60rpm at 40watts (p=0.005) and 60rpm at 40watts was greater than for 60rpm at 20watts (p=0.005). The results indicate that the sensitivity of EE estimated by SW using prediction equation for arm-ergometry trials and wheelchair propulsion were found to be better than the EE estimated by SW using default equation.

Validity of ActiGraph and RT3 in assessing EE

Finally, we examined the ability of using activity counts to predict EE in ActiGraph, RT3A, and RT3W. Both the ActiGraph and RT3A were worn on the upper extremity, which is not in compliance with the manufacturer recommended waist location. However, both of them were able to predict greater variance (68% and 59%, respectively) in the criterion EE than the RT3W worn on the waist (22%), indicating that the upper extremity could be a better place for wearing an AM among manual wheelchair users; justifiably so as this population relies on their upper extremities for all the activities of daily living. This was similar to the study by Pärkkä et al., which found that the ankle was a better place to wear accelerometer and gyro sensors to estimate EE in ambulatory population for common everyday tasks [109]. The variance in the criterion EE explained by the RT3 on waist for wheelchair propulsion and arm-ergometry were very low indicating that movements at the waist in manual wheelchair users may not be reflective of these types of physical activities. When examining the ActiGraph and RT3A, we noticed the RT3A was able to predict greater variance in the criterion EE than ActiGraph for wheelchair propulsion (0.56 vs 0.44), arm-ergometry (0.38 vs 0.13), and all the activities as a whole (0.68 vs 0.59). The correlation results of ActiGraph for wheelchair propulsion (0.67, $p < 0.001$) trials are similar to the correlations found by Washburn and colleagues, between the activity counts from both wrists and EE over the three wheelchair propulsion speeds (0.55 to 0.66, $p<0.01$) [97]. This is possibly due to the tri-axial acceleration sensed by the RT3A versus the uni-axial acceleration sensed by the ActiGraph and is consistent with the results discovered in ambulatory population [82]. Figure 15 shows us that the mean variance in RT3A and ActiGraph for the ten participants can explain greater than 60% of variance in EE. The variance explained by ActiGraph is slightly greater than that explained by RT3A and may be due to high wrist movements involved during deskwork and comparatively less movements in the arm. The variability of the RT3 AMs on the arm and the wrist was found to be high (Figure 15) indicating that the RT3s may perform better in some participants compared to others based on their upper arm usage and biomechanics.

5.1 CONCLUSION

The results of this study indicate that SenseWear AM with the default EE equation is not a valid instrument to measure physical activity and estimate EE in manual wheelchair users with SCI during wheelchair propulsion and arm-ergometry exercise. For resting and deskwork the SW AM closely estimated the EE (0.2% and 6.5%) with respect to the criterion EE in manual wheelchair users with SCI. However, the SW AM significantly overestimated EE during wheelchair propulsion and arm-ergometry exercise by 105% and 32%, respectively.

This was the first study to examine and improve the accuracy of the SW to measure energy expenditure in manual wheelchair users with SCI during various physical activities. From the investigation we found that the EE estimated by SW AM using new regression model equation significantly improved its performance in manual wheelchair users with SCI. With the new prediction equations the percent errors reduced to 17.4% and 7.0% for wheelchair propulsion and arm-ergometry exercise, respectively. The new prediction equation for SW AM was able to differentiate and discriminate (sensitive) EE estimation in physical activities like wheelchair propulsion and arm-ergometer exercises in manual wheelchair users with SCI indicating that it has a potential to be used in manual wheelchair users with SCI. The inability of the new EE prediction equation to pick attributes related to spinal cord injury may indicate that these equations may be used in larger populations of manual wheelchairs users without SCI.

In addition, our findings of the high correlations of acceleration data from RT3 on arm and ActiGraph on wrist compared to the RT3 on waist indicate that acceleration data can play a major role to objectively measure physical activity and estimate EE in manual wheelchairs with SCI. The variance explained by RT3 (0.68, $p<0.001$) on arm and the ActiGraph (0.59, $p<0.001$) on wrist indicate that AMs placed on arm or wrist may be able to better predict EE compared to the AM on the waist.

5.2 LIMITATIONS & FUTURE WORK

The research performed in this study may provide insight for researchers to explore usage of AM to monitor physical activity and estimate EE among manual wheelchair users with SCI. However, there are a few limitations which need to be addressed. The small sample size of the number of participants in this data analysis may have affected the modeling of EE prediction equation by over fitting the data. We plan to overcome this shortcoming by recruiting about 50 participants into this study. Ultimately, the data from this study will be used in conjunction with the data collected from the rest of the participants. With more participants taking part in the study we will be also able to increase the possibility of generalizing the EE prediction equation.

Another limitation of the study may be that we have currently utilized the average of the last six minutes of data. In the future, the performance of EE prediction models for the data averaged over the last four minutes and last two minutes will be determined and compared to the current six minute data. The data collected for each participant was limited to eight minutes for each activity trial in an activity session. Repeated measurement and data collection of participants performing more than one activity session over different visits would probably provide more data that may offer better insights into measuring physical activity and estimating EE. Repeated measurement of EE while performing physical activity may also reduce the errors associated with the EE measured by the metabolic cart. In order to simulate the physical activity participation on a daily basis, the variety of activity trials will be increased to include activities of daily living, instrumental activities of daily living, self care and other physical activities in the natural setting. As activity trials like wheelchair propulsion over dynamometer may not be representative of over ground wheelchair propulsion on different surfaces and slopes, we also aim to study wheelchair propulsion on different surfaces and slopes.

The current data modeling that we performed involved tenfold cross validation which could be significantly improved by splitting the data into training and testing sets. One way of performing the data splitting is to randomly select a percentage of participants to compose a training set while the others are assigned to a testing set. The other way of performing the data splitting is within the participants where, a percentage of data from all the participants are randomly selected as training set while others are selected as testing set. In this study, we propose that between participants data modeling may be more beneficial for future EE estimation. Currently, we are using SW with two axis accelerometer data and we plan to use the new SW with three axis accelerometer data which may increase the accuracy of EE estimation in manual wheelchair users with SCI. Also, we would like to explore more features derived from raw data which have a relationship with physical activity. The features we would like to derive are median, integral, inter-quartile range, low coefficient of variance and high coefficient of variance; which represent central tendency of the measured activity, accumulation of measured activity, variability of moments, lowest variability during each minute and highest variability during each minute, respectively.

Decrease in sensitivity of EE estimated by SW using new EE prediction equation for deskwork and resting compared to the default equation, indicates that one general estimation equation may not be accurate to estimate EE for different activities. We plan to solve this problem by using a two-tier approach, the first is to use a cut-off value of acceleration to discriminate between very light (static) activity and dynamic activity, and a second to use two equations for the two types of activity. Also, on lines similar to SW AM; we would like to try classifying the activity into more categories and then use an activity-specific model. We would like to evaluate sensors like heart-rate monitors and gyro and also analyze the raw data from sensors like accelerometers, galvanic skin resistors and skin temperature to classify the manual wheelchair activity. We would like to try different models, especially non-linear models such as neural network, and Support Vector Machines (SVM).

Wheelchair propulsion activity in manual wheelchair users is comparable to walking in ambulatory population, a major contributor to EE. Consequently we can hypothesize that wheelchair propulsion is a major contributor to EE. To test the above hypothesis we would like to extend our research by introducing the wheelchair rotation datalogger to investigate how wheelchair inclination during travel, distance travelled, speed and acceleration contribute to EE estimation. In order to attain these motion-based parameters we would modify the existing datalogger to include an inclinometer and vibration sensor. We would also attempt high resolution data collection and wireless communication to detect wheelchair propulsion and various other physical activities in real-time. Manual wheelchair users can also utilize their wheelchair as a piece of exercise equipment to maintain their health and fitness during lack of accessible equipment increasing the importance of wheel rotation datalogger.

We would like to evaluate the RT3 on arm, RT3 on waist and ActiGraph on wrist to estimate EE in manual wheelchair users with SCI. In this evaluation, we would like to determine if the regression model from RT3 on an arm is better that the SW AM on an arm as it has a three-axis accelerometer. We will also evaluate EE estimation from multiple activity monitors on body, for example RT3A and ActiGraph or RT3A and RT3W. The idea behind the use of multiple activity monitors is to capture large and small body movements from different locations and compensate each other.

Ultimately, we would like to explore methods to provide real time feedback on physical activity levels to people who rely on manual wheelchair for mobility. The information could be used by the consumers of AMs to perform and achieve the daily quota of physical activity [41, 50, 53, 63, 67, 68, 87, 90, 96, 97]. Achievement of physical activity goals and real time information can aid in behavioral modification to improve and maintain adequate physical activity performance [22, 41]. In addition there is a possibility to use AMs to wirelessly communicate to a computer or a cell phone which would place the information over the internet [41]. Information on the internet can be used to create applications that increase social as well as physical activity network among manual wheelchair users [136]. Through the information exchange, wearable monitors could promote activity and telehealth. Social support can play an important role in meeting daily recommendation of physical activity; sharing information and collaboration to work out together virtually has influence on physical activity levels [137].

In the future, we would like to develop and evaluate new EE prediction models for activity monitors to provide manual wheelchair users with SCI an accurate means to gauge their physical activity participation on a daily basis, and extend the findings to manual wheelchair users with other diagnosis.

APPENDIX A

EVALUATION OF ACTIVITY MONITORS IN PEOPLE WITH SPINAL CORD INJURY

QUESTIONNAIRE

Date: ___/___/______

Gender: ❑ Male (1) ❑ Female (0)

Date of Birth: ___/___/______ (mm/dd/year)

Age: ______

SCI Level _________________________

Completeness of Injury: ❑ Complete ❑ Incomplete

Date of Injury Onset: ___/___/______

Ethnic Origin:

- ❑ African American (1)
- ❑ Asian American (2)
- ❑ Caucasian (3)
- ❑ Hispanic (4)
- ❑ Native American (5)
- ❑ Other (6): __________________________

Manual Wheelchair Make (brand):

☐ Action/Invacare ☐ Permobil

☐ Everest and Jennings ☐ Pride

☐ Kuschall ☐ Sunrise/Quickie

☐ Otto Bock ☐ TiLite/TiSport

☐ Other (please specify): ____________________

Manual Wheelchair Model: ________________

When did you start using a manual wheelchair: ____/____/____ (mm/dd/year)

Which is you dominant hand? ❑ Right ❑ Left

Are you an athlete? ❑ Yes ❑ No

Do you smoke? ❑ Yes ❑ No
If yes, how much per day and what was your age when you started?
Amount per day_____ Age_____

Have you had or do you presently have any of the following conditions?
❑ High blood pressure ❑ Seizures ❑ Lung disease ❑ Fainting or dizziness
❑ Diabetes ❑ High cholesterol ❑ Shortness of breath at rest or with mild exertion
❑ Unusual fatigue or shortness of breath with usual activities

Do you exercise regularly?
- ❑ Yes

	Activity Type	Frequency	Location

- ❑ Occasionally (less than once a week)
- ❑ Not at all

Do you follow any specific dietary intake plan? ❑ Yes ❑ No

In general how do you feel about your nutritional habits?
- ❑ Excellent
- ❑ Very good
- ❑ Good
- ❑ Fair
- ❑ Poor

In general, how do you rate your fitness level?
- ❑ Excellent
- ❑ Very good
- ❑ Good
- ❑ Fair
- ❑ Poor

APPENDIX B

BORG SCALE USED FOR THE STUDY[74]

Value	Category-ratio Scale	
0	Nothing at all	"No Intensity"
0.3		
0.5	Extremely weak	Just noticeable
0.7		
1	Very Weak	
1.5		
2	Weak	Light
2.5		
3	Moderate	
4		
5	Strong	Heavy
6		
7	Very Strong	
8		
9		
10	Extremely strong	"Strongest Intensity"
11	Absolute maximum	Highest possible

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