PHYSICAL ACTIVITY MONITORING SYSTEM FOR MANUAL WHEELCHAIR USERS

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People with disabilities who rely on manual wheelchairs as their primary means of mobility face daily challenges such as mobility limitations and environmental barriers when engaging in regular physical activity. Therefore, our research addressed the need for a valid and reliable physical activity monitor to assess and quantify physical activities among manual wheelchair users (MWUs) in free-living environments. Providing an accurate estimate of physical activity (PA) levels in MWUs can assist researchers and clinicians to quantify day-to-day PA levels, leading to recommendations for a healthier lifestyle. In the first stage we developed and evaluated new classification and EE estimation models for MWUs with spinal cord injury (N=45) using SenseWear, an off-the-shelf activity monitor, designed for the general population without disabilities. The results suggested that researchers and clinicians can use SenseWear to detect and estimate the EE for four activities tested in our study. The second phase of our research project developed an activity monitor especially designed for MWUs. Previous research in community participation of MWUs and the studies discussed above found that wheelchair mobility characteristics are necessary to study PA patterns in MWUs. This requirement led us to develop and evaluate a Physical Activity Monitor System (PAMS) composed of two components: a gyroscope based wheel rotation monitor (G-WRM for tracking wheelchair mobility and an accelerometer that quantifies upper arm movement. We tested PAMS in 45 MWUs with SCI in the structured (laboratory) and semi-structured environments (National

Veterans Wheelchair Gamers 2012). In addition, we also tested a subsection of this population (N=20) a second time, in their home environments. The PAs were classified as resting, arm-ergometry, other sedentary activities, activities involving some wheelchair movement, propulsion, basketball and caretaker pushing. The EE estimation results (error: -9.8%) and the classification results (accuracy: 89.3%) indicate that PAMS can reliably track wheelchair-based activities in laboratory and home environments. Furthermore, we used participatory action design to evaluate the usability of PAMS in six MWUs with SCI. The usability study indicated that users were very satisfied with PAMS and the information provided by the smartphone to the users about their PA levels.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF EQUATIONS

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1.0 INTRODUCTION

1.1 RATIONALE

Lack of regular physical activity (PA) in the general population is a top public health concern [1], and this problem is even more acute among people with disabilities who use manual wheelchairs [2, 3]. Despite the proven health benefits associated with regular PA, such as reduced risk of cardiovascular diseases and other chronic conditions and improved psychological well-being, people with disabilities remain one of the most physically inactive groups in society. Healthy People 2020 indicated that individuals with disabilities are much less active than their non-disabled counterparts (54% inactive vs. 32% in 2008, respectively) and participate in less regular and vigorous physical activity [4, 5]. People with disabilities also experience more secondary conditions such as pain, fatigue, weight gain, and deconditioning [6], many of which are considered preventable through physical activity and exercise interventions [7].

People with disabilities who rely on manual wheelchairs as their primary means of mobility, over 2.8 million persons in the US in 2010 [8], face special challenges in engaging in regular PA, including physiological changes, mobility limitations and environmental barriers [3, 9-11]. Validated objective tools are critical to developing and evaluating interventions that aim at promoting PA and community participation in this population; however, only a limited number of tools are available to gauge PA in this population. For example, PA participation in free-living conditions is usually measured through self-reports or personal logs, which are cumbersome and suffer from social desirability bias and recall. Therefore, in this research we created new models for an existing activity monitor (SenseWear) developed for the general population to estimate energy expenditure in manual wheelchair users (MWUs). We also developed and evaluated a new physical activity monitoring system (PAMS) especially for MWUs. PAMS can capture wheelchair movement and upper extremity movement to quantify PA in MWUs, thereby allowing more accurate assessment of PA levels in MWUs.

1.2 REGULAR PHYSICAL ACTIVITY IN THE GENERAL POPULATION

Regular PA among adults, regardless of the presence of a chronic disease or disability, can increase health and quality of life and decrease the rates of obesity and overweight, coronary heart disease, stroke, high blood pressure, type 2 diabetes, breast and colon cancer, falls, and depression [12, 13]. Therefore, the limited participation in regular PA among adults is a top public health concern in the United States of America (US). In 2010, 35.9% of the US population was obese, with a Body Mass Index (BMI) greater than 30kg/m^2, and 33.3% of the US population was overweight, with a BMI between 25kg/m^2 30kg/m^2 [1, 14]. To address this health concern, the US Department of Health and Human Services and the American College of Sports Medicine and the American Heart Association compiled a list of PA guidelines for adults to "be active, healthy and happy" [15, 16]. These strategies for adults focus on both aerobic and muscle-strengthening PAs. The aerobic PA recommendations suggest performing moderate intensity PA for at least 150 minutes/week, or vigorous intensity PA for at least 75 minutes/week, or an equivalent combination of moderate and vigorous intensity PAs. The muscle-strengthening PA recommendations include performing moderate or high intensity activities involving all major muscle groups two or more days a week [16]. These PA recommendations seem easy to follow, but for the majority of the population it is challenging and overwhelming to keep track of their PA performance on a daily basis.

Based on these recommendations and the previous guidelines by the US Surgeon General [17], the current PA data by Healthy People 2020 indicates that only 31.6% of the adults in the US engaged in no leisure-time PA in the year 2011. Further, Data 2020 interim results for the year 2011 indicates that: a) 48.8% of the adults engaged in aerobic PA of at least 150 minutes/week of moderate intensity, or 75 minutes/week of vigorous intensity, or an equivalent combination, b) 24.2% of the adults engaged in muscle-strengthening activities two or more days/week, and c) 20.8% of adults met the objectives for aerobic and muscle-strengthening PA. Healthy People 2020 assessed the PA participation data through surveys from the National Health Interview Survey, Centers for Disease Control and Prevention, and National Center for Health Statistics. However, due to the high variability of surveys gathered in the form of self-reports and PA logs, public health professionals and researchers cannot easily compare the energy cost or energy expenditure across studies. Therefore, to address this issue a group of experts developed a compendium of PA which lists energy expenditure for various PAs [18-20]. In addition to the compendium of PA, extensive research has investigated the validity and reliability of criterion measures and PA monitors [21-24]. These instruments estimate PA levels among the general population and reduce the burden of recording or remembering PAs performed.

1.2.1 Compendium of PAs for the General Population

Dr. Haskell and his group designed and published the first version of the compendium of PAs in 1993 [20]. The compendium of PAs was designed to standardize the rate of energy expenditure in terms of metabolic equivalent of task (MET) for a wide range of PAs [18]. The PA information was gathered from a number of epidemiological studies or self-report PA questionnaires. MET, according to the compendium, is defined as the "ratio of the work metabolic rate to the resting metabolic rate" (1 MET = 1 kcal/kg/hour or 1 MET = uptake of 3.5 ml/kg/min of oxygen) [25]. The compendium contains a list of PAs and their associated MET values, which were either derived using criterion instruments or estimated using exercise physiology. This tool assists researchers and clinicians in coding and quantifying PAs reported through self-report questionnaires and logs. The taxonomy of the PA list was developed based on the purpose of the activity and includes categories such as leisure time activities, transportation, occupation, home activities, inactivity, and volunteer activities [18]. The energy cost information from the compendium can also assist the development of exercise and weight management plans, and the characterization of PA behaviors, including sedentary, light, moderate and vigorous types of PA. This inexpensive PA compendium allows researchers and clinicians to recommend PA interventions and compare PAs over various epidemiologic studies. Currently, researchers and clinicians across the globe use this compendium to estimate the METs or the energy expenditure in research studies, and to develop PA recommendations for people [18]. Even though there are a number of advantages to using the PA compendium, the limitations of survey-based methods, such as recall bias and social desirability bias, to estimate PA levels has led researchers to develop and evaluate sensor-based monitors to estimate PA [21-24, 26, 27].

1.2.2 Sensor-based Monitors to Estimate PA Levels in the General Population

Sensor-based monitors to estimate PA levels can be classified into criterion or gold standard methods, including direct calorimetry, indirect calorimetry, and doubly labeled water [23, 24, 27, 28]; and PA monitors including motion, physiology, and multi-sensor based monitors [21, 26, 29, 30]. The gold standard methods estimate energy expenditure and METs based on heat loss, gases exchanged by the individual (O_2 inhaled and CO_2 exhaled), and CO_2 and water produced [23, 24, 27, 28]. The PA monitors estimate PA in terms of total energy expenditure, METs and duration of PA based on sensors that detect motion or physiologic changes, or a combination of sensors that detect motion and physiologic changes [21, 26, 29, 30]. Numerous studies have evaluated the validity and reliability of using sensor-based monitors to estimate PA in the general population [21, 26, 31-34].

Total energy expenditure (also referred to as EE) is comprised of resting EE (REE), the thermic effect of food (TEF), and EE due to PAs [35]. Resting EE accounts for 65-75% of total EE and is the result of normal cellular and organ function during resting [36, 37]. TEF accounts for 5-10% of the total EE and is the result of increase in metabolism due to digestion and assimilation of nutrients in food. EE due to PAs accounts for 15-30% of the total EE and is the result of volitional activities such as exercise and regular PA, combined with non-volitional activities such as fidgeting, spontaneous muscle contractions, and maintaining one's posture. Direct calorimetry measures the total heat loss from a participant who performs a set of PAs or stays for a fixed duration of time in a thermally-isolated chamber [27, 28]. The total heat loss due to evaporation, radiation, conduction and convection from the participant is used to estimate total EE. Indirect calorimetry estimates the total EE by measuring the volume of oxygen consumed (VO2) and the volume of carbon dioxide produced (VCO2) by the participant using standard equations [24, 38]. The indirect calorimetry method can be performed using a) a closed-circuit system that measures the change in amount of gases from a reservoir and b) an open-circuit system that measures the amount of gases inhaled and exhaled [24, 38-40]. Open-circuit systems are used to estimate EE during PAs due to the physical restrictions and complexity of the closed-circuit system. Open-circuit systems can be further classified into respiratory chambers, stationary metabolic carts or portable metabolic carts. The doubly labeled water method involves the participant taking an oral dose of water with a known amount of Oxygen and Deuterium (stable isotope)[23, 24]. The total EE is calculated based on the concentration of the isotopes in the urine or saliva of the participant, measured both before and at the end of the experiment (usually 7 days or 14 days). Even though the DLW method is considered very accurate, one of the major limitations of this method is that it gives cumulative EE for both duration and types of activities, compared to the EE that can be measured for specific activities using a metabolic cart.

There are a plethora of PA monitors available for the general population to measure PA. The following section discusses the underlying technology of some of the motion, physiology and multi-sensor based PA monitors. Motion-based PA monitors vary from simple mechanical switch-based pedometers that only count steps to complex micro-electromechanical systems that detect biomechanical motion to estimate steps and other PAs. For example, some of the latest commercial and research-based activity monitors that use accelerometers or Global Positioning Satellite technologies to estimate EE, METs and steps are Omron HJ320 Pedometer, Yamax Digiwalker CW-701 Pedometer, GT3X (The ActiGraph), the RT3 (StayHealthy Inc.), wockets, Nike+ Running, Fitbit, iPhone-based smartphone applications, DirectLife, and Garmin Forerunner® 610[41-47]. The second group, physiology-based activity monitors, estimates EE or the intensity of PA by measuring the heart rate or skin conductance. Some of the physiology-based activity monitors include Polar RCX5, Omron HR-210, mio Alpha, and Affectiva Q Sensor [41, 48-50]. The third group, multi-sensor based activity monitors, incorporates more than one type of sensing (movement and physiology) or multiple sensors of the same type of sensing to estimate PA levels. Some of these multi-sensor based activity monitors include wockets (multiple tri-axial acceleration sensors), Polar RC3 GPS (heart rate and GPS), SenseWear (tri-axial acceleration, galvanic skin response, skin temperature, heat flux and near body temperature), Basis (heart rate, tri-axial acceleration, perspiration, and skin temperature), and PAMSys (tri-axial acceleration, multi-axial angular velocity, and magnetic sensing) [51-56]. Some studies have indicated that the advantages of multi-sensor based activity monitors include detection of resistance-based PAs and variations in individual contexts.

Use of PA monitors to track PA in the general population has increased dramatically in the last ten years as use of accelerometer based pedometers or activity monitors has become fairly widespread. Johannsen et al. evaluated the validity of the SenseWear in estimating total EE for 14 consecutive days among 30 healthy adults and found that the absolute prediction error (MAE) rate when compared with the doubly labeled water method was 8.1% ± 6.8% [26]. In another study, Berntsen et al. found that the SenseWear underestimated total EE with a minute-by-minute MAE of 9% when compared with an indirect calorimeter in 20 adults for a period of 120 minutes during various activities and intensities [33].

1.3 REGULAR PA IN MANUAL WHEELCHAIR USERS

In comparison to the general population, lack of regular PA among people with disabilities who use manual wheelchairs is even more acute [2, 3]. Healthy people 2020 indicated that 54% of individuals with disabilities were inactive and participated in less regular and vigorous PA than the general population [4, 5]. Out of these individuals with disabilities in the US, 2.8 million are wheelchair users who exclusively use their upper extremities for locomotion and other activities of daily living as well as for exercise and recreational activities [10, 57, 58]. In persons with spinal cord injury, physiological changes along with mobility limitations contribute to a large extent to their sedentary lifestyle [10, 58].

The positive effects of PA 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 who use manual wheelchairs [3, 59-63]. However, such PA interventions generally occur in laboratory or other controlled settings [64-68]. PA participation of manual wheelchair users (MWUs) in community settings is frequently assessed through self-reports [69] as there are only a limited number of objective tools that allow researchers and clinicians to gauge PA levels in community settings. In addition, Collins et al. have developed a compendium to quantify energy costs in individuals with spinal cord injury (SCI) [70] as the daily EE in persons with SCI is lower than the general population due to the atrophy of skeletal muscles [71, 72] and the compendium of PA for the general population does not include activities that are typically performed by individuals with SCI.

Washburn et al., indicated that only 13-16% of persons with SCI reported consistent PA [73], and the majority of people with SCI reported virtually no regular PA [74-76].

Tasiemski et al. found that only 20% of the 985 people with SCI in the United Kingdom (UK) who participated in their study performed regular PA, while 26.7% performed less than 120 minutes per week and the rest of 53.3% reported no regular PA [77]. In addition, Buchholz et al. showed that the PA level (PAL), expressed as daily EE due to basal metabolic rate only, was much lower in persons with paraplegia (1.56±0.34 PAL) compared to the recommendation of the World Health Organization (1.75 PAL) [58, 78].

1.3.1 Self-Report Questionnaires in People with Disabilities

As mentioned above, questionnaires are one of the most widely used and least expensive ways of recording PA [79]. Four such instruments which have been specifically constructed for people with disabilities, including wheelchair users, are the Human Activity Profile, the Physical Activity and Disability Survey, the Physical Activity Scale for Individuals with Physical Disabilities (PASIPD), and Physical Activity Recall Assessment of People with SCI [80-83]. Three of the surveys tools designed and evaluated in the last decade are discussed below.

Rimmer et al. have assessed the psychometric properties of the Physical Activity and Disability Survey (PADS) in 103 individuals with disabilities and/or chronic health conditions [80]. PADS was designed to measure low-level PA among persons with physical disabilities and chronic health conditions through assessing information in three sub-scales including exercise, leisure time PA and household activity. The study found significant correlations ($p<0.05$) between PADS subscales and absolute peak VO_2, relative peak VO_2, maximum workload, and time to exhaustion indicating PADS can measure PA among persons with disabilities. Washburn et al. evaluated the construct validity of the 13-item PASIPD through mail surveys in 372 individuals with spinal cord or other locomotor injuries [82]. The PASIPD requested the participants to record the number of days and hours per day of participation in recreational, household, and occupational activities over the previous seven days. Total scores for the PASIPD were calculated by multiplying the average hours per day for each item by a metabolic equivalent value (MET) associated with the intensity of the activity and summing over all items. This study found that participants 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 ($p<0.05$) [82]. Ginis et al. developed and assessed the content validity, test–retest reliability, and convergent validity of the Physical Activity Recall Assessment for People with Spinal Cord Injury (PARA-SCI) [83]. The test–retest reliability results showed that intraclass correlations ranged from 0.45 to 0.91 for the various activity and intensity categories of PARA-SCI. The validity tests showed correlations ranging from 0.27 to 0.88 between PARA-SCI scores and indirect calorimetry for activities. However, because these questionnaires rely on self-report, the PA information collected may suffer from participant bias, inaccuracy of recall of activities, social acceptability bias, and choice of consistent low or high scores on the surveys leading to flooring effects [79-84].

1.3.2 Compendium of PAs for Persons with SCI

Collins et al. studied the energy cost in individuals with SCI as the METs and EE values in this population are different than those in the general population due to anatomical and physiological changes related to injury, and also as most of the PAs are performed in a seated position or from a wheelchair [70]. The research measured EE in persons with SCI for 27 types of PAs, including 12 recreational or sport PAs and 15 activities of daily living. In addition, the study indicated that the 1 MET for individuals with SCI (MET-SCI) should be adjusted to 2.7 $ml \cdot kg^{-1} \cdot min^{-1}$ of volume of oxygen (VO_2) [70] compared to 3.5 $ml \cdot kg^{-1} \cdot min^{-1}$ of VO_2 in the general population to take the physiological changes into consideration [18]. The MET-SCI values for various PAs for individuals with motor incomplete SCI ranged from 1.17 to 16.25 for supported standing and hand cycling activities, respectively. The MET-SCI values for various PAs for individuals with motor complete SCI ranged from 1.27 to 7.74 for dusting and basketball game activities, respectively [70]. The large difference between the maximum values of the MET-SCI between motor incomplete and motor complete SCI is due to the different activity types that were performed by these groups. In addition to studying the PA compendium for persons with SCI, researchers also evaluated and developed sensor based technologies to assess PA in people with SCI who use manual wheelchairs [11, 85-90].

1.3.3 Sensor-based Monitors to Assess PA in MWUs

Research has shown that due to post-injury physiological changes, resting EE and EE due to thermic effect of food are lower in persons with spinal cord injury compared to persons without injury [72, 91, 92]. When looking at the total EE, the EE due to PAs is the most variable component when compared to the resting EE and EE due to thermic effect of food. Wheelchair users have the power to modify this EE component in order to reach their quota of recommended PA. To help wheelchair users realize this quota of PA, researchers evaluated PA measurement tools with varying sensitivity and accuracy to assess PA among

MWUs [11, 70, 80-82, 87, 89, 93]. The PA measurement tools that have been evaluated in MWUs include gold standard measures such as indirect calorimetry and DLW [70, 93], and PA monitors including motion, physiology, and multi-sensor based activity monitors [89, 94-97]. Most of the underlying technologies for these tools, except for the wheel rotation dataloggers, have been discussed in the previous section ("Sensor based Monitors to Estimate PA Levels in General Population").

1.3.3.1 Indirect Calorimetry

Researchers have used stationary and portable metabolic carts as a gold standard to measure EE from different types of wheelchair-related PAs in persons with SCI. Some of the PAs that were performed included arm cranking, rowcycling, circuit training, wheelchair racing, wheelchair tennis, wheelchair basketball and wheelchair rugby [59, 60, 62, 65, 66, 70, 98]. Collins et al. used open-circuit indirect calorimeters to measure and estimate EE for resting and various PAs [70]. The instruments used to estimate EE for resting and PAs were SensorMedics 2900 Metabolic System (Yorba Linda, CA) and Cosmed K4b2 portable metabolic cart (Rome, Italy), respectively. Furthermore, Monroe et al. used a respiratory chamber to compare the daily EE in individuals with and without SCI [92]. The results indicated that the daily EE over 24-hours (7824±305 for persons with SCI and 9941 ± 188 kJ for controls) and the EE adjusted for fat-free mass, fat mass and age (-753 kJ/d) were both lower in individuals with SCI than without SCI.

1.3.3.2 Doubly Labelled Water

Tanhoffer et al. used DLW as a gold standard to compare heart rate monitoring, multi-sensor armband and survey questionnaire methods to estimate EE and PA in people with

SCI in community settings [93]. The study showed how heart rate monitoring, multi-sensor armband, PARA-SCI, and the PASIPD questionnaire methods all overestimated the total daily EE (over and under estimations cancel out) compared to DLW by 13%, 16%, 6% and 1%, respectively. These results should be used with caution as the participants wore the multi-sensor armband and the heart rate monitor for only two days, a more physically active day and a less active day, for at least 12 hours per day, compared to the 14-day DLW assessment. The heart rate monitors were calibrated to each individual using an exercise protocol, a procedure impossible to apply in large populations. In addition, Tanhoffer et al. calculated the total daily EE estimation for PARA-SCI and PASIPD as the sum of the basal metabolic rate (resting) obtained using an indirect calorimeter and activity EE estimated based on the METs of the activities performed. The use of an indirect calorimeter to estimate resting EE rather than using the METs for resting is difficult to apply in large populations.

1.3.3.3 Accelerometers on MWUs

Warms et al. evaluated the validity of the Actiwatch accelerometer (Mini Mitter Company, Bend, OR) by measuring community living physical activity in MWUs with spinal cord injury and comparing Actiwatch activity counts with self-reported activity levels [11]. The Pearson correlation between the activity counts and the self-reported activity intensity varied from low to moderate (0.30-0.77, $p<0.01$) for individual participants, indicating that activity counts can be used to measure activity. In another study, Washburn et al. assessed the validity of the CSA accelerometer (Computer Science and Applications, Inc., Shalimar, FL) worn on the wrists, measuring the energy expenditure during wheelchair propulsion at three different speeds [89]. Significant correlations (0.52-0.66, $p <0.01$) were reported for the activity counts from the CSA accelerometer and energy expenditure over three pushing speeds. However, one of the major limitations when using a single accelerometer is the device's inability to identify whether the PA involves manual wheelchair movement, which would significantly overestimate PA levels.

Postma et al. validated a multiple-sensor (six accelerometers) based activity monitor to detect wheelchair propulsion from a series of representative daily life activities [90]. The sensors were placed on each thigh, each wrist and sacrum (two sensors). The results indicated that the agreement, sensitivity and specificity for detecting wheelchair propulsion from other activities were 92%, 87% and 92%, respectively. The limitations of this study are the direct placement of multiple sensors on the participant's body and that the data recorder has to be constantly carried on the person (~0.7Kg), all of which might be uncomfortable and obtrusive for MWUs on a daily basis. In addition, the study only classified wheelchair propulsion with respect to other activities of daily living that were performed in the study.

1.3.3.4 Wheel rotation datalogger

The Human Engineering Research Laboratories (HERL) developed a Wheel Rotation Datalogger (WRD) that can be mounted on a wheelchair's wheel to detect aspects of mobility such as the distance traveled and the speed of wheelchair users in a free-living environment. Tolerico et al. used a WRD to collect the gross mobility characteristics of MWUs in the National Veterans Wheelchair Games (NVWG) and in community settings [97]. MWUs were found to use their wheelchairs for a mean (SD) distance of 6.7 (1.9) km per day at a speed of 0.96 (0.17) m/s and 2.5 (1.2) km per day at a speed of 0.79 (0.19) m/s in the NVWG and community, respectively. Research by Chaves et al. has shown that wheelchair velocity in MWUs is significantly correlated ($r=0.76$, $p=0.04$) with community participation [99]. Although the WRD is portable, easy to use and can collect gross activity, a major limitation is its inability to capture upper extremity movements. As it cannot capture upper arm movements, it cannot differentiate between the MWU self-propelling from the MWU being pushed by a caregiver; additionally, the WRD is unable to detect and estimate EE for activities such as deskwork or arm-ergometry.

1.3.3.5 Wheel-mounted Accelerometer

Coulter et al. investigated a wheel-mounted tri-axial accelerometer and found high validity for wheel revolutions, absolute angle and duration of movement (ICC(2,1)>0.999, 0.999, 0.981, respectively) in wheelchair users [100]. When compared with the criterion measure (video) the mean (mean ± sd) difference of wheel revolutions estimated by the activity monitor was 0.002 ± 0.016, with an absolute maximum difference of 0.038 revolutions. The mean absolute percentage error was 0.59% for all tasks. Sonenblum et al. used a wheel-mounted tri-axial accelerometer to detect wheelchair movement and measure distance travelled, achieving an accuracy greater than 90% for various wheelchair and wheel types, propulsion techniques, speeds, and wheelchair-related activities of daily living [85]. However, consumers cannot use any of these activity monitors to obtain near-real-time feedback about their mobility characteristics as this information is post-processed based on data stored in the devices. Moreover, these devices have not been evaluated for wheelchair sports such as handcycling, which limits the researchers and consumers ability to track PA during wheelchair sports.

1.3.3.6 Heart Rate Monitors in Wheelchair Users

Hayes et al. and Lee et al. developed individualized heart rate models to predict physical activity in terms of EE and MET, respectively, in MWUs with SCI [95, 96]. Hayes et al. evaluated the accuracy of calibrated heart rate in participants with tetraplegia and paraplegia after conducting a maximum exercise test for predicting EE during five activities of daily living. Their research showed that the heart rate measured and the heart rate derived from individualized regression equations explained 8.3% and 55% of the variance in measured EE for various PAs, respectively [95]. Lee et al. on the other hand, predicted METs in persons with SCI using heart rate ratio information during PA and resting. The Pearson correlation coefficient of heart rate ratio and observed METs was only 0.77 when using group regression, but was 0.93 for individual regression [96]. A limitation of using heart rate to estimate EE or METs is that one needs to perform a range of PAs in laboratory settings with different intensities to develop individualized prediction models.

1.4 ACHIEVING RECOMMENDED PA LEVELS IN MWUS

While MWUs face numerous challenges such as mobility limitations and environmental barriers when engaging in regular PA, research has shown that moderate intensity hand-cycling, wheelchair racing, wheelchair basketball, and wheelchair tennis are sufficient to maintain fitness and prevent cardiovascular diseases [62, 65-68, 98]. Hicks et al. conducted a clinical trial to evaluate the impact of a long-term exercise training program that included progressive arm-ergometry and resistance training in persons with SCI over a duration of nine months (twice per week) [62]. The results showed that the experimental group achieved significant improvements in submaximal arm ergometry power output and upper body muscle strength compared to the control group, which showed no significant changes. The study also demonstrated that in contrast to the control group, the experimental group with training reported significantly less pain, stress and depression after training. Moreover, the experimental group scored higher than the control group with respect to satisfaction with their physical function, level of perceived health and overall quality of life. Maki et al. and Abel et al. showed that persons with SCI can perform hand biking, row cycling, and wheelchair racing at an intensity high enough to improve and maintain cardiorespiratory fitness [66, 98]. In another study Abel et al. demonstrated that the leisure time EE for persons with SCI participating in wheelchair basketball and wheelchair tennis is sufficient to maintain cardiovascular fitness and reach the PA recommendations of the ACSM for the general population [65]. Therefore, participating in this type of leisurely activities might prevent the development of cardiovascular diseases.

1.5 SELF-MONITORING IN THE GENERAL POPULATION

A large number of research studies have used behavioral weight loss interventions to produce clinically significant weight loss among obese or overweight adults. Behavioral interventions focus on improving "knowledge related to adoption and maintenance of eating and activity behaviors to promote weight loss, and strategies to facilitate long-term behavioral change such as barrier identification, problem solving, mastery experiences for self-efficacy, and others" [101]. Many of these interventions rely on a) self-monitoring of diet, PA, and body weight, and b) reducing energy intake, and increasing EE [101-105].

The monitoring of diet, PA and weight was accomplished through telephone interviews and self-monitoring booklets. Reducing energy intake and increasing EE were accomplished through education and training about diet and PA. Many of the behavior-based studies also focused on training in applying stimulus control, stress management and problem solving to manage weight. However, these behavioral interventions are expensive, resource intensive, and only impact a small segment of the overall US population [102] with high rates of obesity and overweight.

Recent research showed that in contrast to the traditional behavior-based weight loss programs, a combination of behavior and technological interventions leads to significantly more weight loss [106-108]. In their review article, Coons et al. discussed thirteen studies published in peer-reviewed journals between 2010 and 2011 that had the following criteria: Randomized Clinical Trial (RCT) with at least one intervention and a comparison condition, a technology-supported intervention with participant interface, and at least one weight loss outcome variable [102]. This review indicated that technology interventions may be efficacious in producing weight loss. Shuger et al. conducted an RCT in 197 sedentary overweight or obese adults to evaluate if electronic feedback about diet and PA is more effective for weight loss [107]. Participants were randomized into a self-directed weight loss program via an evidence-based weight loss manual (standard of care), a group-based behavioral weight loss (GWL) program, the SenseWear armband (SWA) alone, or the GWL plus the SWA, during a 9-month intervention period. The participants in the SWA and GWL+SWA were asked to wear the armband for 16 hours a day, 7 days a week. The participants received near-real-time feedback from a wrist watch about EE, minutes spent in moderate and vigorous PA, and steps per day. The participants also regularly uploaded their weight and SWA data to the Weight Management Solutions web account to get feedback regarding energy balance. At the end of the study, significant weight loss within groups was found in the intervention groups (GWL: 1.86 kg; SWA-alone: 3.55 kg; GWL+SWA: 6.59 kg) but not in the standard of care group (0.89 kg). Comparisons between groups indicated that only the GWL+SWA group achieved significant weight loss compared to the Standard Care group. The authors concluded that continuous self-monitoring using sensor based technology with near-real-time feedback may promote weight loss in sedentary overweight or obese adults. Along similar lines, Pellegrini et al. evaluated and compared weight loss in 51 participants who were randomized to standard behavioral weight loss (SBWL), SBWL+SWA, or SWA only groups for a 6 month period [106]. The SWBL consisted of weekly meetings (three groups and one individual session each month) that focused on behavioral strategies for changing eating and activity behaviors. The SBWL+SWA and the SWA group used SWA similar to the study by Shuger et al. described above [107]. The results showed that SBWL+SWA (−8.7 ± 4.7%), SWA (−6.3 ± 7.1%), and the SBWL (−4.1 ± 6.3%) groups had significant weight loss ($P < 0.001$) at the end of the study. The authors indicated that the use of SWA may provide an effective short-term clinical alternative to standard in-person behavioral weight loss interventions [106].

In addition, Spring et al. conducted an RCT to compare weight loss treatment through standard-of-care group treatment (standard group) or standard and connective mobile technology system (+mobile group) over a 12-month period [108]. The participants in the standard group attended biweekly weight loss groups held by the Veterans Affairs' “MOVE!” program. The sessions were led by dieticians, psychologists, or physicians and included discussion of nutrition, PA, and behavioral change. The +mobile group received standard group care along with a personal digital assistant (PDA) to self-monitor their diet and PA. The participants entered their diet on a regular basis and the PDA provided them with target calories to burn. This study showed that adding a PDA and telephone coaching can enhance weight loss by 3.1% when combined with standard care [108]. From the research discussed here we infer that self-monitoring of diet [103-105], PA [109] and body weight [105] is a necessary condition to lose or maintain weight [106-108]. In this dissertation we focus on the self-monitoring of PA in MWUs.

Current research shows that a combination of behavioral intervention and technological intervention for weight loss results in significant weight loss. The challenge for researchers is finding ways to transfer or translate some of the behavior aspects of counseling into technology in order to meet the weight management needs of large nationwide populations. For example, the developments in technology over the last decade have resulted in activity monitors associated with different types of online tools for tracking energy intake and providing near real-time feedback on EE, minutes spent in moderate and vigorous PA, and steps per day. These tools motivate users to increase their PA levels while controlling their energy intake. Some of these near real-time feedback options include information provided through wrist watches, liquid crystal displays, audio, and smartphones. For example, BodyMedia provides near real-time feedback about steps, calories burned and activity time through BodyMedia FIT Display [110]. Fitbit uses a liquid crystal display to provide feedback about number of steps, stairs climbed, calories burned, and distance traveled [45]. Adidas MiCoach Pacer provides verbal coaching to runners. DirectLife has a series of indicator lights on the Activity Monitor to show progress throughout the day. Furthermore, activity monitors such as BodyMedia, Fitbit, and Nike+ use smartphone applications to provide PA information feedback to users. In addition, many of these activity monitors also provide online counseling from athletic trainers and dieticians on maintaining a healthy weight and log information such as calories consumed, weight and sleep duration to monitor changes and improvements in health status [45, 111]. Based on these technological developments we have incorporated into our research aspects such as providing PA level feedback to MWUs through smartphone applications.

1.6 SIGNIFICANCE OF THE PROBLEM

The current literature and our previous studies reveal the need for a valid and reliable physical activity monitor to assess and quantify PAs in MWUs [11, 79, 85, 87-90, 112-114]. Providing an accurate estimate of PA levels in MWUs can assist researchers and clinicians to quantify day-to-day PA levels in free-living environments, leading to recommendations for a healthier lifestyle [70, 73, 74, 87, 96]. Additionally, researchers can also use this type of PA monitor to study and evaluate repetitive strain injuries related to wheelchair use [115, 116], effectiveness of exercise-based intervention programs at improving health and function [59, 62], and psychosocial aspects and quality of life [62, 63, 76, 79]. Developing such a monitor would allow evidence-based practice in wheelchair usage and prescription [117, 118]. Therefore, in this research we have: a) developed customized algorithms for SenseWear, a commercial activity monitor designed for the general population, to detect various wheelchair related activities and to estimate EE in MWUs and b) developed and evaluated PAMS, which was especially designed to estimate PA levels in MWUs. The development and evaluation of PAMS, a multiple sensor activity monitor worn on the upper arm and placed on the wheel of the wheelchair, involved detecting wheelchair and upper extremity movements to quantify PA levels in MWUs.

1.7 DISSERTATION STRUCTURE

Chapter 2 presents the development and evaluation of new models for an off-the-shelf SenseWear Activity monitor designed for ambulatory population without disabilities that can estimate EE in MWUs with SCI [88]. In Chapter 3, we detail our development and evaluation of classification models to detect four types of wheelchair-related PAs, including resting, wheelchair propulsion, arm-ergometry and deskwork [119]. The four types of wheelchair related PAs included resting, wheelchair propulsion, arm-ergometry and deskwork. Chapter 4 discusses the development and evaluation of the gyroscope based wheel rotation monitor (G-WRM), a component of the PAMS [120]. Chapter 5 describes the EE estimation and classification models developed for use with PAMS while the MWUs performed various types of wheelchair-related PAs in structured (HERL), semi-structured (NVWG) and home environments. Chapter 6 describes the user evaluation and feedback obtained through our usability study of PAMS in six of the MWUs with SCI. Chapter 7 addresses venues for future work and discussion and conclusions related to this dissertation research.

2.0 PREDICTING ENERGY EXPENDITURE OF MANUAL WHEELCHAIR USERS WITH SPINAL CORD INJURY USING A MULTI-SENSOR BASED ACTIVITY MONITOR

2.1 INTRODUCTION

Regular physical activity (PA) in persons with spinal cord injury (SCI) is associated with positive health benefits, such as increased muscular strength and cardiopulmonary fitness, and decreased deconditioning and pain [10]. However, previous research by Washburn and Hedrick [73] and Fernhall et al. [74] showed that only 13% to 16% of persons with SCI reported regular PA. Reduction of PA levels in this population may be due to physiologic changes after SCI, as well as environmental barriers and mobility limitations associated with wheelchair use [70, 72]. One of the prerequisites as well as strategies for promoting regular PA is to provide people with an accurate estimate of everyday PA and energy expenditure (EE) [73, 74, 87]. However, persons with SCI, especially those who use manual wheelchairs for mobility, currently do not have an objective means to self-assess their PA participation and free-living EE. Such information can potentially assist MWUs with SCI to control and regulate their body weight and health [10, 73, 121].

With the advancements in miniature sensing technology, there are a number of accelerometry-based activity monitors designed to estimate free-living EE in the ambulatory population [22, 33]. St-Onge et al. [22] evaluated the validity of a multisensor activity monitor in 45 adults without disabilities under freeliving conditions. The mean signed EE estimated daily from the multisensor activity monitor was 117kcal/d (4.7%) lower than the criterion EE measured with doubly labeled water, with an intraclass correlation of .81 (P.01). Berntsen et al. [33] evaluated four accelerometry-based activity monitors including a multisensor, a single-sensor, and two dual-sensor activity monitors against a metabolic cart in 20 adults without disabilities during various activities and found that they underestimated total EE per minute by 9%, 15%, 5%, and 21%, respectively.

To our knowledge, none of the commercially available accelerometry-based activity monitors can accurately estimate EE in MWUs with SCI, as they typically do not consider the types of physical movement MWUs usually perform. Our group has evaluated the performance of a multisensor activity monitor worn on the upper arm and a triaxial accelerometer worn around the waist in 24 MWUs with SCI during resting, wheelchair propulsion, arm-ergometry exercise, and deskwork [87]. Davis et al. [122] evaluated the performance of a multisensor activity monitor in 10 MWUs with SCI during wheelchair propulsion on a treadmill at different velocities and gradients.

Despite the fact that current activity monitors cannot accurately estimate EE in MWUs with SCI, researchers have used activity monitors to quantify PA in MWUs with SCI [89, 94]. Warms and Belza [94] evaluated the validity of a wrist-worn dual-axial accelerometer to measure community living PA in MWUs with SCI by correlating activity counts from the accelerometer with self-reported activity levels, and the Pearson correlation coefficients varied from .33 to .77. In another study, Washburn and Copay [89] assessed a wrist-worn uniaxial accelerometer in estimating the EE during wheelchair propulsion at three different speeds. Significant correlations (r.52–.66, P.01) were reported between the activity counts from both wrists and EE over the three pushing speeds. Studies by Warms and Belza [94] and Washburn and Copay [89] indicated correlations between activity counts from the activity monitors and PA intensity, but did not provide EE estimation.

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

2.2 METHODS

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

2.2.1 Participants

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

2.2.2 Procedures

The study protocol was described in detail elsewhere [87]. Subjects first completed a basic demographic questionnaire and had their weight (Befour MX490D extra wide wheelchair scale, Befour, Inc., Saukville, WI, USA), height, and skinfold (Lange skinfold caliper, Beta Technology, Santa Cruz, CA, USA) thickness at four body sites (biceps, triceps, subscapular, suprailiac) measured. They were then fitted with a SenseWear (BodyMedia Inc., Pittsburgh, PA 15222, USA) on the right upper arm over the triceps, and a K4b2 portable metabolic cart (COSMED srl, Rome, Italy). The activity session started with a resting routine where subjects were instructed to sit still in their wheelchairs. The resting routine was followed by three activity routines: wheelchair propulsion, arm-ergometer exercise, and deskwork. The wheelchair propulsion routine included two trials of propulsion on a computer-controlled dynamometer with average speeds of .89m/s (2mph) and 1.34m/s (3mph), and one trial on a flat tiled surface with an average speed of 1.34m/s (3mph). The arm-ergometer exercise routine consisted of three trials at 20W resistance and 60 rotations per minute, 40W and 60 rotations per minute, and 40W and 90 rotations per minute, respectively, on an Angio arm ergometer (Lode B.V., Groningen, The Netherlands). During the deskwork routine, subjects performed two tasks: reading a book of their choice for four minutes and taking a typing test on a computer for four minutes. The three activity routines were counterbalanced and the trials within each routine were randomized to counter order and carryover effects. Each activity trial lasted for 8 minutes with a resting period of 5 to 10 minutes between each trial and a period of 30 minutes between each activity routine.

2.2.3 Instrumentation and Data Collection

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

2.2.4 Development of EE Prediction Models

Two EE prediction models were developed including a general model (i.e., one equation for all PA) and an activity-specific model (i.e., multiple equations with one equation for each type of PA). For both cases, the prediction models were developed based on the data from 80% of the total participants (training group, n=36) and evaluated on the remaining 20% of the total participants (validation group, n=9). A stratified approach based on injury level (paraplegia vs tetraplegia) was performed to select subjects into the training and validation groups. Data preparation involved identifying steady-state conditions for each activity trial based on K4b2 [24, 70, 87]. Steady-state conditions were determined by averaging breath-by-breath EE data over 30-second periods, and EE values having coefficients of variation of less than 10% computed over windows of at least one minute were used in the later analysis. To predict the criterion EE, we used three types of variables including the sensor data from the SenseWear, demographic data, and customized data derived from the sensor and demographic data. First, the sensor data from the SenseWear provided us with movement and physiologic information of the participant during activities. Second, the demographics data such as sex, age, height, weight, and completeness of injury provided us with wheelchair user–specific characteristics. Third, a number of custom variables including the nonlinear forms of the sensor and demographic data and combinations of the sensor and demographic data were calculated based on the existing literature in the field of PA monitoring and EE estimation in humans. For example, body mass to the power of .75 is a nonlinear variable considered to be a better predictor of EE than the body mass based on Kleiber's law [123]. On similar lines, height divided by mean absolute deviation is a combination variable that normalizes the arm movement by limb length. The custom variables might not have an intuitive definition, but empirically have a better linear relationship than the sensor and demographic data with the criterion EE. The model development process was data driven, which involves selecting the best variables from a pool of sensor, demographic, and custom variables to predict the criterion EE [124].

A custom "all-possible-regressions" procedure was written in MATLAB software (R2008a, Mathworks Inc., Natick, MA, USA) to develop new general and activity-specific EE prediction models. This procedure was exhaustive, but integrated several approaches to avoid overfitting. First, correlations between any two predictors in the potential predictor set were calculated. For highly correlated pairs (Pearson correlation: $r>0.9$), one of the predictors was removed or two predictors were combined to minimize multicollinearity. If the two variables were obtained from the same sensor (e.g., average acceleration vs. mean absolute deviation in longitudinal direction), the variable that had a higher correlation with the criterion EE was retained; otherwise the variables were combined by multiplying one with the other. The variables retained varied from 20 to 24 predictor variables for the new general and activity-specific models. Every combination of three-predictor variables was grouped together, thus resulting in 1140 to 2024 3-predictor sets for the new general and activity-specific models. Multiple regression models using each predictor set were constructed to estimate criterion EE. We chose to include only three predictors per set in order to reduce overfitting and ensure computational simplicity. Implicit in the modeling process for each predictor set was the use of a cross-validation technique instead of model fit statistics (eg, R^2) as a guard against overfitting the data [124]. Each time, a different set of 6 subjects' data was removed from the total, and the remaining data was used to determine the model's parameters (6-fold cross-validation with 6 subjects per fold). The model was then applied to the held out data and the EE prediction error calculated. All the errors were collated to indicate the predictive quality of the predictor set. The predictor set that yielded the smallest EE prediction error was selected to build the final EE prediction model from the whole training group.

2.2.5 Data Analysis

The new general and activity-specific prediction models were evaluated separately using the validation group (n=9). The estimated EE for the validation group using the manufacturer's model and the two new models was compared with the criterion EE. The comparisons involved calculating the minute-by- minute mean absolute error (MAE) and mean signed error (MSE). We also compared the estimated "per-session" EE by the manufacturer's model and the new models over all the activities for each subject with the criterion EE using per-session MSE. The per-session MSE provided us with the average EE error per subject over the whole session including all the activity trials. The EE for all activities combined was estimated by using activity-specific models for the corresponding activity type before calculating the overall MAE or MSE. In addition, Bland and Altman plots were used to visually assess the agreement between the criterion and estimated minute-by-minute EE[125]. Scatterplots of the criterion EE against the estimated minute-by-minute EE and per-session EE for the validation group were plotted to evaluate the association between these measures. The Pearson moment correlations and intraclass correlations for single measure using a two-way mixed model with consistency were also calculated between the criterion and estimated minute-by-minute EE for the validation group. Statistical significance was set at an α level of .05.

2.3 RESULTS

Demographic characteristics of the subjects are described in Table 1. All the subjects completed the eight activity trials. Because of device malfunction of the K4b2, three trials from three subjects had to be discarded. In addition, five trials from four subjects that did not yield steady-state conditions were also discarded. The general model shown in Equation 1 takes all the four activities into consideration. The activity-specific models are shown in Equation 2 through Equation 5. Table 2 lists the predictors selected for the new models.

Table 3 shows the minute-by-minute MAE and mean absolute percentage difference between the criterion and estimated EE for the validation group. Table 4 shows the minute-by-minute MSE and mean percentage difference between the criterion and estimated EE. Table 5 shows the per-session MSE and percentage difference.

Table 1: Demographic characteristics of the subjects

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

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

Equation 1: General Model.

$$EE\_MET = -1.274203 + 0.004104224 * LPEAKS + 0.3326474 * LMAD + 0.08780239 * MASS\_E\_point75$$

Equation 2: Activity-specific model for resting.

$$EE\_MET = -0.009751037 - 0.00001228313 * HTDivLMAD + 1.176567 * LMAD + 0.03884351 * MASS\_E\_point75$$

Equation 3: Activity-specific model for wheelchair propulsion.

$$EE\_MET = -2.450952 + 0.005949753 * LPEAKS + 0.01841253 * TLMAD + 0.1251561 * MASS\_E\_point75$$

Equation 4: Activity-specific model for arm-ergometry.

$$EE\_MET = -0.5633703 + 0.005884454 * LPEAKS + 0.03319644 * TLMAD + 0.08795310 * MASS\_E\_point75$$

Equation 5: Activity-specific model for deskwork.

$$EE\_MET = -0.07291671 + 0.3559690 * TAVE + 0.9740335 * SQRT\_LMAD + 0.04039672 * MASS\_E\_point75$$

Table 2: Description of variables used in general and activity-specific EE estimation models

EE_MET	EE measured using the K4b2 metabolic cart
LMAD	Mean absolute deviation in longitudinal acceleration
LPEAKS	Average number of peaks per minute in longitudinal acceleration
MASS_E_point75	Body mass raised to the power of 0.75
HTDivLMAD	Height divided by the mean absolute deviation in longitudinal acceleration
TLMAD	Product of mean absolute deviation in transverse and longitudinal acceleration
TAVE	Average transverse acceleration
SQRT_LMAD	Square root of mean absolute deviation in longitudinal acceleration

Table 3: MAE and mean absolute percentage difference of minute-by-minute EE using the manufacturer's model, the new general model, and the new activity-specific model for the validation group.

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

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

Table 4: MSE and mean percentage difference of minute-by-minute EE using the manufacturer's model, the new general model, and the new activity-specific model for the validation group.

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

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

Table 5: MSE and mean percentage difference of per-session EE using the manufacturer's model, the new general model, and the new activity-specific models for the validation group.

Activities	MSE (kcal)			Mean percentage difference (%)		
	Manufact -urer's Model	General Model	Activity-Specific Model	Manufact -urer's Model	General Model	Activity-Specific Model
All Activities	-67.9 ± 48.2	13.3 ± 15.9	12.6 ± 14.6	-51.5 ± 31.6	10.4 ± 11.8	9.6 ± 10.9

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

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

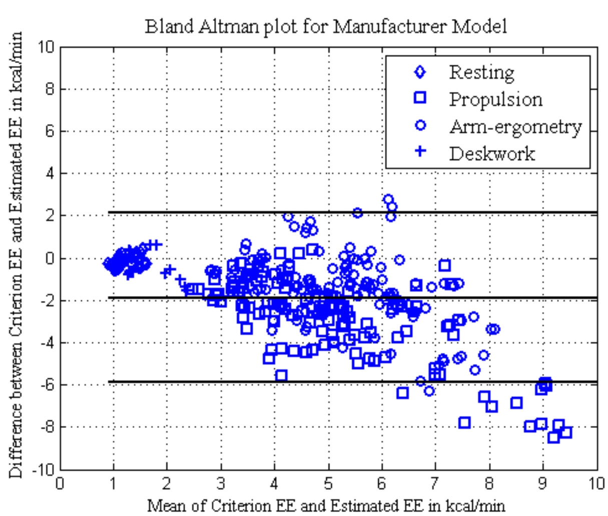


Figure 1: Bland Altman plot for the criterion and estimated EE using the manufacturer's model for the validation group with a mean ± SD value of -1.87 ± 2.04 kcal/min.

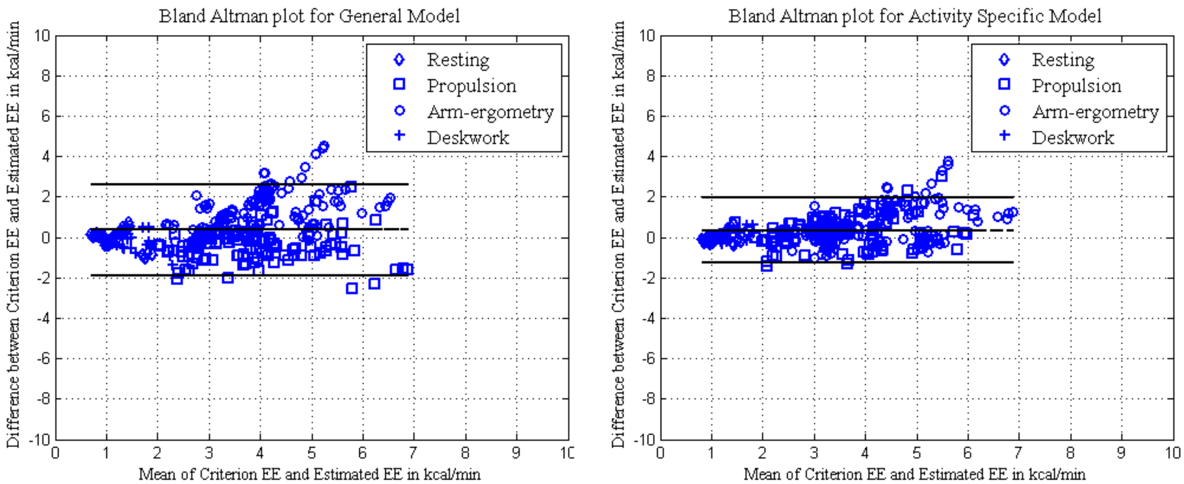


Figure 2: Bland Altman plots for the criterion and estimated EE using the new general and activity specific models for the validation group with a mean ± SD value of 0.37 ± 1.14 kcal/min and 0.35 ± 0.82 kcal/min, respectively.

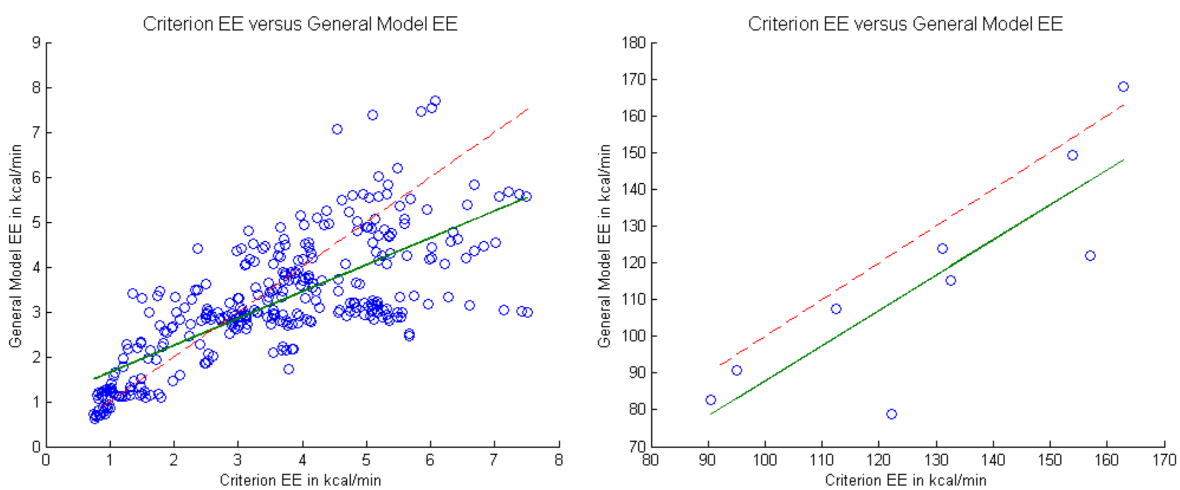


Figure 3: Scatter plots of the criterion and estimated minute-by-minute and per-session EE using the new general model for the validation group. The plots show the EE values for all activities combined.

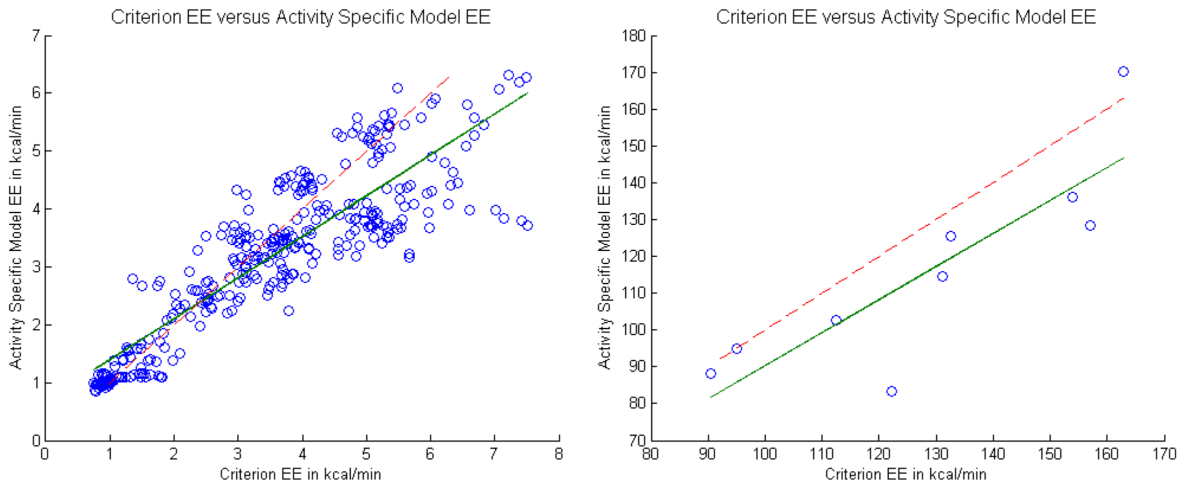


Figure 4: Scatter plots of the criterion and estimated minute-by-minute and per-session EE using the new activity specific model for the validation group. The plots show the EE values for all activities combined.

2.4 DISCUSSION

Research has shown that off-the-shelf activity monitors cannot accurately predict EE in MWUs with SCI [87, 122]. Our previous study [87] using SenseWear has found large EE estimation errors ranging from 24.4% to 125.8% among 24 MWUs with SCI. Davis [122] showed that the mean signed EE by SenseWear (14.3 ± 6.0kJ/min) was much higher than the EE from a metabolic cart (11.4 ± 4.0kJ/min) during wheelchair propulsion on a treadmill. This study with a larger cohort also showed a consistent trend of large EE estimation errors and has led to the development of new EE prediction models.

The new activity-specific and general models developed in this study integrated all-possible-regression and cross-validation techniques to leverage the benefits of exhaustive model search, avoid overfitting, and increase the robustness of the model's performance on unseen data. Our validation results showed high intraclass correlation coefficients between the predicted EE by the new models and the criterion EE, indicating that there is a good agreement between the estimated EE by the new models and the criterion EE [96]. We also compared the two new prediction models and the manufacturer's model with the criterion EE and found that the two new models significantly improved the EE prediction accuracy over the manufacturer's model. We used four measures for the comparison including minute-by-minute MAE and MSE that assess the model's ability to predict EE of performing a single activity for each minute, and per-session MSE that assesses the model's ability to predict EE of performing multiple activities over a period of time. The MAE provides information regarding the magnitude of the prediction error, and the MSE indicates whether the predictions are biased—that is, whether they tend to be disproportionately positive or negative. The minute-by-minute prediction error for the manufacturer's model was much higher than that for the generalized and activity-specific models (see Table 3and Table 4). We also found that the manufacturer's model tended to overestimate EE, while the generalized and activity-specific models underestimated EE with smaller biases (see Table 4 and Table 5).

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

As for the predictors of the general and activity-specific models, of all the demographic variables, the body mass to the power of .75 (MASS_E_point75) was selected as a predictor by all the models. This is consistent with Kleiber's law, which states that any mammal's metabolic rate is proportional to the mammal's mass raised to the power of .75 [123]. The upper limb movements captured by the accelerometer in the SenseWear also played important roles in the EE estimation. The mean absolute deviation variables (LMAD, SQRT_LMAD, TLMAD) captured the variability of the upper limb movements in different directions. The number of peaks (LPEAKS) captured the change of direction in the arm movements. The height divided by mean absolute deviation (HTDivLMAD) was chosen for the resting activity possibly because subjects were not sitting completely still and small arm movements as well as fidgeting were picked up by the accelerometer. Taller individuals tend to have longer arms, and their arm movements are more easily detected by the accelerometer during resting. The predictors chosen in the models are specific for wheelchair-related activities, including the average number of peaks in longitudinal acceleration (LPEAKS) and the product of mean absolute deviation in transverse and longitudinal acceleration (TLMAD) for wheelchair propulsion and arm-ergometry activities. Because the predictors included in the models were not SCI specific (eg, injury level), the models can be used to estimate EE for all MWUs with SCI during the activities discussed in this study.

2.4.1 Study Limitations

Although the EE prediction accuracy was significantly improved with the new predictions models, it was relatively low when compared with the performance of the SenseWear among the ambulatory populations. Johannsen et al. [26] evaluated the validity of the SenseWear in estimating total EE for 14 consecutive days among 30 healthy adults aged 24 to 60 years and found that the absolute prediction error rate when compared with the criterion measure using doubly labeled water was 8.1% ± 6.8%. Berntsen et al. [33] found that the SenseWear underestimated total EE with a minute-by-minute MAE of 9% compared with an indirect calorimeter in 20 adults for a period of 120 minutes during various types of activities and intensities. One possible reason for the relatively low prediction accuracy of the new models could be the small sample size for both the training and validation groups. The small sample size in the training group further limited our ability to achieve a balanced distribution of subjects with different ranges of weight. Subjects in certain ranges may be underrepresented compared with those in other ranges, possibly leading to relatively large prediction errors for validation subjects who fell under the underrepresented ranges. Other limitations include collecting resting EE while the subjects were seated still in their wheelchairs, limited number of PAs, PA trials tested in a structured laboratory setting, and other demographic factors related to the inclusion criteria. It is not yet clear whether the new models can be used to predict EE for free-living activities, and how the models will perform under various conditions (velocities, resistances, and environments). We hope our research will stimulate interest and efforts of other researchers to validate and refine the EE prediction models for MWUs with SCI. We recommend that researchers evaluate our models in their subject groups before use. Recommendations for future studies include testing more subjects with carefully planned recruitment strategies and experimental protocols containing free-living activities, testing the SenseWear among MWUs with other types of disabilities, and possibly developing PA monitors particularly suitable for MWUs.

2.5 CONCLUSIONS

In this study, we developed and evaluated new EE prediction models for MWUs with SCI based on a popular commercially available activity monitor. To our knowledge, this is the first study to develop new EE prediction models for this population based on the SenseWear activity monitor. The new models developed here can be used in clinical applications of using SenseWear activity monitors to estimate EE for MWUs with SCI during the wheelchair-related activities discussed in this study. We expect that the availability of these new models will encourage more research in this area, potentially leading to an accurate PA assessment tool for estimating free-living EE and time spent in light, moderate, and vigorous PA for MWUs with SCI. The availability of PA monitors that accurately estimate EE in MWUs with SCI could potentially facilitate better personal and clinical decisions on PA, energy balance, and healthier lifestyles in MWUs with SCI.

3.0 PHYSICAL ACTIVITY CLASSIFICATION UTILIZING SENSEWEAR ACTIVITY MONITOR IN MANUAL WHEELCHAIR USERS WITH SPINAL CORD INJURY

3.1 INTRODUCTION

Activity classification using wearable activity monitors among the ambulatory population has been well documented [55, 126-129]. The benefits of detecting physical activities (PAs) using wearable devices include the ability to track regular PA, provide accurate energy expenditure (EE) estimation and assist in behavioral modifications that may lead to a healthier active lifestyle in community settings [26, 33, 130-132]. However, there are only a limited number of studies that have detected and classified Pas performed by individuals who rely on wheelchairs for mobility using wearable devices [90, 113, 133]. Identification of wheelchair-related PAs using wearable devices provide not only all the benefits mentioned above but also pertinent information on the functional use of upper limbs, an important factor of upper limb pain and injury prevalent in wheelchair users [134]. The clinical practice guideline 'Preservation of Upper Limb Function Following Spinal Cord Injury,' published by the Paralyzed Veterans of America, has indicated that minimizing the frequency of upper extremity use in wheelchair users during repetitive tasks such as wheelchair propulsion can decrease the risk factor for repetitive strain injury and/or wrist pain [134].

Previous research by Postma et al. showed that a wearable activity monitor consisting of six accelerometers and two electrocardiogram electrodes connected to a portable data recorder (0.7 kg) could detect wheelchair propulsion in ten manual wheelchair users (MWUs) with spinal cord injury (SCI) [90]. The results demonstrated that wheelchair propulsion episodes were detected with an overall agreement, sensitivity and specificity of 92%, 87% and 92%, respectively. In another study, French et al. showed that wheelchair propulsion patterns, surface types and self-propulsion versus external pushing of a wheelchair could be detected using two dual-axis accelerometer based eWatches secured to the wrist and the wheelchair's frame [133]. The results in three persons without disabilities showed that the classification accuracy rates varied from 80 to 90% for arcing versus non-arcing propulsion patterns, carpet versus tile surfaces and self-propulsion versus external pushing using classification algorithms such as k-nearest neighbor and support vector machines. Along similar lines, Ding et al. studied activity classification in 27 MWUs performing a series of representative activities of daily living in a semi-structured setting with an eWatch and a wheel rotation datalogger placed on the wrist and the wheelchair's wheel, respectively [113]. The results indicated that k-nearest neighbor, support vector machine, Naïve Bayes (NB) and decision tree (C4.5) classification algorithms could classify the activities into self-propulsion, external pushing and sedentary activity with an accuracy of 89.4–91.9%. The studies discussed here focused specifically on detecting propulsion activity versus other activities with the help of activity monitoring systems composed of multiple components.

The primary objective of this study was to develop and evaluate machine learning-based classification algorithms to detect PAs including resting, wheelchair propulsion, arm ergometer exercises and deskwork performed by MWUs with SCI based on data collected from an off-the-shelf multisensor-based SenseWear (SW) activity monitor. Our previous research has shown that an activity-specific EE prediction model consisting of four EE estimation equations for the four types of PAs mentioned above had smaller EE estimation errors than a general model consisting of only one EE estimation equation applied for all the activities [88]. Therefore, in order to use the activity-specific EE prediction model in the field, we first need to detect the four types of PAs. Our secondary aim was to evaluate how the activity classification accuracy affects the performance of the activity-specific EE prediction model for MWUs with SCI described in our previous work [88].

3.2 MATERIALS AND METHODS

3.2.1 Experimental protocol

The study was approved by the institutional review board at the University of Pittsburgh and the VA Pittsburgh Healthcare System. The target population of this study was MWUs with SCI. Participants were recruited through the institutional review board approved registries, flyers and advertisements in print media. Convenience sampling was used to recruit participants who expressed an interest in the study. Little or no research has been published on validating activity monitors for EE estimation among MWUs with SCI. Power analysis using a correlational design with $\alpha = 0.05$ (two-tail) and medium effect size (r=0.4) indicated that a total of 40 participants will provide a statistical power of 74% [135]. On the basis of this estimation, in this study we recruited 45 MWUs with SCI to take part in the study and provide a written informed consent before their participation in the study. The data collection for the study took place between February 2009 and May 2011. Participants were included if they were between 18 and 60 years of age, used a manual wheelchair as a primary means of mobility, had an SCI, were at least 6 months post-injury and were able to use an arm-ergometer for exercise. Participants were excluded if they were unable to tolerate sitting for 4 h, had active pelvic or thigh wounds or failed to obtain their primary care physician’s consent to participate in the study. The study required the participants to pay one visit to the Human Engineering Research Laboratories, University of Pittsburgh to complete the data collection. All 45 participants who provided written informed consent participated in the study.

The research study protocol has been described in detail elsewhere [87, 88]. As part of the pre-activity session, the participants answered a demographics questionnaire and had their heights and weights measured. During the activity session, the participants took part in resting and three other activities including wheelchair propulsion, arm-ergometer exercises and deskwork. The three activities were counterbalanced and the trials within each activity were randomized to counter order effects. During the activity session, all participants wore a SW activity monitor on their right upper arm over the triceps and a Cosmed K4b2 portable metabolic cart (COSMED srl, Rome, Italy). The participants performed each activity trial for a maximum period of 8min, with a resting period of 5–10min between activity trials and a period of 30–40min between activities. During the wheelchair propulsion activity, the participants propelled their wheelchairs for two trials of 2 and 3mph on a stationary dynamometer, and a trial of 3mph on a flat-tiled surface. The arm-ergometer exercises included two trials at 60 r.p.m. with 20 and 40W of resistance and a trial at 90 r.p.m. with 40Wof resistance. During the deskwork session, the subjects typed on a computer for 4min and read a book for another 4 min.

3.2.2 Instrumentation and data collection

The SW activity monitor was used to collect the average, the mean absolute difference (variability of upper limb motion) and the number of peaks (turning points of upper limb) in transverse and longitudinal accelerations sampled at 32Hz and recorded at 16Hz; and the average galvanic skin response (skin conductance due to moisture or sweat), skin temperature and near body temperatures sampled at 32Hz and recorded at 1min. The multi-sensor data from the SW was retrieved using the InnerView Research software 7.0 (Bodymedia Inc., Pittsburgh, PA, USA). In addition, a portable K4b2 metabolic cart was synchronized with the SW and used to collect the criterion EE. The EE in terms of kcal/min was retrieved using the Cosmed K4b2 software (version 9.0). The investigators annotated the start and end of each activity trial during data collection, which was further used as the reference for developing and testing of the classification algorithms.

3.2.3 Data analysis

The first step of developing an activity classification algorithm was to separate the data into a training data set and a validation data set. A stratified approach with the injury level (paraplegia versus tetraplegia) as the stratified variable was used to select 80% of the participants into the training data set and 20% into the validation data set. The total amount of activity time was 1645min (about 27.4 h) including 1319min (about 22.0 h) in the training data set (n=36) and 326min (about 5.4 h) in the validation data set (n=9).

The next step was to extract a set of features, which are statistical measures, used to distinguish between the four types of activities. The feature data included characteristic information such as the mean, the mean absolute difference and the number of peaks per minute that were directly obtained from various sensors in the SW activity monitor. In addition, linear and nonlinear features using the multi-sensor data from SW were calculated on the basis of statistical characteristics, such as time domain features, biomechanical and physiological features specific to PAs [88]. We chose a 1-min window size (duration or period) for feature estimation to be consistent with the EE estimation. The features obtained from the SW and the estimated features resulted in a feature space of thousands of variables for the PA classification. We also manually labeled each 1-min activity segment as belonging to one of the four categories, that is, wheelchair propulsion, arm-ergometry, resting and deskwork based on the annotations, which served as a reference for training and testing the activity classification algorithms. The data collected from the SW was processed through data analysis programs written in MATLAB (The Mathworks, Inc., Natick, MA, USA).

We then developed three activity classification algorithms based on the training data set using machine learning algorithms including linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) and NB. For each classification algorithm, we performed the leave-one-subject-out (LOSO) and 6-fold by-subject cross-validation to select the most appropriate features and evaluate the classification algorithm's performance. The LOSO cross-validation method leaves one subject out and then develops the model on the remaining subjects. The model developed on these remaining subjects is evaluated by the left-out subject. This procedure was repeated 36 times, as there were 36 subjects in training group. The 6-fold by-subject cross-validation method is similar to LOSO, except that the subjects are split into six random groups (or folds), and each time a group is left out and the models are developed on the remaining five groups. The 6-fold cross-validation was repeated six times as the total participants in the training data set were 36. In addition to cross-validation the performance of the three activity classification algorithms was also evaluated using the validation data set. Several performance measures were calculated including per-minute precision (true positive/(true positive + false positive)), recall (true positive/(true positive + false negative)), specificity (true negative/(true negative + false positive)) and overall accuracy ((true positive + true negative)/(number of the cases)) [136]. Precision indicates the proportion with which the detected activity is correct. Recall, also known as sensitivity, is the proportion of actual activities that are correctly identified. Specificity is the proportion of activities not performed that are correctly identified, or in other words it is the classification algorithm's ability to distinguish actual true-negative cases. Overall accuracy is the overall performance of the algorithm. We also evaluated how the performance of the activity classification algorithms affected the EE estimation using the activity-specific EE prediction model that was previously developed [88]. In our previous work, the EE estimation based on the activity-specific prediction model assumed 100% activity classification accuracy. However, in this study we evaluated the performance of the activity-specific EE prediction model based on the actual classification results. Similar to our previous work, the estimated EE was compared with the criterion EE from the metabolic cart by calculating the minute-by-minute mean absolute error and the mean-signed error [88].

3.3 RESULTS

The participants included 37 males and 8 females with a mean (SD) age of 40.2 (11.0) years, weight of 78.5 (21.9) kg, height of 178.2 (8.6) cm and manual wheelchair usage of 13.8 (9.1) years. Thirty-eight participants had paraplegia (SCI of T4 and below) and seven participants had tetraplegia (SCI of T3 and above). Detailed demographics has been discussed in our previous work [88]. Table 6 shows the performance of the LDA, QDA and NB classification algorithms applied to the training data set (n=36) using the LOSO and 6-fold by-subject cross-validation methods. The results showed that the classification accuracy was less dependent on the algorithms, but more dependent on the type and number of features. For the sake of brevity, we have chosen to present detailed results of the QDA and NB classification algorithms. Table 7 shows the classification performance in terms of the precision, recall, sensitivity and overall accuracy of the QDA and NB classification algorithms using four features in the validation data set. The overall classification performance was 96.3% and 94.8% for QDA and NB classification algorithms, respectively. Table 8 shows the confusion matrix, which is a visual representation of the actual or true activity and the activity detected by the classification algorithm. The results from Table 8 indicate that the misclassification often occurred between wheelchair propulsion and arm-ergometry exercises, which involve repetitive upper extremity usage. Furthermore, Table 9 shows the EE estimation errors including the mean absolute error and mean-signed error for the validation data set (n=9) when the activity-specific EE prediction model was used in conjunction with the QDA or NB classification algorithms with four features.

Table 6: Classification performance in terms of the overall accuracy for the LDA, QDA, and NB classifiers to detect four wheelchair related activities with varied number of features using LOSO and 6-fold by-subject cross validation methods on training dataset.

Cross validation	Machine Learning Algorithms	Number of Features					
		1	2	3	4	5	10
LOSO	LDA	70.28	82.13	88.64	91.56	92.88	94.67
	QDA	74.08	83.77	90.69	93.44	94.39	96.2
	NB	74.08	82.76	91.56	93.67	93.95	93.95
6-Fold by-subject	LDA	69.95	78.75	84.85	88.84	91.78	94.39
	QDA	73.44	82.51	91.12	93.38	94.4	94.66
	NB	73.44	82.78	91.99	93.54	94.26	95.47

Note: The overall accuracy is in percentage (%).

Table 7: Classification performance in terms of the precision, recall, specificity, and overall accuracy (%) of the QDA and NB classifiers using four features to detect the four wheelchair related activities in the validation dataset.

Class	**% QDA**				**% NB**			
	Precision	Recall	Specificity	Overall	Precision	Recall	Specificity	Overall
Resting	100.0	97.1	100.0	99.7	100.0	97.1	100.0	99.7
Propulsion	92.8	98.3	95.7	96.6	94.1	94.1	96.6	95.7
Arm-ergometry	99.3	93.7	99.5	96.9	95.0	93.7	96.2	95.1
Deskwork	94.1	100.0	99.3	99.4	91.4	100.0	99.0	99.1

Note: The overall classification performance was 96.3% and 94.8% for QDA and NB classifiers, respectively.

Table 8: Confusion matrix for the QDA and NB classifiers using four features to classify the four wheelchair related activities in the validation dataset.

	QDA				**NB**			
Class	**Resting**	**Propulsion**	**Arm Ergometry**	**Deskwork**	**Resting**	**Propulsion**	**Arm Ergometry**	**Deskwork**
Resting	33	0	0	1	33	0	0	1
Propulsion	0	116	1	1	0	111	7	1
Arm-ergometry	0	9	133	0	0	7	133	2
Deskwork	0	0	0	32	0	0	0	32

Table 9: EE estimation error in terms of the mean absolute error and mean signed error for the validation dataset when the activity-specific EE prediction model was used in conjunction with the QDA or NB classifiers with four features.

	QDA				NB			
	Mean Absolute Error per Minute		Mean Signed Error per Minute (SD)		Mean Absolute Error per Minute		Mean Signed Error per Minute (SD)	
Class	kcal	%	kcal	%	kcal	%	kcal	%
Resting	0.2	18.2	0.0 (0.3)	-4.3 (21.4)	0.2	18.2	0.0 (0.3)	-4.3 (21.4)
Propulsion	0.6	16.5	0.2 (0.7)	1.9 (22.4)	0.7	18.7	0.0 (1.0)	-0.1 (25.3)
Arm-ergometry	0.9	18.8	0.7 (1.0)	11.6 (20.1)	0.9	18.8	0.7 (1.0)	11.8 (20.1)
Deskwork	0.2	13.4	0.0 (0.2)	-0.4 (16.1)	0.2	13.4	0.0 (0.2)	-0.4 (16.1)
All Activities	0.7	17.4	0.4 (0.9)	5.3 (21.5)	0.7	18.2	0.3 (1.0)	4.6 (22.8)

3.4 DISCUSSION

Accessible activity monitors in wheelchair users will allow users themselves, researchers and clinicians to track regular PA, EE estimation, PA levels in community settings and functional use of upper limbs, which is related to pain and injury prevalence in wheelchair users. Results from this study indicate that the SW activity monitor along with custom machine learning classification algorithms, such as LDA, QDA and NB can be used to classify wheelchair-related PAs in MWUs. Compared with the study conducted by Postma et al. who used six activity monitors to detect wheelchair propulsion episodes from a series of activities, we used a single SW activity monitor to achieve a higher classification accuracy (96% for QDA classification algorithm versus 92%) with a larger number of subjects (n=45 versus n=10) [90]. Similarly, the classification algorithms discussed here outperformed those in the previous studies by Ding et al. and French et al., who classified wheelchair-related PAs by using two devices in smaller number (n=27) of wheelchair users and three non-wheelchair users, respectively [113, 133].

We used several strategies to reduce overfitting during the classification algorithm development. As shown in Table 6, the classification accuracy improved with an increased number of features, indicating that a reasonable number of features are necessary to classify multiple PAs. Given the number of participants in the study, we chose to use a small feature set including four features for further analysis of the classification algorithms, as we wanted to strike a balance between accuracy and overfitting of the classification algorithms to unseen participants. Furthermore, the results showed that the LOSO cross-validation technique that tends to have higher variance and lower bias in a small sample had similar performance to the 6-fold by-subject cross-validation technique. This led us to use the LOSO cross-validation for classification algorithm development, which helps improve the generalizability of the classification algorithms to unseen participants. The four features chosen for the QDA classification algorithm were: the resultant acceleration, and three other variables derived from the mean absolute difference and number of peaks of the transverse acceleration. Similarly, the four features for the NB classification algorithm were: the resultant acceleration and three other variables derived from the mean absolute difference of the transverse acceleration, and mean absolute difference and number of peaks of the longitudinal acceleration. The features chosen by both the QDA and NB classification algorithms included directional, total motion and frequency of upper arm movement information from the SW's accelerometer, indicating that the classification algorithms were sensitive to movement-based variables when classifying the wheelchair-related PAs. Even though the QDA classification algorithm yielded slightly higher accuracy than NB, the NB classification algorithm is computationally simpler and has greater potential for real-time activity classification.

In our previous work we developed an activity-specific EE prediction model, which involves detecting the type of PA before applying a specific EE estimation equation for the detected PA [88]. However, our previous work evaluated the model performance assuming the types of PAs that can be detected and classified with 100% accuracy. With over 95% classification accuracies yielded by the QDA and NB classification algorithms, we found that the performance of the activity-specific EE prediction model was minimally affected by the actual classification results. The previous study showed that the mean absolute error and mean-signed error for all activities were 16.8% and 4.9±20.7%, respectively [88]. In this study, the mean absolute error and mean-signed error for all activities were 17.4% and 5.3±21.5% for the QDA classification algorithm, respectively, and 18.2% and 4.6±22.8% for the NB classification algorithms, respectively. The results in Table 8 also showed that the wheelchair propulsion and arm ergometry activities were occasionally misclassified by QDA and NB classification algorithms; yet the misclassification may not significantly affect the EE prediction as the two activities have similar EE. Further, the activity-specific EE estimation equations and the classification algorithms share some common variables including the mean absolute difference of transverse acceleration, and the mean absolute difference and average number of peaks of longitudinal acceleration [88].

One limitation of this study is the small number of PAs tested in the protocol. In addition, the activities were performed in a controlled laboratory setting and prescribed in a precise manner such as propelling a wheelchair and exercising with an arm ergometer at a certain speed and/or intensity. Future studies should evaluate a larger number of PAs in the home and community of MWUs. To our knowledge, there is no device that can be directly used by wheelchair users to classify PAs and estimate EE. We chose to investigate the potential of SW activity monitor in this population owing to its ready availability in the market and multi-sensor capabilities.

3.5 CONCLUSION

Availability of physical activity monitors for MWUs can empower them to monitor everyday PA participation and EE, and make informed decisions toward healthier behaviors. The high classification accuracy of the QDA and NB classification algorithms and the low EE estimation errors when using the actual classification results suggest that the SW activity monitor can be used to classify and estimate the EE for the four activities tested in this study among MWUs with SCI.

4.0 DEVELOPMENT AND EVALUATION OF A GYROSCOPE- BASED WHEEL ROTATION MONITOR FOR MANUAL WHEELCHAIR USERS

4.1 INTRODUCTION

Wheeled mobility is associated with majority of wheelchair related Physical Activities (PAs) and activities of daily living in manual wheelchair users (MWUs). Research has shown that wheel rotation monitors can be used to assess mobility characteristics, activity levels, and wheelchair use of MWUs in laboratory, community and nursing home settings [85, 97, 100, 137, 138]. However, there are only a limited number of monitoring tools available for manual wheelchair users (MWUs) [85, 96, 97, 100, 139]. This is especially striking as the general population can choose from a wide array of activity monitors to track their activities in the community in terms of steps, intensity of PA, duration of PA, and energy expenditure [23, 26, 29, 30, 128]. The availability of activity monitors for MWUs can help researchers and clinicians in the fields of rehabilitation science, kinesiology, and health and physical activity to study mobility characteristics and evaluate mobility related interventions in this population. In addition, such tools could facilitate self-monitoring among MWUs by providing accurate feedback regarding the speeds and distances travelled during wheelchair-related PAs. Research has shown that moderate intensity activities are sufficient to maintain fitness and prevent cardiovascular diseases for MWUs [65, 66].

The existing measurement tools for MWUs have varying sensitivity and accuracy in estimating speeds and distances traveled by wheelchair users. These tools either use a pendulum and reed switch-based method [97] or accelerometer-based method [85, 100, 139] to sense wheel rotations. Tolerico et al [97] evaluated the validity of a pendulum and reed switch-based device on a double drum that simulates wheelchair use. The percentage errors for the device when estimating the speeds varying from 0.8 to 1.8 m/s were found to be 1 and 5%, respectively. Coulter *et al.* [100] investigated a wheel mounted tri-axial accelerometer and found the device was highly accurate in estimating wheel revolutions, absolute angle and duration of movement (ICC (2,1) > 0.999, 0.999, 0.981, respectively) when 14 wheelchair users were asked to propel their wheelchairs forward and backward along a course. Sonenblum *et al.* [85] evaluated a wheel-mounted tri-axial accelerometer in detecting wheelchair movements and estimating distances traveled. They found that the device had accuracy greater than 90% for various wheelchair and wheel types, propulsion techniques, speeds, and wheelchair-related activities of daily living including propulsion, food preparation, handwashing, loading a dishwasher, entering a bathroom stall, and using an elevator. In another study, Gendle *et al.* mounted a tri-axial accelerometer below the wheelchair seat to assess PA of wheelchair users [139]. The research found that the activity counts derived from the accelerometer were significantly different between light and moderate effort ($P < 0.01$) trials with high between-trial reliability ($r \geq 0.85$). The difference between the studies by Sonenblum *et al.* and Gendle *et al.* was the placement of the accelerometer on the wheel [85] versus under the wheelchair seat [139] resulting in wheel rotation measurement and the wheelchair acceleration measurement, respectively. None of these activity monitors has indicated that they can estimate speeds and distances over a spectrum of wheelchair-related PAs from regular wheelchair propulsion to wheelchair sports such as handcycling. Also, these monitors were not designed to provide real-time feedback to wheelchair users.

In this study, we developed and evaluated a wireless gyroscope-based wheel rotation monitor (G-WRM) that can estimate speeds and distances traveled by wheelchair users during regular wheelchair propulsion as well as wheelchair sports such as handcycling and provides real-time feedback to users through a smartphone application. We evaluated the validity of the G-WRM in measuring angular velocities and estimating speeds and distances through a series of laboratory based tests. We also conducted a series of tests on the battery life and wireless data transmission of the G-WRM.

4.2 METHODS

4.2.1 Development

The G-WRM uses a gyroscope to detect angular velocities of the wheelchair's wheel, which are then converted into wheel revolutions, and distances and speeds traveled by wheelchair users. The choice of using a gyroscope sensor instead of an accelerometer was based on a pilot study where we tested a wheel-mounted tri-axial accelerometer (range: ±39.24 m/s^2 or ± 4 g) and the G-WRM for a range of speeds during a handcycling trial. Figure 5 shows the results of the pilot study for the handcycling trial, which indicated that the wheel rotation pattern using a three axis accelerometer was clear (sinusoidal pattern) for low speeds, but not for high speeds. The results showed that with the increase of traveling speeds, the accelerometer signals of the two axes in the plane of wheel rotation separated from one another with one of them becoming saturated with consistent low values. In addition, the acceleration sensed by the accelerometer combined the wheel rotation movements and the linear forward or backward movements, which could be computationally expensive to differentiate if real-time feedback is to be provided. The same problem also exists with the pendulum and reed switch design [97], which can provide relatively accurate estimation of distances and speeds traveled by wheelchair users in the community settings. However, laboratory tests have shown that this method could underestimate speeds when a wheelchair travels at speeds greater than 2.5 m/s (5.6 miles per hour) [140]. Our observation of the problem with the existing devices at higher speeds has led us to design and develop a gyroscope based G-WRM that can capture a range of speeds from wheelchair propulsion to handcycling.

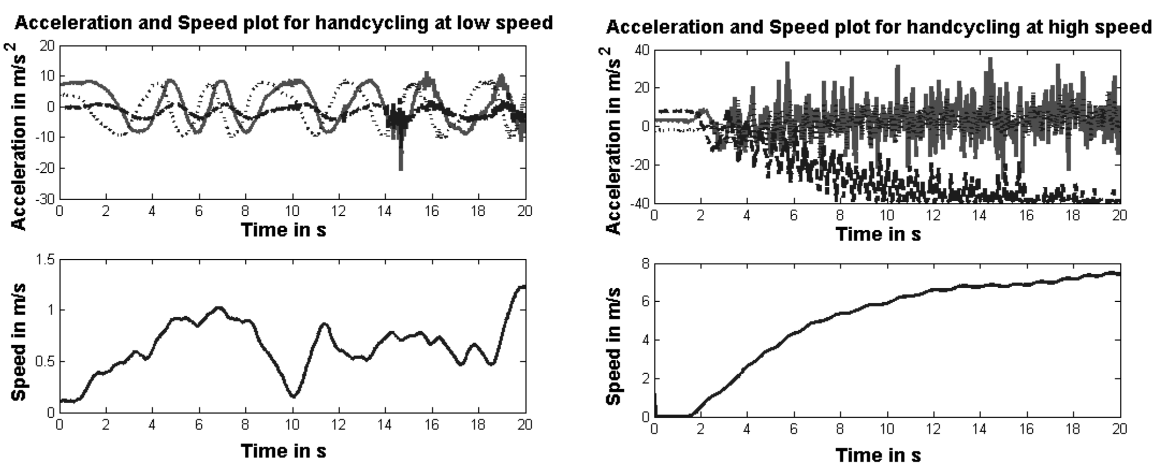


Figure 5: Acceleration and speed plots from a three axis accelerometer and a G-WRM, respectively, for handcycling at low and high speeds.

4.2.2 Instruments

The G-WRM (Figure 6) is a self-enclosed rechargeable device that can be attached to the spokes of the wheel of a wheelchair or a handcycle. The G-WRM was built upon our previous pendulum and reed switch device to reduce the development time. The G-WRM contains six reed switches mounted 60° apart on a printed circuit board and a two-axis gyroscope with low (±1500°/second) and high angular velocity ranges (±6000°/second) allowing us to capture speeds up to 64 km per hour (40 miles per hour) for a 0.61 m (24-inch) wheel. The gyroscope can be sampled with frequencies varying from 64 samples per second (64 Hz) to 1 sample per minute to suit various speeds from wheelchair sports such as handcycling and wheelchair racing to everyday wheelchair propulsion. The reed switches are triggered by a pendulum and magnet assembly, which is mounted in the G-WRM casing. However, the reed switches were not used to estimate speeds and distances in this study. We only used the G-WRM's gyroscope to measure angular velocities, which were then converted to speeds and distances traveled. Furthermore, the G-WRM has a Bluetooth communication module through which the mobility data can be sent to a smartphone and a micro secure digital (SD) memory card that can store the mobility data locally. The G-WRM is also paired with an Android-based mobile application (Figure 7), designed to allow wheelchair users to receive real-time feedback on their movements including distance, speed, and duration of mobility [141].

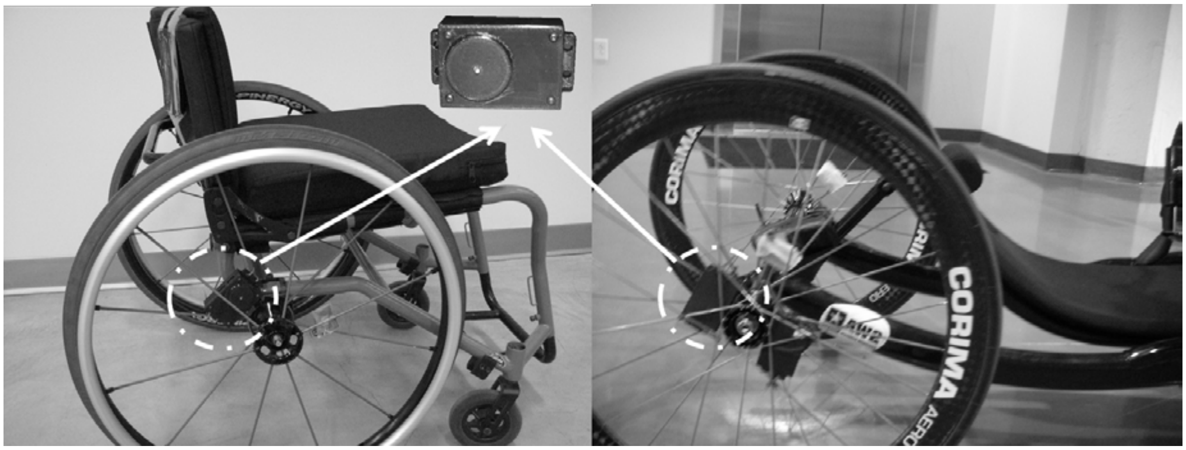


Figure 6: G-WRM secured to the spokes of a manual wheelchair and a handcycle.

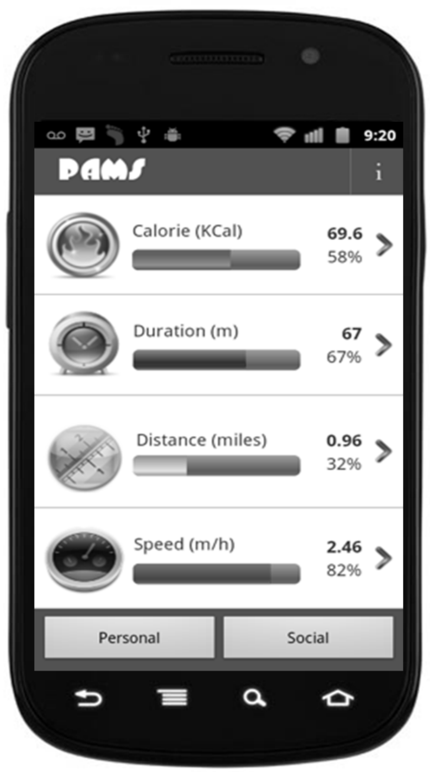


Figure 7: The Android application for the G-WRM.

4.2.3 Calibration protocol

The calibration protocol involved collecting raw gyroscope data from the G-WRM when the device was attached on a ST20 Computer Numerically Controlled (CNC) lathe (HAAS Automation, Inc., Oxnard, CA, USA) that was set at known angular velocities (Figure 8). The gyroscope data were collected from six repeated trials of 2 minutes at speeds of 40, 60 and 80 rotations per minute (rpm), respectively, in both clockwise (forward) and counterclockwise (reverse) directions. The gyroscope data were then used to develop offset values and basic calibration equations for both clockwise and counterclockwise directions to maximize sensitivity of the gyroscope to detect various angular velocities. The angular velocity information from the gyroscope was later used to estimate linear speeds and distances traveled by a wheelchair user.

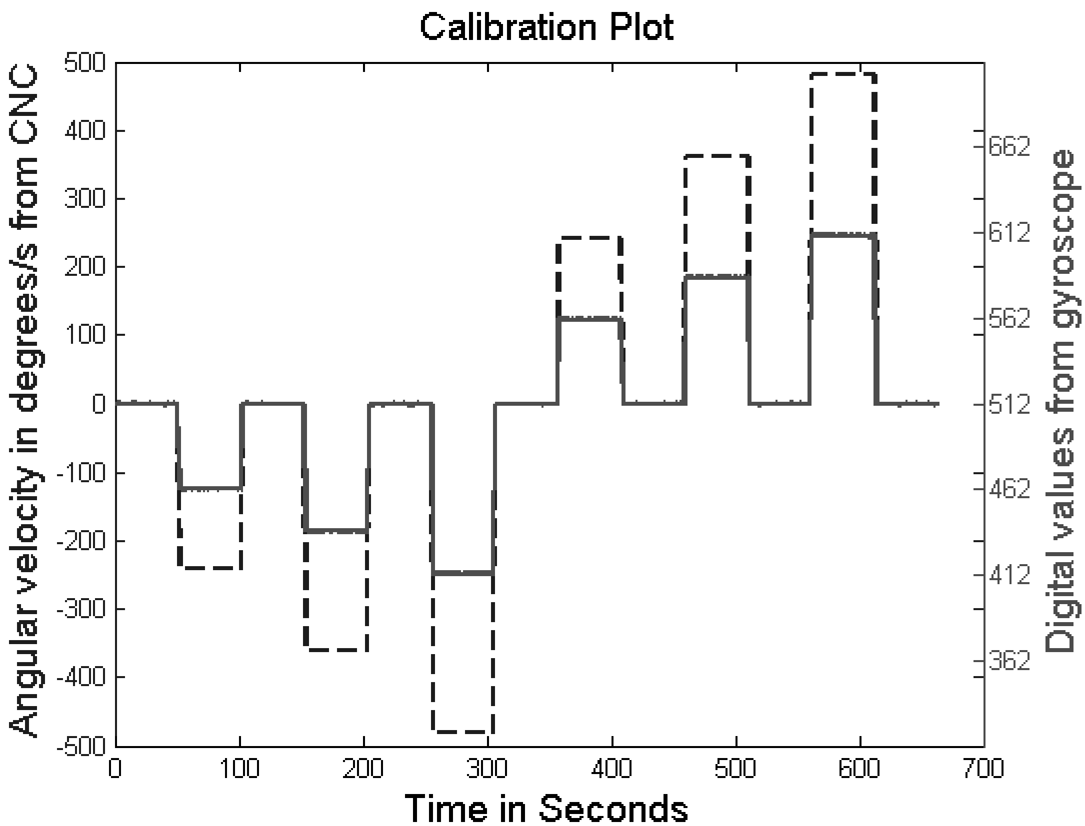


Figure 8: Plot of raw sensor values from the G-WRM's gyroscope (solid line) and during various angular velocity tests (dotted line) on the CNC lathe.

4.2.4 Experimental protocol

We evaluated the validity of three randomly chosen G-WRM prototypes in measuring angular velocities, and estimating speeds and distances traveled by a wheelchair using a number of laboratory based tests. We assessed the G-WRM's wireless function by measuring data loss. We also evaluated the battery capacity of the G-WRM in wireless mode and storage mode (via the SD card), respectively.

4.2.4.1 Validity of measuring wheelchair movements

CNC lathe test

To evaluate the validity of the G-WRM in measuring angular velocities, we secured each G-WRM to the chuck of a lathe and ran the lathe for 10 minutes of duration each at angular velocities of 40, 60, and 80 rpm in both clockwise (forward) and counterclockwise (reverse) directions, respectively. Each test condition was repeated three times.

Double-drum test

To evaluate the validity of the G-WRM in estimating linear speeds, we secured each G-WRM to the spokes of a manual wheelchair set up on a double drum (ISO 7176-08) [142] with drive wheels on one drum and castors on the other drum. The two drums run at slightly different velocities, with the back running at 1 m/second (2.24 miles per hour) and the front at 0.95 m/second (2.12 miles per hour), in order to simulate road hazards commonly encountered by wheelchair users. The test was conducted with and without slats (Figure 9) to simulate propulsion during curb drops and flat surface, respectively. The tests were repeated twice for a duration of 6 hours in both forward and backward directions.

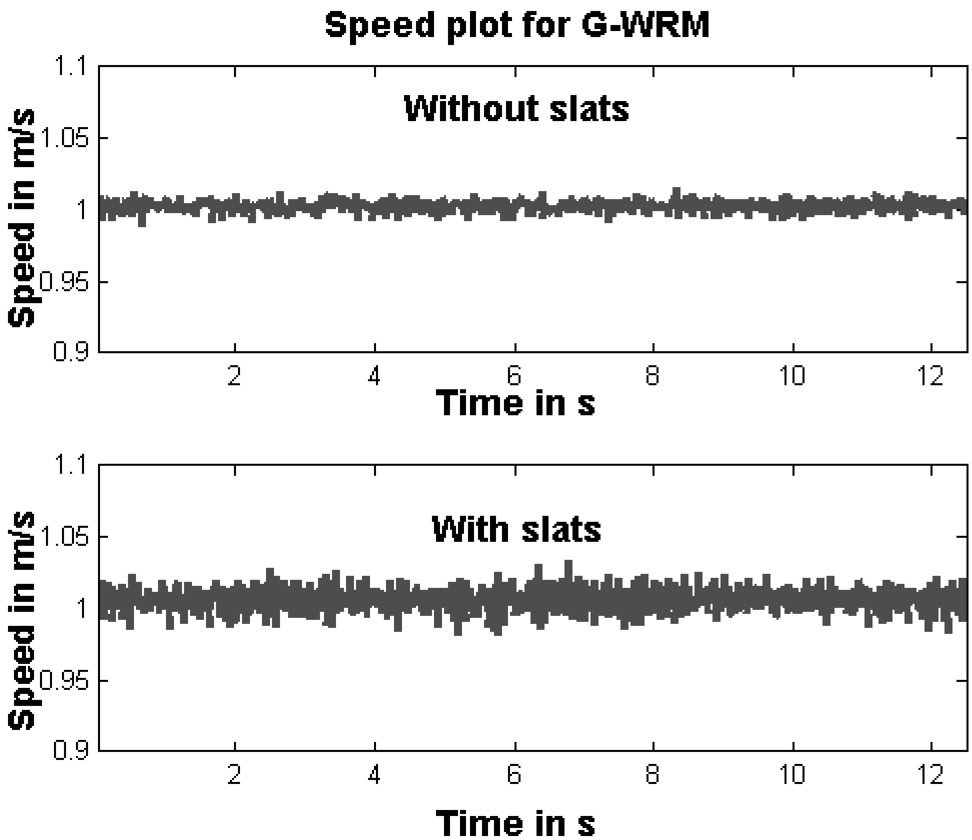


Figure 9: Plot of speed estimated by the G-WRM on double drum with and without slats.

Wheelchair propulsion test

To evaluate the validity of the G-WRM in estimating distances traveled during regular wheelchair propulsion, we conducted a total of 54 trials (see Table 10) for nine tasks with each task repeating six times on concrete flooring surface. During all these trials, an investigator experienced in wheelchair use propelled either a manual wheelchair with a camber of 2.5° or a rugby chair with a camber of 15.5°. For the first 48 trials, we used the measured distance via a tape measure between the start and end points as the criterion measure. The G-WRMs were secured to the spokes of the manual wheelchair' s or rugby chair's wheel. For the last six trials, we used the measured distance via a SmartWheel (Three River Holdings, Inc. Mesa, AZ, USA) and a three-dimensional passive motion capture system (model MX, Vicon Peak; Lake Forest, CA, USA) as the criterion measure. The G-WRMs were secured to the spokes of the SmartWheel. The SmartWheel is a clinical tool that can measure wheelchair propulsion kinetics including distances traveled. We followed standardized calibration procedures for VICON and SmartWheel as per the manufacturer' s specifications.

Table 10: Wheelchair propulsion tasks performed.

Sl. No.	Propulsion Task
1.	Propelling straight forwards (10m) on a flat tile surface with a camber of 2.5°
2.	Propelling straight forwards (15m) on a flat tile surface with a camber of 2.5°
3.	Propelling straight forwards (20m) on a flat tile surface with a camber of 2.5°
4.	Propelling straight backwards (10m) on a flat tile surface with a camber of 2.5°
5.	Propelling up and down a ramp (slope of 2.7°, length 12.19m) on a flat tile surface with a camber of 2.5°
6.	Propelling straight forwards (10m) on a flat tile surface with a camber of 15.5°
7.	Propelling straight forwards (15m) on a flat tile surface with a camber of 15.5°
8.	Propelling straight forwards (20m) on a flat tile surface with a camber of 15.5°
9.	Propelling straight forwards (18m) on a flat tile surface with a camber of 2.5°

Handcycling test

To evaluate the validity of the G-WRM in estimating distances traveled during handcycling, we attached the G-WRM to the spokes of an Invacare Top End Force R X handcycle (Invacare Corporation, Elyria, OH, USA). An investigator who is an experienced wheelchair user with disability performed handcycling for nine laps on a cycling track with asphalt concrete surface. The G-WRM 1 was secured to the inner wheel and the G-WRMs 2 and 3 were secured to the outer wheel with respect to the center of the track. For this test, we used the total track length of 7.24 km (0.805 km for 9 laps) as the criterion measure.

4.2.4.2 Battery life test

We evaluated the G-WRM's battery life by performing tests in wireless mode where the data were sent continuously to a smartphone and in standalone SD card mode where the data were stored locally without wireless transmission. During the wireless mode testing, we conducted six trials for each G-WRM where we collected data continuously through a smartphone at 64 and 1 Hz for three times, respectively, until the battery was drained. During the standalone SD card mode testing, we conducted three trials for each G-WRM where we sampled the data continuously at 64 Hz and stored the data in the SD card at 1 Hz for three times until the battery was drained.

4.2.4.3 Wireless data transmission test

We evaluated the G-WRM's Bluetooth performance by examining the data loss rate. We conducted nine trials for each G-WRM where we transmitted the data sampled at 64 Hz from the G-WRM to a smartphone for 1, 3, and 24 hours, respectively, with each condition repeating for three times.

4.2.5 Data collection and analysis

The data collected from the G-WRM included gyroscope signals and the number of reed switches that were triggered at a sampling rate of 64 Hz (15.62 millisecond). An Android smartphone was used to wirelessly collect data from the G-WRM for all trials except the battery life test at the standalone SD card mode. The angular velocities detected by the G-WRM's gyroscope were used to calculate the speeds and distances traveled. The chuck rotating speeds of the CNC lathe were used as the criterion measure during the CNC lathe test. The roller speeds of the double drum were used as the criterion measure during the double-drum test. The measured distances using a tape measure and using the SmartWheel and VICON system were used as the criterion measure during the wheelchair propulsion test. The track length was used as the criterion measure during the handcycle test. The data analysis software was written in MATLAB® (version 7.12 R2012b, The Mathworks Inc., Natick, MA, USA) and used to process and analyze data from the G-WRM and criterion measures.

The comparisons between the estimated measures from the G-WRM (i.e. angular velocities and speeds and distances traveled) and criterion measures were performed by calculating the absolute difference, mean difference, percentage errors and standard error of measurement for each trial. Intraclass correlation coefficients (ICC (3,1)) for single measure using two-way mixed model with consistency were used to assess the agreement between the estimated and criterion measures. ICC values of 0.9 or greater are deemed excellent if the lower bounds are greater than or equal to 0.75 [143]. The Bland-Altman plots were also used to assess the agreement between the criterion measures and the G-WRMs [125]. The points on the Bland-Altman plots represent the mean (x-axis) and the difference (y-axis) of the criterion measures and the G-WRMs. All statistical analysis was performed using SPSS software (version 15.0, SPSS Inc., Chicago, IL, USA), with the statistical significance at an alpha level of 0.05.

4.3 RESULTS

Table 11 shows the results from the CNC lathe test and the double-drum test. Table 12 shows the results from the wheelchair propulsion test. The average absolute percentage errors for distances traveled combining the three G-WRMs for the forward (10, 15, and 20 m) and backward propulsion trials (10 m) was 0.58% with a camber of 2.5°, and 0.88% with a camber of 15.5°. This indicates that a camber of 15.5° did not significantly affect the G-WRMs distance estimation. The ICC (3,1) values for the three G-WRMs for the forward propulsion trails (10, 15, and 20 m) with cambers of 2.5° and 15.5° varied from 0.999 to 1.000 (lower bound: 0.997–1.000 and upper bound: 1.000–1.000). The Bland-Altman plots were also used to assess the agreements between the G-WRMs and the criterion measures during the wheelchair propulsion test (Figure 10and Figure 11). The distances estimated by G-WRM 1, G-WRM 2, and G-WRM 3 for the handcycling test were 7.17, 7.24, and 7.31 km, which correspond to error percentages of 1.06, 0.04, and -0.88%, respectively, compared to the track distance of 7.24 km (805 m per lap). The securement of G-WRM 1 to the inner wheel with respect to the center of the handcycling track may have contributed to slightly higher underestimation of the distance traveled in the trial. The results indicate that the G-WRMs can accurately measure angular velocities and distances for regular wheelchair propulsion and handcycling with an accuracy greater than 95%.

Table 11: The estimation errors of G-WRMs for bench tests with CNC lathe for angular velocity and double drum for linear speed.

Tests	Absolute Error in percentage (%)			Mean Percentage Error (SD)			Standard Error of Measurement		
	G-WRM 1	G-WRM 2	G-WRM 3	G-WRM 1	G-WRM 2	G-WRM 3	G-WRM 1	G-WRM 2	G-WRM 3
CNC Lathe									
Forward and Backward at 40 rpm	0.12	0.03	0.64	0.12 (0.05)	0.00 (0.04)	0.00 (0.70)	0.02	0.02	0.29
Forward and Backward at 60 rpm	0.15	0.40	0.40	0.15 (0.08)	0.01 (0.44)	0.01 (0.43)	0.03	0.18	0.18
Forward and Backward at 80 rpm	0.17	0.53	0.34	0.17 (0.07)	0.06 (0.58)	0.03 (0.38)	0.03	0.24	0.15
Double Drum									
Forward and Backward without Slats	0.66	0.73	1.22	0.27 (0.91)	-0.36 (0.78)	-0.91 (0.90)	0.41	0.35	0.37
Forward and Backward with Slats	2.11	1.88	2.19	-2.11 (0.56)	-1.88 (0.58)	-2.19 (1.03)	0.19	0.22	0.52

Table 12: The estimation errors of G-WRMs for various wheelchair propulsion tasks.

Propulsion Test	**Absolute Error in percentage**			**Mean Percentage Error (SD)**			**Standard Error of Measurement**		
	G-WRM 1	G-WRM 2	G-WRM 3	G-WRM 1	G-WRM 2	G-WRM 3	G-WRM 1	G-WRM 2	G-WRM 3
Forward (10m)	0.49	0.59	0.61	-0.49 (0.15)	0.16 (0.82)	-0.52 (0.81)	0.05	0.27	0.27
Forward (15m)	0.63	0.88	0.60	-0.46 (0.65)	-0.05 (1.19)	0.33 (0.76)	0.20	0.38	0.24
Forward (20m)	0.18	0.58	0.65	-0.15 (0.17)	-0.34 (0.53)	0.34 (0.69)	0.05	0.17	0.22
Backward (10m)	0.44	0.94	0.60	0.44 (0.21)	-0.94 (0.16)	-0.60 (0.19)	0.07	0.06	0.07
Forward on a ramp	0.42	0.82	0.53	-0.39 (0.34)	-0.82 (0.39)	-0.06 (0.68)	0.08	0.09	0.16
Forward with camber (10m)	0.39	1.38	0.85	0.39 (0.20)	1.38 (0.52)	0.85 (0.18)	0.08	0.21	0.07
Forward with camber (15m)	0.74	0.77	1.16	0.74 (0.24)	-0.77 (0.23)	1.16 (0.19)	0.09	0.08	0.07
Forward with camber (20m)	0.53	0.78	1.30	0.53 (0.33)	-0.78 (0.15)	1.30 (0.28)	0.13	0.06	0.12
Forward with SmartWheel (18m)	0.17	0.65	0.68	0.09 (0.24)	0.65 (0.15)	-0.53 (0.47)	0.09	0.06	0.18
Forward with VICON (18m)	0.48	0.46	0.82	-0.46 (0.84)	0.13 (0.77)	-0.80 (1.05)	0.19	0.17	0.24

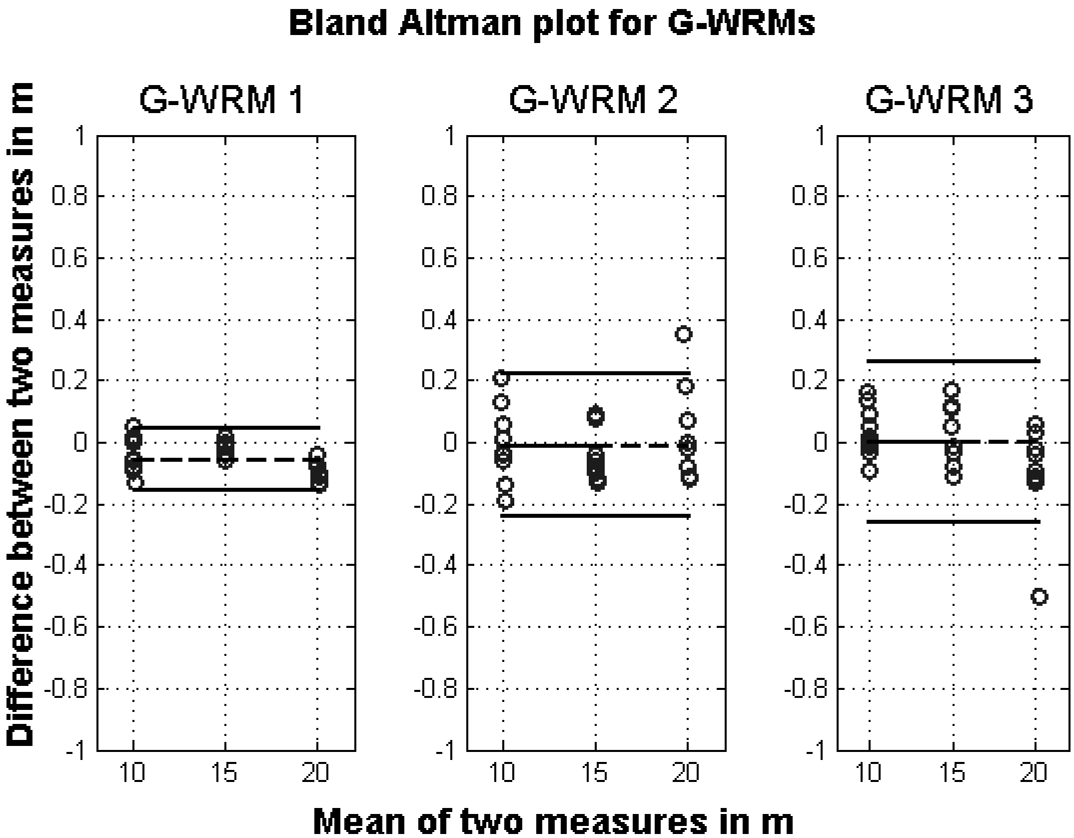


Figure 10: Bland–Altman plot of distances measured using tape measure versus distances estimated from the G-WRMs during wheelchair propulsion trials for 10, 15 and 20 m distances on a flat surface.

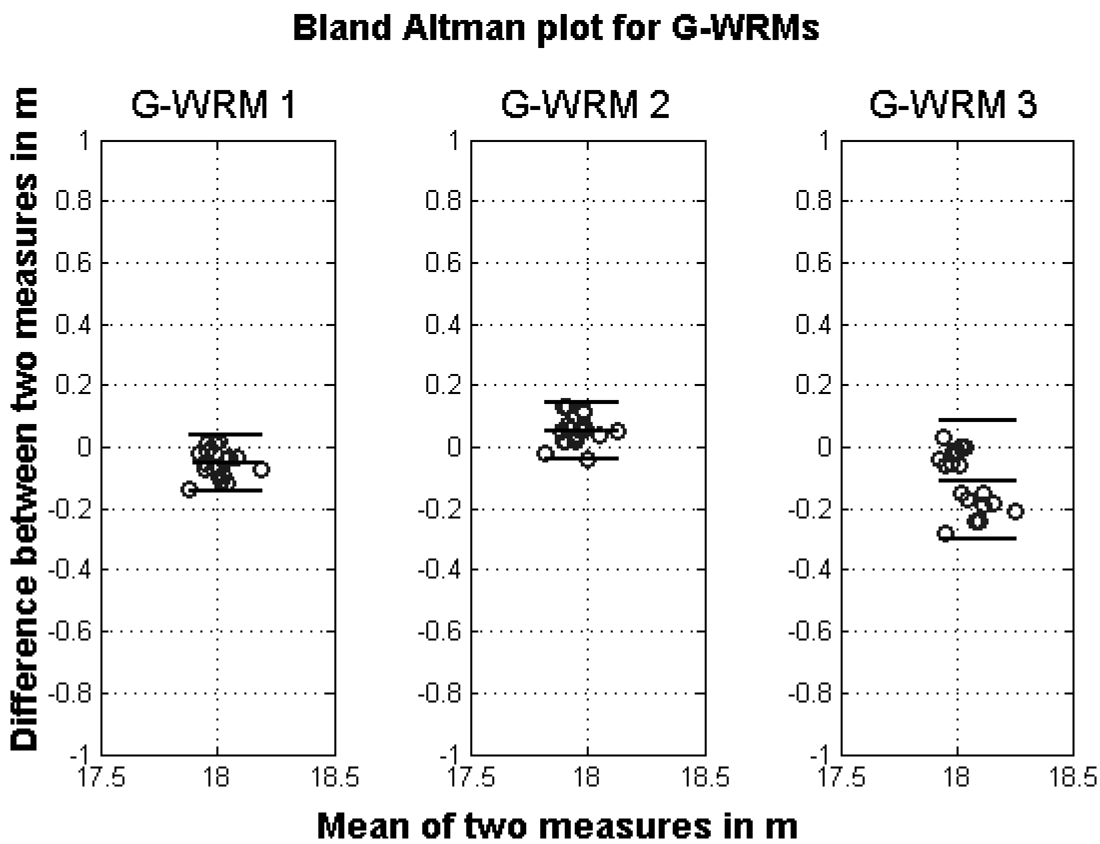


Figure 11: Bland–Altman plot of distances estimated using VICON versus distances estimated from the G-WRMs during wheelchair propulsion trials for a distance of 18 m on a flat surface.

The G-WRM' s battery life test in wireless mode indicated that the G-WRMs were able to collect and transmit data at a frequency of 64 Hz and 1 Hz for an average duration of 27 hours and 21 minutes, and 35 hours and 38 minutes, respectively. The G-WRM's battery life tests in standalone SD card mode data indicated that the G-WRMs were able to collect data continuously at 64 Hz and store the data in the SD card at 1 Hz for and 139 hours and 54 minutes. The wireless data transmission test indicated that the average data loss rates for data sampled and transmitted at 64 Hz from the G-WRMs to a smartphone for durations of 1, 3 and 24 hours were 0.3, 0.3, and 0.1%, respectively.

4.4 DISCUSSION

An accurate wheel rotation monitor for wheelchair users can be an important clinical and consumer tool for tracking activity levels of this population. The activity information could also help inform wheelchair maintenance, justify wheelchair prescription, and monitor outcomes for clinical interventions. To address this need, we have utilized advancements in miniature senor technology to develop a compact and easy-to-use wheel rotation monitor to track mobility-related variables such as linear speeds and distances traveled by wheelchair users. In addition, the ability of the G-WRM to provide the mobility parameters to consumers in real-time through smartphone applications opens up a wide variety of mobile health tracking possibilities ranging from community-based PA interventions by clinicians to goal settings by individuals themselves to improve their health and PA behavior.

The results from this study indicate that the G-WRMs can accurately measure angular velocities and estimate speeds and distances traveled by wheelchair users over a spectrum of activities from everyday wheelchair propulsion to wheelchair sports such as handcycling. The absolute and mean percentage errors were lower than 3% for all the tests. While the absolute percentage error provides a single measure of each of the G-WRMs' performance, the average error with standard deviation provides the tendency of the G-WRMs to over- or under-estimate for various trials. The higher percentage error for estimating linear speed during the double-drum test with slats was due to the wheelchair regularly bouncing which may be associated with slightly higher speeds. Multiple criterion measures used during the tests allowed us to assess both the engineering validity and real-world performance of G-WRMs during wheelchair-related activities. For example, the advantage of using SmartWheel and VICON measurement systems is that they track the distance traveled by the wheelchair user irrespective of whether the user is traversing in a straight line. In addition, the high ICC values indicate a strong agreement between the estimated measures by G-WRMs with criterion measures. The Bland-Altman plots (Figure 10 and Figure 11) showed that the mean differences were close to zero and more than 95% of the values lie within mean ± 2SD, indicating excellent agreement between the G-WRMs and criterion measures. We also found that it is important to calibrate each of the G-WRMs to accurately estimate angular velocities, as there can be slight variations between the gyroscope sensors. Furthermore, the battery tests indicate that the G-WRM can be used to continuously collect data for a full day while transmitting the information to a smart phone and for at least five continuous days while saving the data on a SD card. The Bluetooth tests indicate that the G-WRM can transmit data continuously with minimal data loss.

Comparing the results of this study with Coulter *et al.*' s study, we find that the average absolute error for all tasks (0.59%) and the ICC values for activPAL in Coulter *et al.*' s study are similar to our results, indicating that the G-WRM is a comparable device to track everyday mobility [100]. On similar lines, the performance of the G-WRM in estimating distances traveled is close to the results of Sonenblum *et al.,* [85] who use an accelerometer-based device to track wheelchair movement. However, both studies only tested their devices with regular wheelchair propulsion [85, 100]. The utility of accelerometer-based devices in monitoring wheelchair sport activities is unknown. In our study, we have developed and evaluated G-WRM that can be used across the range of wheelchair related activities from propulsion to handcycling. In addition, the use of a gyroscope sensor instead of an accelerometer allows us to directly obtain angular velocity of the wheelchair's wheel as compared to translating the acceleration values to rotation angles for calculating wheel rotations. This process of using angular velocities directly to estimate linear speeds and distances traveled reduces computational complexity, which allows us to provide wheelchair users with real-time feedback through smartphone applications.

One of the limitations of the G-WRM is that the device in itself may not be able to distinguish between self-propulsion and being pushed by a caretaker. However, the G-WRM can be used in conjunction with wearable accelerometers to track upper arm-movement to distinguish self-propulsion and external pushing [113]. Another limitation of this study is that the G-WRM was evaluated by only two test participants instead of a group of wheelchair users. In addition, most of the data collected and analyzed from the G-WRMs were collected at 64 Hz, which could be reduced for many real-world clinical applications. The G-WRM mentioned here has the capacity to be used independently or in conjunction with other motion and physiological-based wearable devices that wirelessly send data via Bluetooth to detect wheelchair users' activity type and context in community settings. Future improvements in G-WRM will involve optimizing the sampling rate of the gyroscope based on the speeds detected during various types of wheelchair-related activities and utilizing the passive reed switches to trigger data collection from the gyroscope only during active wheelchair use to conserve and extend the battery life. We are also working on combining the G-WRM and an upper arm worn accelerometer to estimate energy expenditure of wheelchair users. We plan to evaluate the usability of the G-WRM and the smartphone application with wheelchair users. Furthermore, we are currently in the process of identifying small businesses that are interested in collaborating with the Human Engineering Research Laboratories to commercialize the G-WRMs and make this technology available to multiple stakeholders including researchers, clinicians, and consumers.

4.5 CONCLUSIONS

To our knowledge, this is the first study to develop and evaluate a gyroscope based wheel rotation monitor to estimate speeds and distances traveled by wheelchair users. The G-WRM is a versatile device that can be used to estimate speeds and distances over a spectrum of wheelchair-related PAs from regular wheelchair propulsion to wheelchair sports such as handcycling.

5.0 DETECTING WHEELCHAIR-RELATED ACTIVITIES AND ESTIMATING ENERGY EXPENDITURE USING A PHYSICAL ACTIVITY MONITOR SYSTEM

5.1 INTRODUCTION

Regular physical activity (PA) levels among persons with disabilities (54% rated as 'inactive' in 2008) are significantly lower than the PA levels of the general population (32% rated as 'inactive' in 2008) [4]. Among people with disabilities are wheelchair users, whose sedentary lifestyle due to mobility limitations, physiological changes, environmental barriers, and limited accessibility of exercise equipment leads them to participate in much less PA [3, 9, 58, 144, 145]. Moreover, obesity rates in persons with disabilities are much higher than in persons without disabilities (36% vs. 23% in 2008) [146]. Among those with disabilities, in wheelchair users, lack of regular PA and reduced energy expenditure due to limited use of large muscles of the body has led to even higher obesity and overweight levels [91, 147]. In addition, repeated use of upper extremities to perform transfers to and from their wheelchairs, and to propel manual wheelchairs often causes shoulder pain and injury in wheelchair users [134]. The publication *Preservation of Upper Limb Function Following Spinal Cord Injury*, a clinical practice guideline for health-care professionals, indicates that repetitive use of upper arms in wheelchair users during propulsion increases their risk of upper extremity pain and injury [134]. To address the dual purpose need of achieving optimal regular PA and reducing the risk of upper extremity injury for wheelchair users we have developed a physical activity monitoring system sensor that can track their regular PA levels and wheelchair based activities such as wheelchair propulsion.

Sensor-based physical activity monitors have been extensively used to detect and estimate PA levels in the general population [21, 26, 29, 30, 33, 55, 148]. The advantage of sensor-based activity monitors over self-report or log based PA monitoring is that they reduce PA tracking errors that result from recall and social acceptability biases that occur with the latter. Further, advances in micro-electromechanical based sensors have led to the development of small wearable activity monitors which are unobtrusive and can collect data over multiple days, making them more convenient to use than other methods [128, 149]. However, none of these commercially available activity monitors designed for the general population can accurately estimate PA in wheelchair users, as these devices typically do not take into account the types of PAs performed by wheelchair users. Therefore, researchers have evaluated the performance of various types of sensor based activity monitors among persons who use wheelchairs in regards to estimating and tracking PAs [11, 73, 85, 95-97, 100]. The technology underlying these activity monitors can be classified into those that track movement, those that track changes in physiologic conditions, or those that utilize a combination of both. These developments in activity monitor technology have led us to develop a physical activity monitoring system for wheelchair users.

In general, accelerometer-based activity monitors have been used to evaluate community living, energy expenditure during three different speeds of propulsion, and wheelchair movement [11, 85, 89, 100]. Warms et al. found that the activity counts from a wrist-worn accelerometer had low to moderate correlation (0.30-0.77, $p<0.01$) with self-reported activity intensity for individual participants [11]. In another study using wrist-worn accelerometers, Washburn et al.

found significant correlations (0.52-0.66, p <0.01) between the activity counts from an accelerometer and energy expenditure over three pushing speeds [89]. However, a major limitation with using a single accelerometer on the wrist is the device's inability to identify whether the PA involves manual wheelchair movement, which results in PA levels being significantly overestimated. Other research used wheel mounted tri-axial accelerometers to detect wheelchair movement. For example, Coulter et al. investigated a wheel-mounted tri-axial accelerometer and found high validity for wheel revolutions, absolute angle and duration of movement (ICC(2,1)>0.999, 0.999, 0.981, respectively) in wheelchair users [100]. Along similar lines, Sonenblum et al. used a wheel-mounted tri-axial accelerometer to detect wheelchair movement, and this device measured the distance travelled with an accuracy greater than 90% for various wheelchair and wheel types, propulsion techniques, speeds, and wheelchair-related activities of daily living [85]. Unfortunately, consumers cannot use this type of activity monitor to obtain near-real-time feedback about their mobility characteristics as this information is post processed based on the data stored in the devices.

Tolerico et al. used a third type of monitor, a reed switch and pendulum-based Wheel Rotation Datalogger (WRD), to collect gross mobility characteristics of manual wheelchair users (MWUs) in the National Veterans Wheelchair Games (NVWG) and in community settings [97]. This study revealed that the MWUs used their wheelchairs for a mean (SD) distance of 6,745.3 (1,937.9) m/day at a speed of 0.96 (0.17) m/s and 2,457.0 (1,195.7) m/day at a speed of 0.79 (0.19) m/s in the NVWG and community, respectively. Although the WRD is portable, easy to use and can collect gross activity, a major limitation is its inability to capture upper extremity movements. This constraint hinders the device in distinguishing between self-propulsion and external pushing; additionally, the WRD is unable to estimate energy expenditure.

Researchers have utilized heart rate monitors to develop individualized heart rate models to estimate PA in terms of EE and MET in MWUs with spinal cord injury (SCI) [95, 96]. Hayes et al. showed that calibrated heart rate, using a maximum exercise test, in participants with SCI explained 55% of variance in EE for five activities of daily living compared to only 8.3% of variance in EE explained by the measured heart rate [95]. On the other hand, Lee et al. showed that individualized regression in persons with SCI using the heart rate ratio during PA and resting to estimate METs was better correlated (0.93) than the group regression of heart rate ratio (0.77) to predict METs [96]. A limitation of using heart rate monitors, however, is that the regression models need to be individualized by performing a range of PAs with different intensities in laboratory settings.

Researchers have also evaluated the use of multiple sensors (e.g. many accelerometers) or multi-sensor (different sensors) to detect and estimate PA levels in wheelchair users. Postma et al. validated an activity monitoring system consisting of six accelerometers placed on each thigh, each wrist and the sacrum (two sensors) to detect wheelchair propulsion from a series of representative daily life activities. This activity monitor detected wheelchair propulsion with respect to other wheelchair-related activities with an overall agreement of 92%, a sensitivity of 87% and a specificity of 92%. Hiremath et al. evaluated and developed new models for the multi-sensor based SenseWear activity monitor to detect four activities: resting, wheelchair propulsion, arm-ergometry and deskwork [88, 119]. The SenseWear activity monitor consists of an accelerometer, galvanic skin response, skin temperature, and near body temperature sensors. The results indicated that the classification accuracy for detecting four wheelchair-related PAs was 96.3% for Quadratic Discriminant Analysis and 94.8% for Naïve Bayes algorithms. The average EE estimation error using the activity-specific EE prediction models for the four wheelchair-related activities was 5.3±21.5%.

Based on our previous research and the emerging fields of mobile health (mHealth) and self-monitoring technologies, we developed an activity monitor system that tracks PA levels and provides feedback through smartphones [102-105]. The primary aim of this study was to evaluate the performance of a physical activity monitoring system that consists of two components: a gyroscope based wheel rotation monitor (G-WRM) for capturing wheelchair wheel movement and a wearable accelerometer device (wocket) that tracks upper arm (PAMS-Arm) or wrist (PAMS-Wrist) accelerations in wheelchair users [120, 141]. The G-WRM and the wocket transmit the sensor information wirelessly to an Android-based smartphone, which provides the user with near-real-time feedback. Our secondary aim was to evaluate if the PAMS-Arm or PAMS-Wrist incorporating multimodal information (G-WRM and wocket) was a better PA level estimator than the individual devices (G-WRM, wocket on arm, or wocket on wrist). Finally, a tertiary aim was to evaluate whether the wocket worn on the upper arm (arm wocket) was a better PA level estimator than the wocket worn on the wrist (wrist wocket).

5.2 METHODS

The study was approved by Institutional Review Boards of the University of Pittsburgh and the VA Pittsburgh Healthcare System. The study was conducted at the Human Engineering Research Laboratories (HERL), University of Pittsburgh, at the National Veterans Wheelchair Games (NVWG) 2012 held in Richmond, VA and in the participants' home environments.

5.2.1 Subjects

A total of 45 persons with SCI took part in the study. Subjects were included in the study if they met the following inclusion criteria: 18-65 years of age, used a manual wheelchair as their primary means of mobility (> 80% of their ambulation), and had a diagnosis of SCI. Subjects were excluded from the study if they were unable to tolerate sitting for three hours, had active pelvic or thigh wounds (pressure ulcers), had a history of cardiovascular disease, or were pregnant (based on self-report).

5.2.2 Procedures

The first part of the study was performed by 45 MWUs with SCI in the structured laboratory environment at HERL (N=25) or in the semi-structured convention center environment at NVWG (N=20). A subsection of the population who took part at HERL (N=20) also participated in the study for a second time in their home environments. The sample size was determined based on a power analysis performed using G*Power 3.1.0 [150] and our previous study, which found significant correlations ($p<0.05$) between the criterion EE and mean absolute deviation of acceleration in both transverse (0.72) and longitudinal (0.77) directions for SW AM worn on the upper arm [87]. Based on an F-test for repeated measures ANOVA (within factors design) with two repetitions, an effect size of 0.25 (medium), an alpha of 0.05, correlation among repeated measures of 0.5, and a non-sphericity correction epsilon (ε) of one, we determined we could obtain over 80% of power with 34 subjects.

5.2.2.1 Protocol at HERL or NVWG

Pre-Activity Session

Before testing, the researcher explained the purpose and overall procedure of the study to the participants. After signing the informed consent, participants filled in a questionnaire that included questions on demographics (e.g., gender, ethnicity, age, injury level, and time of injury), wheelchair information (e.g., brand and model), and health and activity history. Body weight was measured to the nearest 0.5 kg using a Befour MX480D Wheelchair scale (Befour, Inc., WI, USA). Body height was either self-reported or measured to the nearest 0.1cm by taking the sum of the sitting height, sitting depth, and lower leg length [151] using a Stanley® Tape Rule (The Stanley Works, CT, USA). Skinfold measurements were performed at four sites (biceps, triceps, subscapular and suprailiac) using the Lange® skinfold caliper (Beta Technology, Inc., CA, USA) to the nearest 1mm.

Activity Session

Subjects were asked to perform at least ten physical activities (PAs) other than resting from a list of PAs. The PA list included: 1) propelling their wheelchair on a tile surface at a self-selected medium pace, 2) propelling their wheelchair on a tile surface at self-selected fast pace, 3) propelling their wheelchair on a medium pile carpet at a medium or slow pace, 4) propelling their wheelchair up and down a ramp at a self-selected pace, 5) being pushed in a wheelchair on a tile surface, 6) being pushed in a wheelchair on a medium pile carpet, 6) being pushed in a wheelchair up and down a ramp, 7) playing wheelchair basketball, 8) folding laundry, 9) performing deskwork involving reading and using a computer, 10) playing darts, 11) using a resistance band (Thera-band), 12) exercising on an arm ergometer at a self-selected pace and resistance. These activities include a range of common everyday activities that involve different parts of the body and varying levels of intensity. Subjects who participated in the study at HERL were instructed to refrain from eating at least 2 hours prior to and from exercising at least 12 hours prior to the experiment. The subjects wore a Cosmed K4b2 portable metabolic cart (COSMED srl, Rome, Italy), which collected the criterion EE for all the activities they chose to perform. For subjects who participated in the study at NVWG, the portable metabolic cart was optional. If the subjects reported in the questionnaire that they had not had food 2 hours prior and had not performed exercises in the previous 12 hours, they were asked whether they would wear a portable metabolic cart. The resting trial involved collecting the baseline EE for six minutes while the subjects sat still in their wheelchairs.

During testing, the subjects were secured with a portable metabolic cart (if appropriate, as described above) and a Polar Heart rate monitor (Polar Electro Inc., NY, USA). Subjects were also secured with the physical activity monitoring system (PAMS), which included a gyroscope based wheel rotation monitor (G-WRM) and an accelerometer on the arm (wocket), as well as four other wockets secured to the participant's wrist and waist, under the seat, and to the wheel. Each of these devices was described in detail if the participant had any questions. The research team then explained the activities to the subjects. In cases where subjects wished to try out a particular trial before performing it, they were asked to do so during a warm-up period of one to two minutes prior to the actual trial. All subjects used their own manual wheelchairs and performed each activity for a minimum of 6 minutes, with at least a 3-minute break between activity trials. One of the investigators noted the start and stop time for each activity trial. The activities were recorded on video, serving as a reference for subsequent timing and independent classification of the activities performed. The investigators collected data from the portable metabolic cart, the PAMS, the wockets, and the heart rate monitor. Subjects rated each activity trial on Borg's modified rate of perceived exertion (RPE) scale after each activity trial (range of scores possible, 6-20). Each testing session lasted for about three hours. All devices were time synchronized prior to each subject's testing.

5.2.2.2 Protocol in Home Environment

Participants were invited to do a follow-up session if they were from the Pittsburgh region (within 60 miles of HERL) and were willing to use the PAMS while they performed 10 daily activities and a resting trial in their home environment. The follow-up session was scheduled within 6 months of their testing in the HERL environment and involved an activity session similar to the one performed in the laboratory environment.

Activity Session

Subjects were asked to perform a minimum of 10 PAs for at least 6 minutes per activity, and they could choose from the list of PAs performed in the laboratory environment or add new PAs that they wanted to perform in their home environments. The PAs that were performed in addition to the PAs mentioned above were: 1) propelling in their home on a tile or carpet surface, 2) propelling in the community on asphalt surface, grass or ramp surface, 3) watching television, 4) simulating eating, 5) sweeping the floor, 6) preparing food/simulating cooking, 7) making bed, 8) using dumbbells, 9) using handgrip, 10) washing dishes, 11) wheelchair pushups, 12) filing papers, 13) checking mail, 14) arranging groceries, 15) vacuuming, 16) doing laundry, 17) cleaning the table, and 18) playing video games on game systems such as the Wii. The resting trial involved collecting the baseline EE for six minutes while the subjects sat still in their wheelchairs. Following resting the participants performed the 10 PAs with a protocol similar to the Activity Session in the laboratory environment, which included securing the instruments, performing PAs, collecting data from devices, and collecting the rate of perceived exertion data. Each testing session lasted for about two hours.

5.2.3 Instrumentation and Data Collection

The criterion device for EE measurement was a Cosmed K4b2 (COSMED srl, Rome, Italy) portable metabolic cart comprising an analyzer unit, a battery pack, and a face mask covering the subject's mouth and nose. The analyzer unit and the battery pack were placed on the chest and the back of the subject, respectively. Participants wore the face mask attached to a head gear which channeled the air exhaled through a ventilation turbine and a sampling line into the analyzer unit. The analyzer unit measured the quantity of oxygen (O_2) and carbon dioxide (CO_2) in the expired air to estimate EE per breath. Research studies have shown that the K4b2 is both reliable and valid for the general population [32, 152]. In addition, a number of studies have used K4b2 in persons with SCI to measure EE and the volume of oxygen (VO_2) consumption [65, 70, 153]. The K4b2 was calibrated for every subject or every six hours before use to ensure its accuracy. Cosmed 9.2 software was used to retrieve and analyze the breath-by-breath data collected by the portable metabolic cart. The participants also wore a Polar T31 heart rate monitor secured to their chest with an elastic strap; it wirelessly transmitted heart rate information to the K4b2 via a wireless receiver.

The PAMS consisted of a G-WRM secured to the spokes of the wheelchair wheel and a wocket worn on the participant's upper arm. The G-WRM (Human Engineering Research Laboratories, University of Pittsburgh, Pittsburgh, PA, USA) is a self-enclosed rechargeable Bluetooth-based wireless device that contains six reed switches and a two-axis gyroscope to measure angular velocity of the wheelchair wheel [120]. The G-WRM measured angular velocity which was then converted into wheelchair velocity and distance traveled using the wheelchair diameter. Angular velocity from the G-WRM was sampled at 64 samples per sec (64Hz) during the testing and then down-sampled to one value per second to capture wheelchair velocity for various PA trials. The wocket (Northeastern University, Boston, MA, USA) is a small Bluetooth-based wireless accelerometer that captures body motion using a tri-axial capacitive micro-machined accelerometer [149]. The PAMS's wocket was attached to the upper arm of the participant using an adjustable Velcro Nylon replacement strap. Four other wockets were secured to the participant's wrist and waist, under the wheelchair seat, and to the wheelchair wheel. Sensor data collected from the wockets included tri-axial acceleration at 40Hz. Both the G-WRM and the five wockets were calibrated prior to the subject testing. An Android cellphone was secured to the participant's waist to collect the data from the G-WRM and wockets.

5.2.4 Data Preparation and Feature Extraction

Post-activity sessions, the raw data collected from the K4b2 and the G-WRM and wockets was cleaned and prepared for analysis. For each participant, the cleaned data was visually inspected in order to time synchronize and identify any sensor malfunction or erroneous data. The next step was to extract a set of time domain and frequency domain features (Appendix A), which are statistical measures used to distinguish between various types of wheelchair related PAs. The time domain features such as mean, mean absolute deviation and peaks are simple to extract and can be used to classify activities that are substantially different. The frequency domain features such as total power between a band of frequencies, energy and entropy provide the capability to allow differentiation of activities based on the key frequency of movement (wheelchair propulsion and arm-ergometry). However, the cost of using frequency features is the need for higher computation. Therefore, in this study we developed models with and without frequency domain features. In addition to the time and frequency domain features we also added subject parameters such as weight, height, gender, age, injury characteristics, wheelchair weight and basal metabolic rates to see if these variables were substantial predictors of EE estimation for various activities. Furthermore, we created new features based on a combination of subject parameters and time domain features to study if these features can estimate the variation in the EE for wheelchair-based PAs. The features were extracted based on a 1 minute window size to be consistent with the EE estimation. Data collected from the K4b2 and the G-WRM and wockets was processed through data analysis programs written in MATLAB (The Mathworks, Inc., Natick, MA, USA).

Following feature extraction the data was separated into training and testing datasets to enable development of PA classification and EE estimation models. In this study we evaluated using multiple types of cross validation (CV) including: 1) using 10-fold-CV on 80% of the subjects' data to develop and train new models and then testing these new models on the remaining 20% of the subjects' data (80-20CV), 2) using 50% of each subject's data to develop models and testing the new models on the remaining 50% of each subject's data (50-50CV), and 3) leaving one subject out cross (LOSO) CV. Training and testing (validation) datasets for the 80-20CV were prepared using a stratified approach with injury level (paraplegia versus tetraplegia) and gender (male versus female) in order to allocate 80% of the participants into the training dataset and 20% into the testing dataset. The LOSO cross-validation method left one subject's data out and then developed the model on the remaining (N-1) subjects. The model developed on these remaining (N-1) subjects was evaluated on data from the left-out subject.

The data preparation steps resulted in a combined dataset of 3836 minutes (63 hours and 56 minutes) from PAMS, the wrist wocket and the metabolic cart. The combined dataset consisted of 1555 minutes, 1001 minutes, and 1270 minutes of data for the HERL, NVWG and Home environments, respectively. The majority of the data analysis for developing regression models involved including all the EE data collected as it was difficult to attain a steady state among many of the PAs performed in this study. However, a small amount of analysis was also performed using steady-state EE. Steady-state conditions (EE in kcal/min) for each activity trial were obtained by first averaging breath-by-breath measures over 30 second periods [70] and then choosing EE values having coefficients of variation of less than 10% computed over a 1-minute window [24]. Steady state analysis led to 2183 minutes of steady state data (57.1%) for the combined dataset.

5.2.5 Development of PA Classification Models

The classification of the wheelchair-based PAs was broken down into a two-step process. First, the PAs were classified into three classes including PAs that are near stationary (distance travelled < 1.8 m/min), PAs that might involve wheelchair movement (1.8m/min >=distance travelled<=12m/min), and PAs that have consistent wheelchair movement (distance travelled >12m/min). We chose this distance threshold based on the distance travelled by the participants for various PAs in this study. The PAs that might have involved wheelchair movement for this study included eating, sweeping the floor, preparing food, making the bed, cleaning the room, filing papers, playing darts, checking mail, doing laundry, and cleaning the car. The stationary and the moving PAs were further classified into: a) resting, arm-ergometry, and other household activities; b) wheelchair propulsion, caretaker pushing and basketball, respectively. The other household activities in the stationary category included deskwork, folding clothes, using a resistance band, playing video games, and doing wheelchair pushups.

We developed and evaluated various types of classification algorithms, including Naïve Bayes (NB), Decision Tress (DT) and Support Vector Machines (SVM). The classification models for G-WRM, PAMS (G-WRM and wocket on arm), wocket on arm, G-WRM and wocket on wrist, and wocket on wrist were developed using the 80-20CV to select the most appropriate features and evaluate the algorithms' performance. Additionally, we have developed and evaluated various types of classification algorithms for PAMS-Arm using the 50-50CV and LOSO cross validation methods to assess if their performance is better than the 80-20CV method. We also developed classification algorithms for individual devices (G-WRM, wocket on arm, and wocket on wrist) and combinations of devices (PAMS, and G-WRM and wocket on wrist) to study their performance with respect to detecting various wheelchair based PAs. As discussed previously the G-WRM alone cannot distinguish between PAs such as wheelchair propulsion or care-taker pushing [120]. But G-WRM along with a wocket on the arm can combine complementary information from the wheelchair and the upper arm movement to better detect wheelchair based PAs. In addition, because a wrist wocket captures substantially more movement than the wocket on the upper arm for light non EE intensive activities such as deskwork or household activities, we performed PA detection using G-WRM and a wocket on the wrist to determine whether the wrist wocket was a better predictor of wheelchair based PAs compared to the upper arm wocket.

5.2.6 Development of EE Prediction Models

We developed multiple EE estimation models to estimate activity-specific EE during stationary PAs, PAs that had small wheelchair movements, and PAs that had substantial wheelchair movements. In this way, we obtained seven EE estimation models for resting, arm-ergometry, other PAs while being stationary, PAs that had small wheelchair movements, wheelchair propulsion, caretaker pushing and basketball. Linear regression analysis using the 10-fold-CV method was used to identify key features and to develop EE estimation models in 80% of the subjects' data. The regression models were then evaluated on the remaining 20% of the subjects' data that was not used during the training phase through 80-20CV. In this study regression models were developed using the 80-20CV for the following combinations and individual devices: PAMS-Arm (G-WRM and arm wocket), PAMS-Wrist (G-WRM and wrist wocket), G-WRM, arm wocket and wrist wocket. Additionally, we have developed multiple EE estimation models for PAMS-Arm using the 50-50CV and LOSO CV methods to assess if their performance is better than the 80-20CV method. We also developed multiple EE estimation models for PAMS-Arm using 80-20CV on the steady state data to compare if these models had less EE error than the models obtained from all the data (steady and non-steady state). The number of features for each model was limited to five so that we could limit the computation needed to apply these models for near-real time EE estimation on Android-based phones. Further, the model development process was data driven, involving selecting the best variables from a pool of sensor, demographic, and a combination of sensor and demographic variables to predict EE.

5.2.7 Data Analysis

The performance of the activity classification algorithms was evaluated using several performance measures including: 1) precision: indicates the proportion with which the activity is detected correctly, 2) recall (or sensitivity): indicates the proportion of actual activities that are correctly identified, 3) specificity (or True Negative rate): indicates the proportion of activities not performed that are correctly identified, 4) accuracy: indicates the proportion of true positives and true negatives with respect to the total cases, and 5) overall accuracy: indicates the overall performance of the algorithm. Most of the data analysis presented here shows the key variables identified and the accuracy of classification.

We performed comparisons between the criterion EE from the portable metabolic cart and the estimated EE from the combined and individual devices by calculating the mean absolute error, mean signed error, and percentage errors. Intraclass correlation coefficients (ICC (3,1)) for single measure using a two-way mixed model with consistency assessed the agreement between criterion EE and the EE estimated by the PAMS-Arm, PAMS-Wrist and individual devices. Bland and Altman plots assessed the agreement between the criterion and estimated EE [125]. In addition, the overall performance of PAMS-Arm, PAMS-Wrist, G-WRM, arm wocket, and wrist wocket was evaluated by sequentially applying the best classification and regression models on the training and the testing data (80-20CV). All statistical analysis was performed using IBM SPSS Statistics software (ver. 20.0, IBM Corporation, NY, USA), with the statistical significance at an alpha level of 0.05.

5.3 RESULTS

Forty five MWUs with SCI participated in this study. Out of the total number of participants, 39 were male and 6 were female with a mean (SD) age of 41.0 (12.6) years, weight of 78.1 (18.1) kg, height of 1.8 (0.1) m, and body fat percentage of 20.58% (6.3%). The injury level of the participants varied from C5 to L5, with 14 participants having injuries at or above T3 and 31 participants having injuries at or below T4. Twenty three of the 45 participants had an incomplete injury. The average number of years participants had used a manual wheelchair was 12.6 (8.6) years. Self-reported PA indicated that 36 participants performed some form of regular PA; 5 performed occasional PA; and 4 performed no regular PA. Thirty one of the 45 participants reported themselves to be non-smokers. The perceived nutritional level reported by participants varied from excellent to poor with 4 reporting excellent, 15 reporting very good, 16 reporting good, 9 reporting fair and 1 reporting poor. The perceived fitness level reported by participants varied from excellent to fair with 3 reporting excellent, 15 reporting very good, 16 reporting good, and 11 reporting fair.

All 45 participants completed the study. Out of this total number, 37 finished 10 trials, 7 finished 9 trials and 1 finished 8 trials. Most of these activity trials (701 out of 707 trials) were performed for 6 minutes per trial as requested, while 6 trials were between 2-4 minutes. Due to device malfunction of the metabolic cart K4b2, trials from two participants (22 trials out of 707 trials) could not be retrieved and were discarded. This led to a total of 685 trials for the K4b2, with 679 trials between 5 to 6 minutes and 6 trials of 2 to 4 minutes. Due to device malfunction of the G-WRM and wockets, data from 24 trials (out of the 707) was lost as a result of a Bluetooth blockage or battery discharge.

Table 13 summarizes the following information: the metabolic costs in kcal/min from the K4b2 metabolic cart, the volume of oxygen consumed per kg of the participant (VO_2/kg) from the K4b2 metabolic cart, the MET from the metabolic cart, the MET-SCI, the heart rate (beats/min), the rating of perceived exertion, and the number of subjects who completed each activity trial. Using the MET-SCI values as a reference, we identified arm-ergometry, wheelchair propulsion, basketball, floor sweeping, cleaning a room, making the bed, doing laundry and doing wheelchair pushups as moderate intensity activities (MET-SCI between 3.0 and 6.0), and the remaining wheelchair-based PAs in this study as light intensity activities (MET-SCI<3.0) [70]. The metabolic costs for different types of PAs, calculated based on our study's MET-SCI values, were very similar to the MET-SCI values from Collins et al. (Table 14). Figure 12 shows the patterns for metabolic costs (EE and MET-SCI), RPE, and heart rate were similar for various wheelchair-related PAs.

Table 13: Metabolic costs in terms of EE, METs, heart rate, rate of perceived exertion, and number of subjects and minutes per activity for various wheelchair-based physical activities.

Activity Trial	No. of Subjects	No. of Minutes	Heart Rate in beats/min		EE in kcal/min		VO_2/Kg in ml/min/kg		MET		MET SCI		RPE	
			Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD	Mean	STD
Resting	43	363	69.9	16.2	1.1	0.3	3.1	0.8	0.9	0.2	1.1	0.3	6.0	0.1
Arm-Ergometry	43	500	96.0	19.0	3.0	1.2	8.2	3.5	2.3	1.0	3.0	1.3	10.9	2.2
Darts	33	214	91.1	15.3	2.7	0.8	7.2	2.1	2.1	0.6	2.7	0.8	8.7	2.0
Deskwork	43	574	79.1	14.2	1.5	0.6	4.3	1.7	1.2	0.5	1.6	0.6	7.5	2.1
Folding Clothes	42	343	92.5	17.6	2.3	0.6	6.2	1.6	1.8	0.4	2.3	0.6	8.6	2.3
Propulsion	43	901	101.2	20.5	3.5	1.5	9.5	3.9	2.7	1.1	3.5	1.5	11.0	3.1
Caretaker Pushing	42	341	75.3	14.2	1.3	0.4	3.4	1.0	1.0	0.3	1.3	0.4	6.4	1.3
Resistance	43	367	86.2	15.2	2.0	0.7	5.4	1.8	1.6	0.5	2.0	0.7	10.0	2.3
Basketball	19	112	110.2	19.7	4.5	1.7	12.8	4.3	3.7	1.2	4.8	1.6	12.6	2.7
Eating	17	17	73.0	13.2	2.0	0.4	5.6	2.2	1.6	0.6	2.1	0.8	7.5	2.1
Sweeping Floor	14	90	96.2	15.8	3.0	0.9	8.4	2.9	2.4	0.8	3.1	1.1	10.9	3.1
Preparing Food	11	68	87.6	17.9	2.3	0.6	6.2	1.8	1.8	0.5	2.3	0.7	7.7	1.6
Making Bed	1	6	90.6	7.3	2.7	0.6	8.1	1.7	2.3	0.5	3.0	0.6	7	0.0
Cleaning Room	4	26	97.8	27.7	2.3	0.6	8.6	2.0	2.5	0.6	3.2	0.7	8.7	2.9
Filing papers	2	12	91.8	16.1	1.1	0.2	5.1	0.9	1.5	0.2	1.9	0.3	7.5	2.1
Check mail	2	8	89.9	12.9	2.3	0.6	7.4	1.5	2.1	0.4	2.7	0.6	6.0	0.0
Laundry	2	16	89.2	7.0	2.7	0.4	9.4	1.1	2.7	0.3	3.5	0.4	9.0	2.6
Video Game	1	6	72.3	2.8	1.9	0.2	4.2	0.4	1.2	0.1	1.6	0.2	13.0	0.0
Cleaning Car	1	6	76.6	7.0	2.7	0.6	6.7	1.4	1.9	0.4	2.5	0.5	7.0	0.0
Wheelchair Pushups	1	6	97.0	15.4	2.6	0.7	10.0	2.6	2.9	0.7	3.7	1.0	13.0	0.0

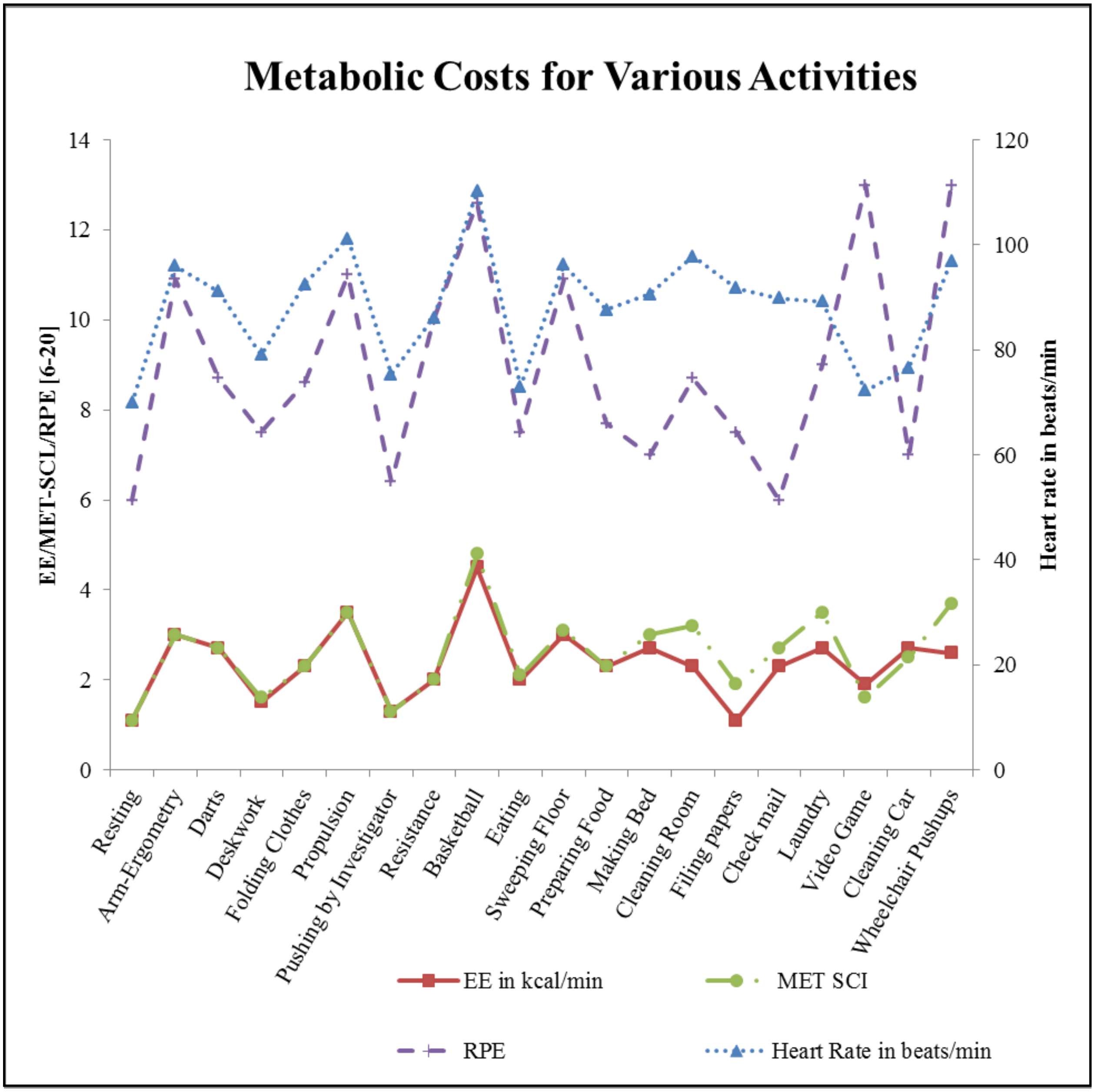


Figure 12: Plot of Metabolic costs (EE, MET SCI), RPE and heart rate for various wheelchair based PAs.

Table 14: Average metabolic costs from Collins et al. from the Compendium of PAs for persons with SCI.

Activity	Number of subjects	EE in kcal/min		VO_2 in ml/kg/min		SCI MET	MET-SCI PAMS Study
		mean	STD	mean	STD	mean	Mean
Arm Cranking	26	3.7	1.1	10.0	3.9	3.7	3.0
Darts	7	2.1	0.3	5.6	1.1	2.1	2.7
Deskwork	27	1.6	0.4	3.9	1.0	1.5	1.6
Wheeling	133	3.2	0.9	8.8	2.0	3.3	3.5
Basketball	10	5.6	1.3	15.3	3.4	5.7	4.8
Dusting and Vacuuming	38	2.5	0.8	6.6	1.5	2.4	3.1
Bed Making	31	3.0	0.7	7.9	1.5	2.9	3.0
Laundry	39	2.6	0.6	6.8	1.2	2.5	3.5

Table 15 shows the performance of best classification algorithms using 80-20CV for detecting and classifying wheelchair-based PAs into the following categories: moving, may be moving, and not moving PAs (see Appendix B for all the algorithm performances). Table 16 shows the performance (80-20CV) of various algorithms for detecting and classifying moving (M) PAs and non-moving PAs (see Appendix B for all the algorithm performances). The moving PAs were further classified into wheelchair propulsion, caretaker pushing, and basketball. The Non-Moving (NM) PAs were further classified into resting, arm-ergometry, and other activities. Figure 13 shows how the classifier picked up an acceleration-based feature (std_y_rtUarm). Similarly, Table 17 and Table 18 show the performance of various algorithms for PAMS-Arm at detecting and classifying wheelchair-based PAs using 50-50CV and LOSO CV, respectively. Since the performance of the classification algorithms using 50-50CV and LOSO CV were similar to the 80-20CV we decided to use the classification algorithms developed using the 80-20CV.

Table 15: Performance of various algorithms for detecting and classifying wheelchair based PAs into moving, may be moving, and not moving PAs.

Device	Training Accuracy	Testing Accuracy	Features	Model
PAMS-Arm	0.9356	0.9801	rms_v_G-WRM, mcr_v_G-WRM	SVM
PAMS-Wrist	0.9356	0.9801	rms_v_G-WRM, mcr_v_G-WRM	SVM
G-WRM	0.9356	0.9801	rms_v_G-WRM, mcr_v_G-WRM	SVM
Arm wocket	0.7870	0.7873	Ratio1DomFreq_w_Pwr_xyz_rtUArm, mad_med_xyz_rtUArm	J48
Wrist wocket	0.8074	0.7932	mean_x_rtWrist, entropy_WO_dcComp_xyz_rtWrist	J48

Table 16: Performance of various algorithms for detecting and classifying moving (M) PAs and non-moving (NM) PAs.

Device	M/NM	Training Accuracy	Testing Accuracy	Features	Model
PAMS-Arm	NM	0.8678	0.8495	2DomFreqPwr_xyz_rtUArm, stdev_z_rtUArm, ampl_xyz_rtUArm	J48
PAMS-Arm	M	0.9557	0.9340	stdev_y_rtUArm, ampl_y_rtUArm, entropy_v_G-WRM	SVM
PAMS-Wrist	M	0.9713	0.9387	Ratio1DomFreq_w_Pwr_xyz_rtWrist, mean_x_rtWrist, 3DomFreqPwr_xyz_rtWrist	J48
PAMS-Wrist	NM	0.9032	0.8638	3DomFreqPwr_xyz_rtWrist, mean_x_rtWrist, 1DomFreqPwr_xyz_rtWrist	J48
G-WRM	NM	0.6197	0.5018	rms_v_G-WRM, zcr_v_G-WRM, entropy_v_G-WRM	NB
G-WRM	M	0.9206	0.8773	3DomFreqPwr_v_G-WRM, mcr_v_G-WRM, entropy_v_G-WRM	J48
Arm wocket	M	0.9612	0.9151	Ratio1DomFreq_w_Pwr_y_rtUArm, 3DomFreqPwr_y_rtUArm, rms_x_rtUArm	J48
Arm wocket	NM	0.8678	0.8495	2DomFreqPwr_xyz_rtUArm' 'stdev_z_rtUArm' ampl_xyz_rtUArm'	J48
Wrist Wocket	M	0.9713	0.9387	Ratio1DomFreq_w_Pwr_xyz_rtWrist, mean_x_rtWrist 3DomFreqPwr_xyz_rtWrist	J48
Wrist Wocket	NM	0.9032	0.8638	3DomFreqPwr_xyz_rtWrist, mean_x_rtWrist, 1DomFreqPwr_xyz_rtWrist	J48

Table 17: Performance of various algorithms for detecting and classifying wheelchair based PAs into moving, may be moving, and not moving PAs for PAMS-Arm using 50-50 CV.

Activity	Training Accuracy	Testing Accuracy	Variables	Model
Moving/ Nonmoving / May be moving	0.9399	0.9394	'mean_v_DL_right_correct' 'mcr_v_DL_right'	NB
	0.9405	0.9435	'mean_v_DL_right_correct' 'mcr_v_DL_right'	J48
	0.9431	0.9383	'rms_v_DL_right' 'mcr_v_DL_right'	SVM
Moving	0.9551	0.9508	stdev_y_rtUArm, entropy_v_G-WRM, ampl_xyz_rtUArm	NB
	0.9567	0.9662	Ratio1DomFreq_w_Pwr_y_rtUArm, 3DomFreqPwr_y_rtUArm, corr_x_xyz_rtUArm	J48
	0.9504	0.9492	stdev_y_rtUArm, entropy_v_G-WRM , ampl_xyz_rtUArm	SVM
Nonmoving	0.8250	0.8501	mcr_xyz_rtUArm, corr_y_xyz_rtUArm, entropy_WO_dcComp_x_rtUArm	NB
	0.8622	0.8838	3DomFreqPwr_y_rtUArm, ZMAD+XMAD, stdev_z_rtUArm	J48
	0.8527	0.8588	mcr_xyz_rtUArm, mcr_z_rtUArm, NumPeaks_v_G-WRM	SVM

Table 18: Performance of various algorithms for detecting and classifying wheelchair based PAs into moving, may be moving, and not moving PAs for PAMS-Arm using LOSO CV.

Activity	Training Precision	Variables	Model
Moving / Nonmoving / May be moving	0.9238	mean_v_G-WRM, mcr_v_G-WRM	NB
	0.9293	mean_v__G-WRM, mcr_v_G-WRM	J48
	0.9231	mean_v_G-WRM, mcr_v_G-WRM	SVM
Moving	0.9536	2DomFreqPwr_xyz_rtUArm, ampl_x_rtUArm, energy_v__G-WRM	NB
	0.9435	Ratio1DomFreq_w_Pwr_y_rtUArm, 3DomFreqPwr_y_rtUArm, corr_x_xyz_rtUArm	J48
	0.9469	stdev_y_rtUArm, entropy_v_DL_right, ampl_y_rtUArm	SVM
Nonmoving	0.8213	mcr_xyz_rtUArm, corr_y_xyz_rtUArm, mcr_z_rtUArm	NB
	0.8576	2DomFreqPwr_xyz_rtUArm, ampl_z_rtUArm, var_hist_xyz_rtUArm	J48
	0.8527	mcr_xyz_rtUArm, mcr_z_rtUArm, ampl_x_rtUArm	SVM

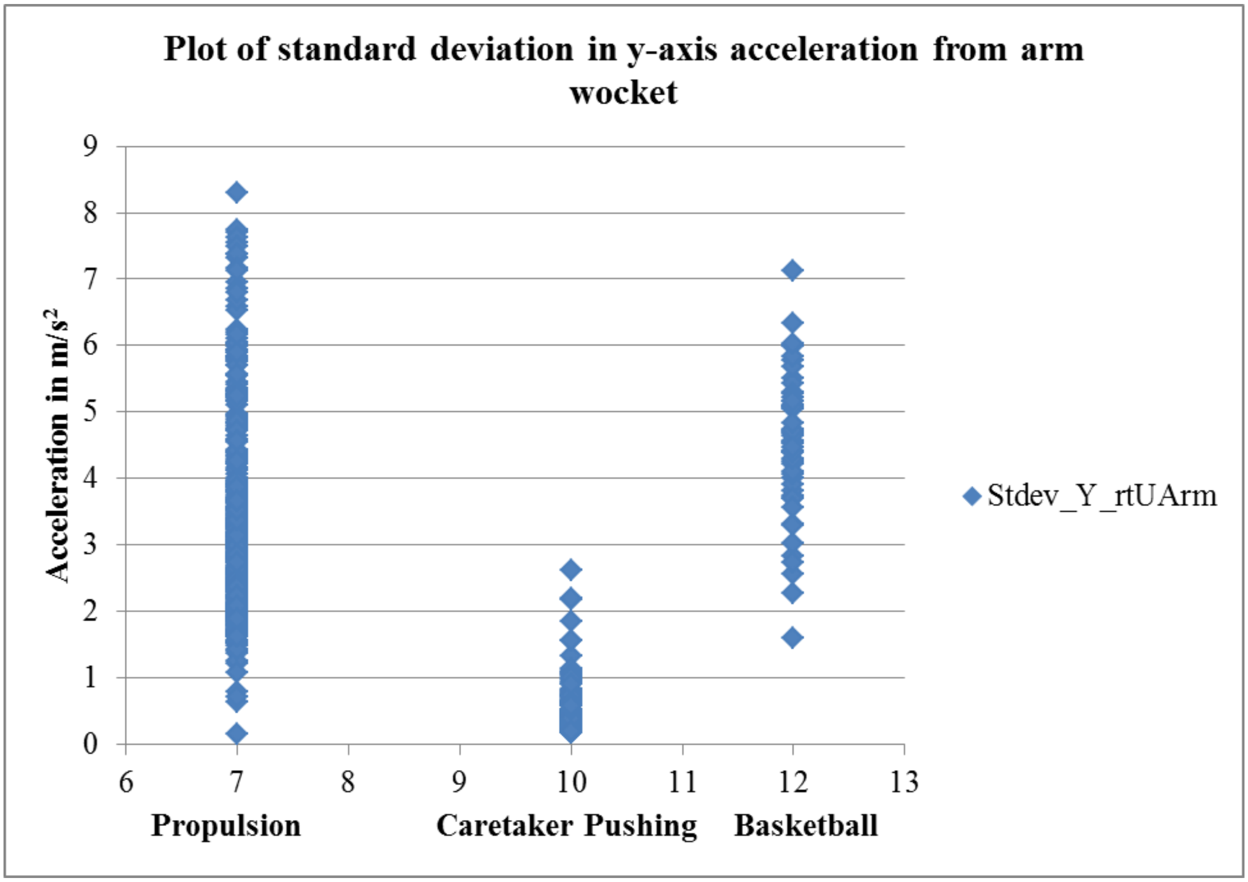


Figure 13: Plot of the acceleration feature chosen by the classification algorithm for PAMS-Arm to classify and detect propulsion, caretaker pushing and basketball activities.

Table 19 shows the classification performance for wheelchair based PAs for the sequential classification of first detecting PAs that are near stationary, that might involve wheelchair movement or have consistent wheelchair movement, followed by detecting the PAs within stationary and consistent wheelchair movement PAs. The results are shown in terms of True Positive Percentage (TP%), True Negative % (TN%), Precision, Recall, True Negative Rate (TN Rate), Accuracy and Overall Accuracy for the best classifiers for PAMS-Arm, PAMS-Wrist, G-WRM, arm wocket, and wrist wocket. In addition Table 20 shows the confusion matrix for PAMS-Arm, where the best classification algorithms (from Table 15) were used to classify wheelchair based PAs. Table 21 shows the performance of various algorithms for PAMS at detecting and classifying moving (M) PAs and non-moving (NM) PAs using non-frequency domain-based features.

Table 19:Classification performance in terms of TP%, TN%, Precision, Recall or sensitivity, Specificity or TN Rate, Accuracy and overall accuracy for the best classifiers on the validation dataset for PAMS-Arm, PAMS-Wrist, G-WRM, Arm wocket, and wrist wocket.

Device	Activity Trial	TP%	TN%	Precision	Recall	TN Rate	Accuracy %	Overall Accuracy %
PAMS-Arm	Resting	46.81	99.34	0.88	0.47	0.99	94.43	**89.26**
	Arm-ergometry	92.39	99.51	0.98	0.92	1.00	98.21	
	OA not moving	96.43	91.46	0.81	0.96	0.91	92.84	
	Propulsion	99.26	98.10	0.95	0.99	0.98	98.41	
	Caretaker Pushing	93.62	99.56	0.96	0.94	1.00	99.01	
	Basketball	56.67	100.00	1.00	0.57	1.00	97.42	
	May be moving	100.00	98.17	0.57	1.00	0.98	98.21	
PAMS-Wrist	Resting	68.09	97.59	0.74	0.68	0.98	94.83	**88.47**
	Arm-ergometry	93.48	98.05	0.91	0.93	0.98	97.22	
	OA not moving	87.86	95.04	0.87	0.88	0.95	93.04	
	Propulsion	97.04	97.83	0.94	0.97	0.98	97.61	
	Caretaker Pushing	95.74	99.34	0.94	0.96	0.99	99.01	
	Basketball	53.33	99.79	0.94	0.53	1.00	97.02	
	May be moving	100.00	98.17	0.57	1.00	0.98	98.21	
G-WRM	Resting	0.00	100.00	N/A	0.00	1.00	90.66	**65.41**
	Arm-ergometry	0.00	100.00	N/A	0.00	1.00	81.71	
	OA not moving	100.00	61.98	0.50	1.00	0.62	72.56	
	Propulsion	90.37	96.74	0.91	0.90	0.97	95.03	
	Caretaker Pushing	78.72	99.12	0.90	0.79	0.99	97.22	
	Basketball	60.00	97.67	0.62	0.60	0.98	95.43	
	May be moving	100.00	98.17	0.57	1.00	0.98	98.21	
Arm Wocket	Resting	46.81	99.34	0.88	0.47	0.99	94.43	**70.38**
	Arm-ergometry	89.13	95.38	0.81	0.89	0.95	94.23	
	OA not moving	79.29	82.37	0.63	0.79	0.82	81.51	
	Propulsion	65.19	97.01	0.89	0.65	0.97	88.47	
	Caretaker Pushing	55.32	97.15	0.67	0.55	0.97	93.24	
	Basketball	50.00	99.58	0.88	0.50	1.00	96.62	
	May be moving	83.33	92.46	0.21	0.83	0.92	92.25	
Wrist Wocket	Resting	2.13	99.34	0.25	0.02	0.99	90.26	**74.55**
	Arm-ergometry	93.48	99.27	0.97	0.93	0.99	98.21	
	OA not moving	83.57	90.08	0.76	0.84	0.90	88.27	
	Propulsion	85.93	99.46	0.98	0.86	0.99	95.83	
	Caretaker Pushing	82.98	88.16	0.42	0.83	0.88	87.67	
	Basketball	23.33	99.79	0.88	0.23	1.00	95.23	
	May be moving	75.00	94.09	0.24	0.75	0.94	93.64	

Table 20: Confusion matrix for PAMS-Arm on validation dataset (20% of subjects' data not used for training) using the best algorithms to classify wheelchair based PAs.

True\Predicted	Resting	Arm-ergometry	PAs not moving	Propulsion	Caretaker Pushing	Basketball	May be moving
Resting	**22**	0	24	0	0	0	1
Arm-ergometry	0	**85**	6	0	0	0	1
PAs not moving	3	2	**135**	0	0	0	0
Propulsion	0	0	0	**134**	1	0	0
Caretaker Pushing	0	0	0	2	**44**	0	1
Basketball	0	0	1	5	1	**17**	6
May be moving	0	0	0	0	0	0	**12**

Table 21: Performance of various algorithms for PAMS-Arm using 80-20 CV to detect and classify moving (M) PAs and non-moving (NM) PAs using non-frequency domain-based features.

M/ NM	Training Accuracy	Testing Accuracy	Features	Model
NM	0.8423	0.8315	mcr_xyz_rtUArm, corr_y_xyz_rtUArm, zcr_z_rtUArm	NB
M	0.9308	0.8962	stdev_y_rtUArm, ZMAD*XMAD, mean_v_G-WRM	NB
NM	0.8694	0.8100	mcr_xyz_rtUArm, ampl_x_rtUArm, stdev_hist_xyz_rtUArm	J48
M	0.9584	0.9387	stdev_xyz_rtUArm, ampl_x_rtUArm, mean_v_G-WRM	J48
NM	0.8561	0.8602	mcr_xyz_rtUArm, mcr_z_rtUArm, ampl_z_rtUArm	SVM
M	0.9511	0.9387	stdev_y_rtUArm, ampl_y_rtUArm, mean_v_G-WRM	SVM

Table 22 shows the mean signed error for each activity-specific equation using the five features obtained using 10-fold cross validation on 80% of the subjects' data. The regression models were also evaluated using the 20% of subjects' data not used for training. Appendix C shows the five features that were chosen for the regression analysis to estimate wheelchair-based PAs for PAMS, G-WRM and wrist, G-WRM, wocket on arm and wocket on wrist. Similarly, Table 23 and Table 24 show the EE errors for activity-specific equations developed for PAMS-Arm using 50-50CV and LOSO CV, respectively. Additionally, Table 25 shows the EE errors for activity-specific equations developed for PAMS-Arm using 80-20CV on steady state data. Since the EE errors for developing EE equations using 50-50CV and LOSO CV were similar to the 80-20CV, we decided to develop EE estimation equations based on the 80-20CV. In addition, we used all the EE data collected (3836 minutes) for regression equation development using 80-20CV compared to the steady state analysis data (2183 minutes) as the latter had similar training errors and larger variation in EE and movement sensor data. Further, we also evaluated the performance of the classification and the regression equations by first applying classification algorithms to the validation dataset (20% of subjects' data not used for training) and then applying the corresponding activity specific regression equations (Table 26 and Table 27). The EE estimated by the activity specific equations was compared with the EE measured from the metabolic cart using MAE, MSE and Intraclass correlation coefficients. The EE estimated by the activity-specific equations were also evaluated by Bland Altman plots. Figure 14 and Figure 15 show the Bland Altman plots for EE estimated by the activity-specific equations for various PAs and other activities not involving wheelchair movement in PAMS on the validation dataset. The x-axis is the average of the EE measured and the EE estimated in Kcal/min. The y-axis is the difference between the EE measured and the EE estimated in kcal/min. From the BA plots we can see that a majority of the points (>95%) lie within the mean±2SD, indicating an agreement between the EE estimated and criterion EE. Figure 16 and Figure 17 show that for most of the activities the MSE and MAE for PAMS-Arm and PAM-Wrist were lower than those for the individual devices (G-WRM and wocket on wrist or arm).

Table 22: Mean signed error for each activity-specific equation using the five features obtained by 10-fold cross validation on 80% of subject's data and tested on the 20% of subjects' data not used for training.

Device	**PAMS-Arm**		**PAMS-Wrist**		**G-WRM**		**Arm Wocket**		**Wrist Wocket**	
Activity	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
Resting	-7.05	-5.32	-6.82	-6.94	-7.00	-5.35	-6.92	-6.82	-6.82	-6.94
Arm-ergometry	-14.44	-1.66	-7.69	5.34	-18.30	-7.58	-16.08	-6.14	-9.05	-31.61
OA Not moving	-10.14	-11.86	-9.73	-12.61	-12.10	-11.32	-10.14	-11.86	-9.73	-12.61
May be moving	-5.99	-7.27	-6.57	-1.50	-7.23	0.24	-5.99	-7.28	-6.57	-1.50
Propulsion	-7.50	-11.66	-5.16	-7.81	-6.31	-15.95	-8.99	-14.32	-10.95	-16.47
Caretaker pushing	-6.66	-0.96	-7.45	-4.77	-7.38	-6.39	-6.66	-0.96	-7.21	-5.66
Basketball	-1.87	-15.64	-1.91	-20.14	-1.70	-18.46	-2.70	-28.81	-5.13	-33.12

Table 23: Mean signed error for each activity-specific equation using the five features obtained by 10-fold cross validation for PAMS-Arm on 50% of each subject's data and tested on 50% of the remaining data not used for training.

Activity	**Training Precision**	**Testing Precision**	**Features**
Resting	-6.80	-5.96	LeanBodyMass, var_hist_y_rtUArm, Ratio1DomFreq_w_Pwr_v_G-WRM 3DomFreq_y_rtUArm, HeightSqRoot
Arm-ergometry	-10.21	-13.84	LeanBodyMass, 2DomFreq_xyz_rtUArm, Completeness, mcr_z_rtUArm, YMAD*HeightSqrt
OA Not moving	-7.08	-7.74	Ratio1DomFreq_w_Pwr_xyz_rtUArm, Mufflin_BMR, stdev_xyz_rtUArm, mcr_x_rtUArm, LeanBodyMass
May be moving	-7.24	-9.61	LeanBodyMass, stdev_y_rtUArm, Ratio1DomFreq_w_Pwr_v_G-WRM, 3DomFreq_x_rtUArm, mad_med_v_G-WRM
Propulsion	-3.84	-5.15	stdev_xyz_rtUArm, MassPow0.75, backtrend_xyz_rtUArm, 3DomFreqPwr_v_G-WRM, is_male
Caretaker pushing	-6.00	-7.97	LeanBodyMass, ZMAD*HeightSq, backtrend_x_rtUArm, 1DomFreq_xyz_rtUArm, 2DomFreq_y_rtUArm
Basketball	-1.81	-2.58	backtrend_v_DL_right, 3DomFreq_v_DL_right, Mufflin_BMR, mad_med_xyz_rtUArm, backtrend_xyz_rtUArm

Table 24: Mean signed error for each activity-specific equation using the five features obtained by LOSO validation for PAMS-Arm on all the subjects' data.

Activity	MAE	Training Accuracy	Features
Resting	20.02	-6.32	LeanBodyMass, 3DomFreqPwr_v_G-WRM, stdev_v_G-WRM, corr_z_xrtUArm, var_hist_z_rtUArm
Arm-ergometry	19.21	-4.93	stdev_xyz_rtUArm, mean_v_G-WRM, LeanBodyMass, backtrend_xyz_rtUArm, mean_x_rtUArm
OA Not moving	20.49	-6.08	mad_mean_xyz_rtUArm, LeanBodyMass, Ratio1DomFreq_w_Pwr_xyz_rtUArm, TotalPower_z_rtUArm, 2DomFreqPwr_z_rtUArm
May be moving	25.69	-8.95	Ratio1DomFreq_w_Pwr_y_rtUArm, stdev_hist_y_rtUArm, WHO_RMR, mcr_y_rtUArm, WHORMR_div_LBM
Propulsion	37.46	-17.35	Ratio1DomFreq_w_Pwr_v_G-WRM, freqRatio_hist_z_rtUArm entropy_xyz_rtUArm, zcr_xyz_rtUArm, corr_blank1_rtUArm
Caretaker pushing	19.43	-5.65	Mufflin_BMR, stdev_z_rtUArm, rms_x_rtUArm, var_hist_xyz_rtUArm, var_hist_z_rtUArm
Basketball	30.62	-10.95	Ratio1DomFreq_w_Pwr_x_rtUArm, WHO_RMR, HeightDivYMAD, 2DomFreq_z_rtUArm, zcr_xyz_rtUArm

Table 25: Mean signed error for each steady state based activity-specific equation using the five features obtained for PAMS-Arm by 10-fold cross validation on 80% of subjects' data and tested on the 20% of the remaining subjects' data not used for training.

Activity	Training Precision	Testing Precision	Features
Resting	-4.01	-11.78	LeanBodyMass, var_z_rtUArm, energy_WO_dcComp_y_rtUArm, 2DomFreq_y_rtUArm, freqRatio_hist_x_rtUArm
Arm-ergometry	-12.81	-8.03	is_male, freqRatio_hist_x_rtUArm, 2DomFreq_v_G-WRM, mcr_x_rtUArm, entropy_y_rtUArm
OA Not moving	-7.22	-7.75	mad_mean_xyz_rtUArm, LeanBodyMass, WHORMR_div_HBBMR, freqRatio_hist_z_rtUArm, 3DomFreqPwr_y_rtUArm
May be moving	-5.83	6.86	LeanBodyMass, stdev_hist_xyz_rtUArm, Ratio1DomFreq_w_Pwr_z_rtUArm, NumPeaks_x_rtUArm, NumPeaks_xyz_rtUArm
Propulsion	-3.55	-0.13	mad_mean_y_rtUArm, MassPow0.75, 3DomFreqPwr_v_G-WRM, backtrend_xyz_rtUArm, mad_med_v_G-WRM
Caretaker pushing	-4.25	2.67	Mufflin_BMR, entropy_x_rtUArm, corr_z_xrtUArm, 2DomFreqPwr_v_G-WRM, 2DomFreqPwr_z_rtUArm
Basketball	-1.01	-28.12	LeanBodyMass, stdev_z_rtUArm, corr_x_xyz_rtUArm, mcr_y_rtUArm, mad_med_v_G-WRM

Table 26: EE estimation performance for activity-specific (AS) equations on the validation dataset (20% of subjects' data not used for training) post-classification for PAMS and G-WRM and wocket on wrist.

Device	Activity	EE Met		EE AS		MAE	MSE		ICC(3,1)			
		Mean	SD	Mean	SD	Mean	Mean	SD	ICC	LB	UB	P
PAMS-Arm	Resting	1.09	0.27	1.21	0.21	19.41	-14.02	0.79	0.77	0.48	0.90	<0.05
	Arm-ergometry	3.25	1.27	2.98	0.66	31.83	-2.13	0.49	0.47	0.19	0.66	<0.05
	OA not moving	1.86	0.85	1.93	0.78	30.47	-15.04	0.21	0.73	0.64	0.80	<0.05
	Propulsion	3.65	1.99	3.47	0.93	31.69	-11.56	0.28	0.69	0.57	0.78	<0.05
	Caretaker Pushing	1.3	0.39	1.25	0.28	14.10	0.25	0.40	0.82	0.68	0.90	<0.05
	Basketball	3.57	1.31	4.61	1.62	35.18	-31.96	2.25	0.84	0.56	0.94	<0.05
	May be moving	3.66	1.02	2.90	0.34	27.69	12.14	1.77	0.40	-0.47	0.76	0.13
	Overall	2.65	1.63	2.58	1.19	29.04	-9.82	0.07	0.82	0.79	0.85	<0.05
PAMS-Wrist	Resting	1.22	0.57	1.17	0.26	21.20	-4.00	0.58	0.62	0.30	0.80	<0.05
	Arm-ergometry	3.15	1.27	2.87	1.05	23.29	3.85	0.34	0.85	0.77	0.90	<0.05
	OA not moving	1.91	0.86	1.91	0.39	28.73	-12.32	0.24	0.63	0.48	0.73	<0.05
	Propulsion	3.64	2.01	3.50	1.21	26.09	-8.39	0.24	0.84	0.78	0.89	<0.05
	Caretaker Pushing	1.4	0.64	1.31	0.27	16.28	-1.51	0.43	0.68	0.43	0.82	<0.05
	Basketball	3.61	1.30	4.30	2.02	28.64	-14.77	1.76	0.91	0.75	0.97	<0.05
	May be moving	3.66	1.02	2.97	0.32	29.69	9.26	2.18	0.61	0.05	0.84	0.02
	Overall	2.65	1.63	2.53	1.26	25.19	-5.65	0.06	0.89	0.87	0.91	<0.05

Note: EE measured (EE Met), EE Activity Specific, Mean Absolute Error in percentage (MAE), Mean Signed Error (MSE) and Intraclass correlation coefficients with lower bound (LB), upper bound (UB) and significance values for various devices and their combinations are shown below.

Table 27: EE estimation performance for activity-specific (AS) equations on the validation dataset (20% of subjects' data not used for training) post-classification for G-WRM, wocket on arm and wrist.

Device	Activity	EE Met		EE AS		MAE	MSE		ICC(3,1)			
		Mean	SD	Mean	SD	Mean	Mean	SD	ICC	LB	UB	P
G-WRM	OA not moving	2.22	1.21	1.91	0.39	39.22	-6.88	0.17	0.35	0.18	0.49	<0.05
	Propulsion	3.75	2.04	3.86	1.11	37.56	-22.24	0.40	0.78	0.69	0.84	<0.05
	Caretaker Pushing	1.32	0.56	1.27	0.35	18.27	-1.99	0.61	0.72	0.47	0.85	<0.05
	Basketball	2.72	1.07	3.57	1.46	45.98	-36.93	1.86	0.82	0.61	0.91	<0.05
	May be moving	3.66	1.02	2.96	0.25	31.77	8.73	2.24	0.37	-0.54	0.75	0.15
	Overall	2.65	1.63	2.52	1.19	37.15	-11.65	0.10	0.79	0.75	0.82	<0.05
Arm Wocket	Resting	1.09	0.27	1.27	0.26	22.58	-18.32	0.77	0.84	0.64	0.93	<0.05
	Arm-ergometry	3.38	1.35	2.98	0.03	31.04	-2.04	0.39	-0.01	-0.49	0.32	0.51
	OA not moving	1.81	0.88	1.79	0.35	30.10	-12.73	0.20	0.59	0.45	0.70	<0.05
	Propulsion	3.93	2.12	3.73	0.92	37.30	-13.89	0.46	0.62	0.43	0.74	<0.05
	Caretaker Pushing	1.30	0.37	1.29	0.36	13.91	-1.22	0.45	0.85	0.72	0.92	<0.05
	Basketball	3.80	1.14	4.64	1.44	28.25	-24.11	1.75	0.77	0.36	0.92	<0.05
	May be moving	2.99	1.01	2.83	0.46	27.34	-4.12	0.70	0.43	-0.03	0.68	0.03
	Overall	2.65	1.63	2.54	1.09	29.76	-9.78	2.65	0.79	0.76	0.83	<0.05
Wrist Wocket	Resting	2.91	0.86	1.54	0.06	42.11	42.11	5.69	-0.28	-18.82	0.92	0.58
	Arm-ergometry	3.18	1.28	2.90	0.77	22.48	0.50	0.35	0.75	0.61	0.83	<0.05
	OA not moving	2.14	1.17	1.98	0.42	29.53	-8.39	0.23	0.56	0.39	0.68	<0.05
	Propulsion	3.62	2.07	3.66	0.81	47.19	-25.65	0.51	0.50	0.28	0.65	<0.05
	Caretaker Pushing	1.30	0.56	1.32	0.27	20.89	-9.74	0.27	0.68	0.52	0.79	<0.05
	Basketball	4.03	1.25	5.88	2.23	65.86	-53.25	6.93	-0.04	-4.22	0.79	0.52
	May be moving	3.36	1.19	2.76	0.43	23.19	10.41	0.68	0.69	0.41	0.84	<0.05
	Overall	2.65	1.63	2.53	1.13	31.03	-10.01	0.08	0.76	0.72	0.80	<0.05

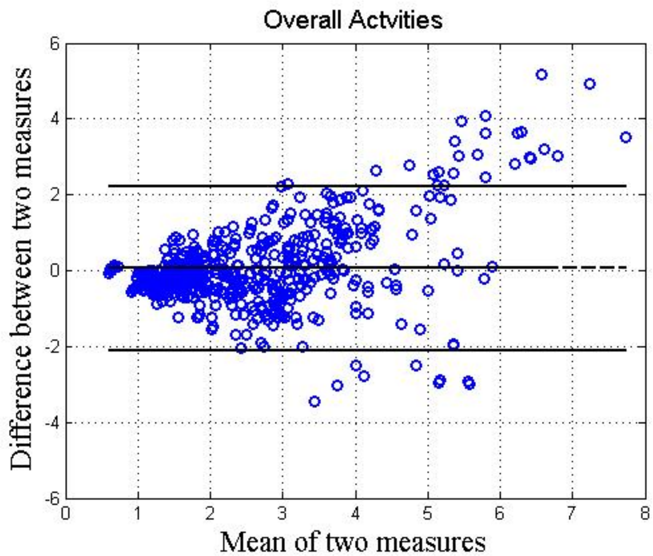


Figure 14: Bland and Altman plot of EE estimated using activity-specific equations for PAMS and EE measured for the various wheelchair-related PAs in the validation dataset.

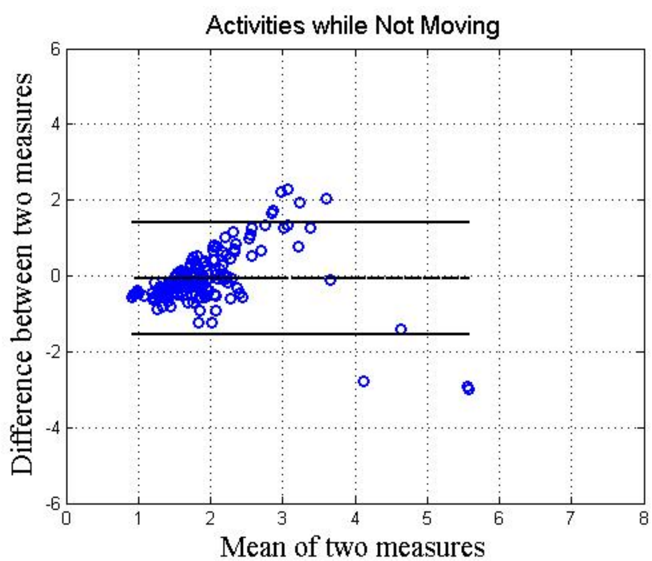


Figure 15: Bland and Altman plot of EE estimated using the activity-specific equation for other activities not involving wheelchair movement and EE measured for the various wheelchair-related PAs in PAMS on the validation dataset.

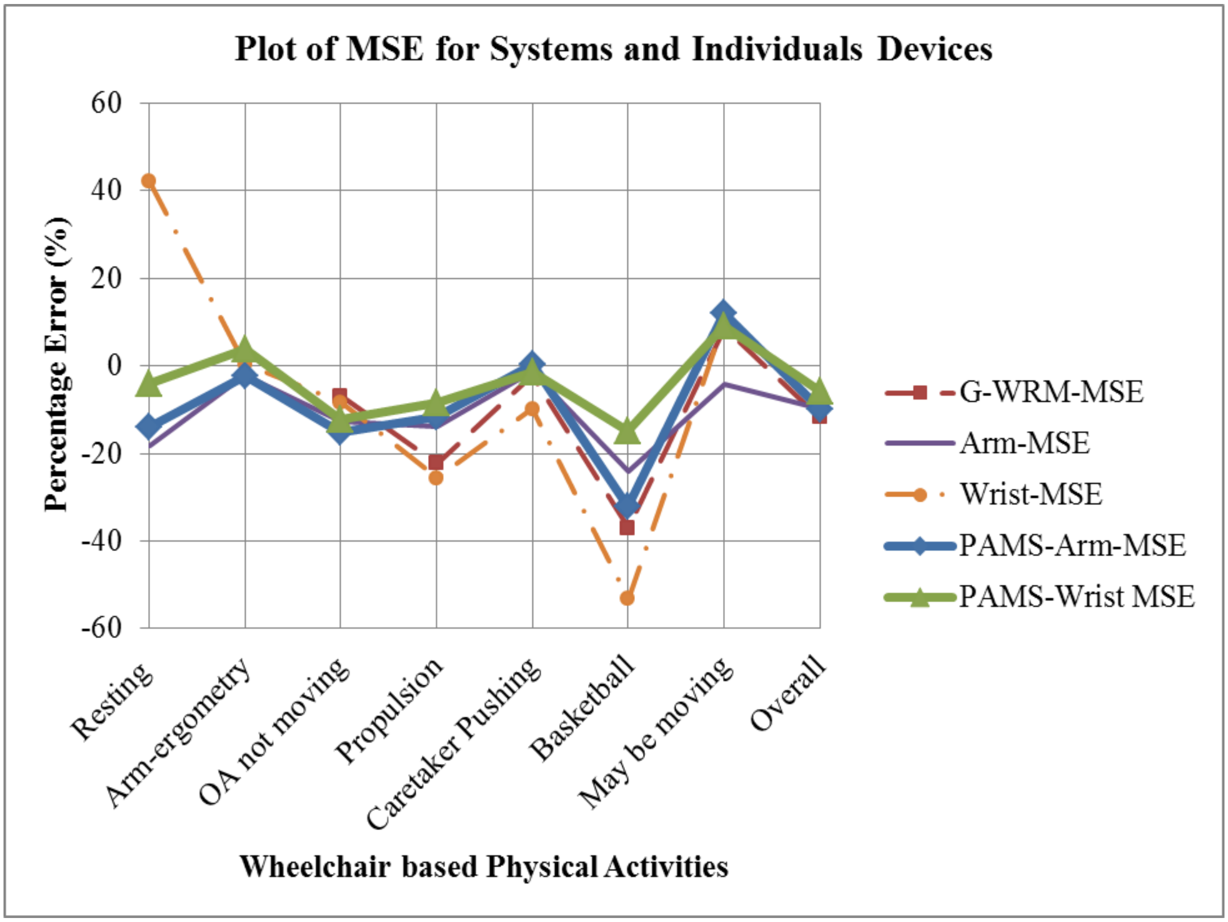


Figure 16: The Mean Signed Error (MSE) for PAMS-Arm, PAMS-Wrist, G-WRM, arm wocket, and wrist wocket.

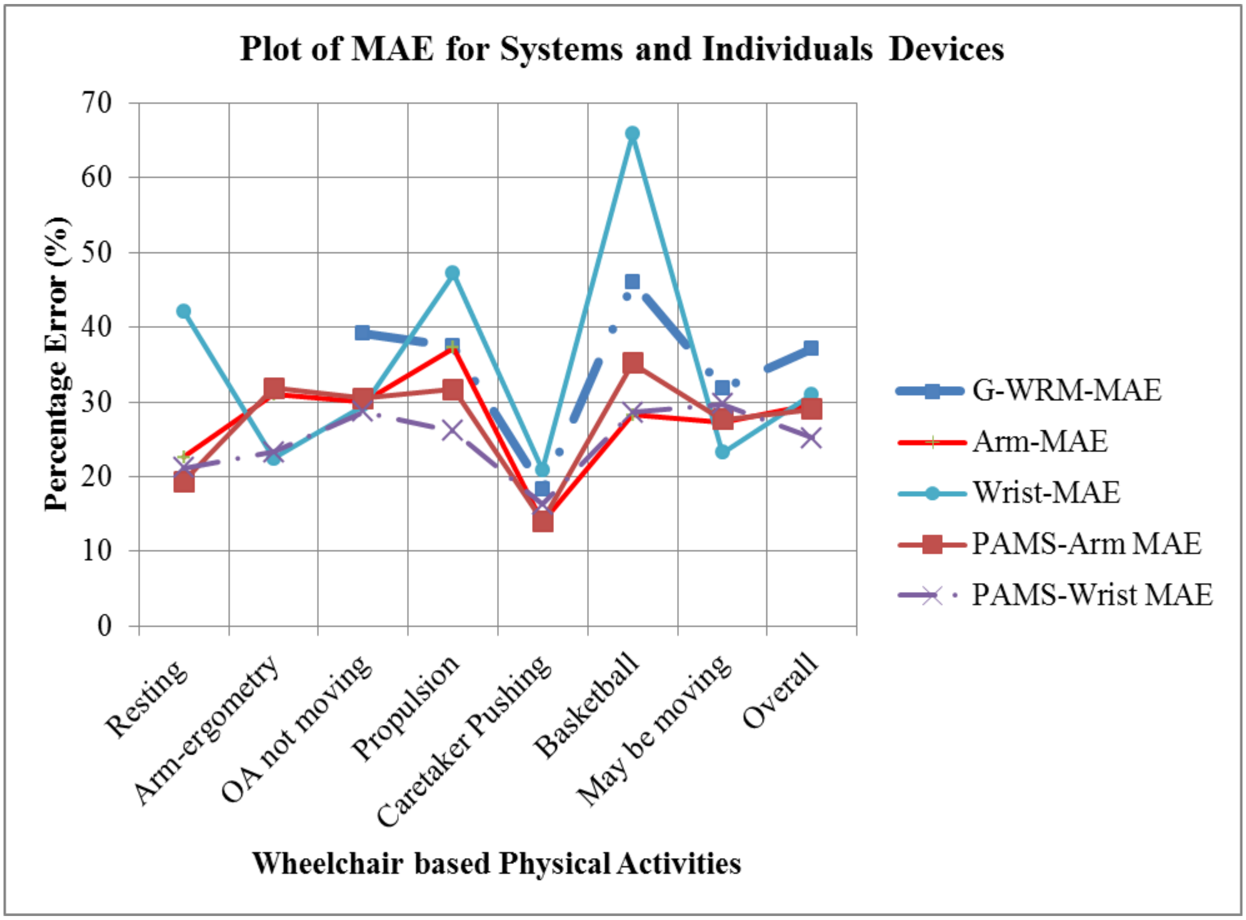


Figure 17: The Mean Absolute Error (MAE) for PAMS-Arm, PAMS-Wrist, G-WRM, arm wocket, and wrist wocket.

The duration of light, moderate and high intensity PAs for the validation dataset was calculated by estimating METs, defined as the ratio of EE during a certain PA with respect to EE during resting for each participant. The duration of light, moderate and high intensity PAs based on the EE measured by k4b2, and EE estimated by PAMS-Arm and G-WRM are shown in Table 28. The PAMS-Arm over-estimated for low intensity PAs and underestimated for moderate and high intensity PAs. Similarly, the G-WRM over-estimated for low intensity PAs and underestimated for moderate and high intensity PAs. The results indicate that PAMS-Arm was better in estimating the light, moderate and high intensity activity durations than the G-WRM compared to the criterion measure.

Table 28: Light, Moderate and High Intensity PA duration based on METs.

METs based Intensity	Actual mins	Estimated mins	
	Metabolic cart K4b2	**PAMS-Arm**	**G-WRM**
Light	387	406	488
Moderate	116	97	15
High	5	3	0

5.4 DISCUSSION

The classification algorithms used in the first phase to detect PAs that involve wheelchair movement indicated that PAMS-Arm, PAMS-Wrist, and the G-WRM device were better predictors compared to the arm or wrist wockets, as G-WRM accurately detected the presence of wheelchair movement. The key features involved in the G-WRM based classification algorithm were the root mean square and mean cross rate of velocity, both related to wheelchair movement. The classification accuracies for the arm and wrist wockets were very similar, but lower than G-WRM for features involving the ratio of power of the dominant frequency with the total power, total movement, and entropy of acceleration. These features from the arm and wrist wockets could not distinguish PAs dependent on wheelchair movement as well as the G-WRM's features.

During the second phase of classification, PAs were classified within moving or non-moving wheelchair related PAs. The results for this stage indicated that the arm and wrist wockets are better predictors of PAs than the G-WRM. From the features identified by the classification algorithms we see that majority of them were frequency-based features, as the PAs involve volitional upper arm movements. An interesting result was the reasonably high classification accuracy (92% for training and 88% for testing) of the G-WRM for moving PAs which involved propulsion, basketball and caretaker pushing (Figure 13). The probable reason for the G-WRM's ability to distinguish caretaker pushing from propulsion and basketball was that the same investigator pushed all the participants. This pushing of wheelchair users by one individual may have resulted in a specific type of speed or acceleration pattern that the G-WRM was sensitive to. Future studies should try to evaluate whether the G-WRM is capable/able to distinguish caretaker pushing from propulsion when various caretakers push wheelchair users. Furthermore, the classification results for the 50-50CV (half subject out CV) and LOSO yielded a range similar to the 80-20CV, indicating that the training and testing datasets have large PA or movement variation within trials and between subjects.

An in-depth classification performance analysis (Table 19) of the best classifiers indicated that PAMS-Arm and PAMS-Wrist had similar overall classification accuracy (89.26% vs. 88.47%), precision (lower precision for resting and may be moving) and recall (lower recall for resting and basketball). The analysis revealed that multimodal sensor information from G-WRM and wocket for PAMS-Arm and PAMS-Wrist has higher accuracy than the individual devices (G-WRM and wockets). The confusion matrix analysis (Table 20) for PAMS indicated that the majority of the PAs were rightly predicted (diagonal elements). Further the analysis indicated that the misclassified PAs (non-diagonal) were classified into PAs that were biomechanically similar; for example, resting was classified as other household PAs in stationary category and basketball as PA that may involve wheelchair movement as the basketball activity may involve intermittent wheelchair movement. Even though misclassification resulted in lower classification accuracies, grouping activities into similar type of wheelchair-based activities led to EE or MET values similar to the EE or MET values obtained for correctly identified activities. It is also evident that the wockets on arm or wrist have higher accuracy than the G-WRM because the arm plays a major role in all the type of PAs studied here. In addition, the overall classification performance of arm and wrist wockets (70.38% vs. 74.55%) was close, with the wrist wocket having a slightly higher accuracy. These results, along with the results from the combined devices above, indicate that the features chosen by the algorithms for arm and wrist wockets detect wheelchair-based PAs, thus leaving users the option of where to wear the wocket based on their comfort or preference.

Since many of the classifier algorithms used frequency-based features to detect and classify PAs, we also evaluated the classification performance for non-frequency domain based features. The analysis (Table 16 and Table 21) indicated that the classification accuracy for PAMS-Arm was similar for non-moving activities (0.87 vs. 0.87 for training and 0.85 vs. 0.81 for testing) and moving activities (0.96 vs. 0.95 for training and 0.93 vs. 0.94 for testing). Comparing the features chosen by the classifier algorithms for data containing frequency and non-frequency based data indicated that the classifier algorithms picked slightly different features with similar type of movement information, such as rate versus frequency and change in distance versus entropy. For example the mean cross rate of acceleration in resultant direction (mcr_xyz_rtUArm) was chosen by the classifier using non-frequency based data instead of the power of second dominant frequency (2DomFreqPwr_xyz_rtUArm) for non-moving PAs; and the mean velocity of the G-WRM (mean_v_G-WRM) was chosen instead of the entropy of the velocity of the G-WRM feature (entropy_v_G-WRM) for moving PAs. In future, we plan to develop classification and regression algorithms for the monitoring systems if we encounter difficulties implementing frequency-based features on smartphone (Android) platforms.

Our algorithms' overall classification accuracy for the detection of wheelchair based PAs (PAMS-Arm: 93.6% for training and 98.0% for testing), and the detection of PAs involving wheelchair movement (PAMS-Arm: 95.6% for training and 93.5% for testing) was similar to Sonenblum et al.'s detection of wheelchair movement for various wheelchair-related activities of daily living (90-96%) [85]. This resemblance, in addition to our previous validation of G-WRM [120], indicates that our system can measure wheelchair use in activities of daily living. Additionally, the classification performance results (overall accuracy: 96%, sensitivity: 99% and specificity: 98%) for detecting wheelchair propulsion using PAMS-Arm were slightly higher than the results of Postma et al., who detected wheelchair propulsion compared to other activities (overall agreement: 92%, Sensitivity: 87% and specificity: 92%) [90]. The advantage of our system is the reduced number of devices: G-WRM on wheel and arm wocket instead of the six-accelerometers based activity monitoring system used by Postma et al. The overall classification accuracies for PAMS-Arm (89.3%) and PAMS-Wrist (88.5%) were lower compared to those in our previous study, during which we used the SenseWear activity monitor to detect resting, wheelchair propulsion, arm-ergometry and deskwork activities (96.3%) [119]. The lower classification accuracy was probably due to testing of a larger number of wheelchair-based PAs, performed at a self-chosen pace obtained in structured, semi-structured and unstructured natural environments.

The next step in this study was estimating EE, an actionable parameter that wheelchair users can act on to attain a healthier lifestyle. The EE data collected for the various wheelchair-based PAs in this study provided us with a large range of EE (1.1kcal/min for resting to 4.5kcal/min) and MET-SCI values for light (<3 METs) and moderate intensity (3-6 METs) PAs (Table 13 and Figure 12). These activities were grouped into seven broad categories of wheelchair-related PAs for developing activity-specific regression equations. Activity specific EE estimation errors during training for PAMS-Arm and PAMS-Wrist were similar for most wheelchair-related PAs, with the exception of arm-ergometry exercise and stationary PAs. The probable reason for a higher EE error by PAMS-Arm is that upper arm movement is significantly less compared to the wrist movement for arm-ergometry and stationary PAs. Also, we found that the activity-specific equation for basketball activity for both PAMS (-15.6%) and G-WRM and wocket on wrist (-20.1%) overestimated EE for basketball in the testing dataset. This overestimation could be due to variation in participants' style of playing basketball and shooting at the net. Our development of regression equations indicated that most of the EE estimation equations chose demographic features such as weight of the person, lean body mass, height and gender, as total EE during resting and PAs for an individual depends on these parameters [154]. In two of the regression equations (arm-ergometry and propulsion) for the wrist, the equation chose each person's injury characteristics (paraplegia versus tetraplegia) as one of the predictors. Choice of injury characteristics may be related to the higher mobility of persons with paraplegia, who can use triceps muscles, compared to persons with tetraplegia, who may not be able to control or use triceps muscles due to the level of injury. Use of triceps in persons with paraplegia can lead to higher self-chosen speeds during arm-ergometry and propulsion activities. However, there were three regression equations (arm-ergometry for PAMS-Arm, arm-ergometry for arm wocket, and basketball for wrist wocket) that did not use the demographic characteristics mentioned above for EE estimation. This indicates that the EE estimation equations for these PAs found that movement variables better explained the variance in the EE. However, estimating EE based on movement data alone may result in large EE errors. The EE estimation performance results using 50-50CV (half subject out CV) and LOSO for PAMS-Arm yielded an EE error range similar to the performance of EE estimation models using 80-20 CV. This EE error similarity reveals that the training and testing datasets have large EE variation within trials and between participants allowing us to continue using the EE models obtained from 80-20CV for the remainder of the analysis.

Further, the EE estimation error post-classification showed that the overall EE error based on mean signed error (EE overestimated cancels out EE underestimated) was lowest for PAMS-Wrist (-5.7%) followed by PAMS-Arm (-9.8%) and arm wocket (-9.8%), followed by similar values for the wrist wocket (-10.0%) and G-WRM (-11.7%). However, these results should be interpreted with caution, as the overall error is a good indicator only if all the activities were performed for the same duration (Figure 16 and Figure 17). Also, the classification algorithm for stationary PAs for G-WRM failed to classify and detect resting and arm-ergometry PAs for the validation dataset due to the lack of wheelchair movement for these PAs. Another important measure that needs to be considered during EE estimation is the MAE where the over (negative error) and under (positive error) estimations of EE don't cancel each other out. The MAE values for PAMS-Arm (19.4% to 35.2%), PAMS-Wrist (16.3% to 29.7%), G-WRM (18.3% to 39.3%), arm wocket (13.9% to 37.3%) and wrist wocket (20.9% to 42.1%) show that the movement and demographic based variables did not predict the EE with low MAE (<10%). However, the EE estimated for PAMS-Arm and PAMS-Wrist had moderate to high ICC values for the majority of PAs compared to individual devices (G-WRM and wockets on arm or wrist), thus indicating that the EE values estimated by these systems are consistent with the EE measured by the portable metabolic cart. Bland Altman plots for PAMS-Arm indicated that the EE estimated by the new regression models was balanced with over and under estimation of EE for up to 5kcal/min; the new equations tended to overestimate the EE above 5kcal/min. This may be due to the nonlinear relationship between EE and the movement of the arm and the wheelchair in participants performing wheelchair PAs. In future we plan to study this relationship by evaluating nonlinear models and a combination of linear and nonlinear variables to estimate EE.

The correlations for the estimated EE and the criterion EE (ICC=0.84; range: 0.78 to 0.89; $p<0.05$) for PAMS-Wrist during wheelchair propulsion were higher than the correlations found by Washburn et al. [89]. Washburn et al. found significant correlations (0.52-0.66, $p <0.01$) between the activity counts from a wrist worn accelerometer and EE over three pushing speeds [89]. A possible reason for this mismatch is the variability in participants' wheelchair propulsion. Our participants performed wheelchair propulsion at a slow, medium or fast pace (self-selected) on various types of surfaces, thus providing us with more diverse data than that obtained from the three speeds studied by Washburn et al.[89].

Furthermore, the EE estimation errors for PAMS-Arm (MAE 14.1% for caretaker pushing to 35.2% for basketball and MSE: -32.0% for basketball to 12.1% for may be moving) during the seven PAs were much higher than the EE estimation error for SenseWear (MAE: 13.4% for deskwork to 18.2% for resting and MSE: -4.3% for resting to 9.9% for Arm-ergometry) during the four PAs from our previous study [88]. The higher variation in our current study is due to the following reasons: a much larger number of wheelchair-based PAs collected in both laboratory and community settings; the merging of these numerous PAs into seven groups; collection of data at two time points for 20 participants; and the participants performing PAs at a self-selected pace or pattern.

One of the limitations of this study was that a large percentage of our participants self-reported that they were physically active on a regular (n=36) or occasional basis (n=5). Thus, the PA levels reported here are significantly higher compared to those in Washburn et al., who indicated that out of their subjects only 13-16% of persons with SCI reported consistent PA [73], and the majority reported virtually no regular PA [74]. However, our high PA levels might have been inflated due to self-reported PA levels, which tend to have a social acceptability bias.

Another limitation of this study is the inclusion of a large cohort of veterans with SCI tested during the National Veterans Wheelchair games (N=20). The majority of the veterans who took part in this study probably had a better standard of care regarding assistive technology; however, they still had current PA and health levels similar to the general population. Future studies should recruit a greater percentage of MWUs from the general population. Additionally, our study only recruited individuals with SCI to limit the influence of various disabilities on energy expenditures during wheelchair related PAs. However, the biomechanical aspects of wheelchair propulsion and performing activities of daily living are similar among individuals with different disabilities. Recruiting individuals with other disabilities would enable us to develop classification algorithms and EE estimation equations to quantify PA levels among different groups of persons with similar disabilities.

Moreover, the classification and EE models developed here are based on arm acceleration and wheelchair velocity, both movement-based variables. Future work should develop PAMs to incorporate other forms of physiologic sensing, such as galvanic skin response, skin temperature, near body temperature, and heart rate, in order to detect resistance-based PAs. We are in the process of evaluating and developing PAMS so that it can be reliably deployed into longitudinal testing of one to two weeks in the community. In future, we plan to study specific movement related features, which could assist researchers and clinicians with quantifying upper arm movement associated with carpal tunnel syndrome or overuse syndrome.

5.5 CONCLUSIONS

PA level measurement in wheelchair users can assist consumers to reach an optimal PA which can lead to a healthier lifestyle. In this study, we have developed and evaluated new classification and EE prediction models for MWUs based on upper arm and wheelchair movements detected with the help of a physical activity monitoring system. The new prediction models we developed can estimate PA levels in MWUs with SCI in laboratory and community settings. We hope that the availability of our physical activity monitoring system will encourage researchers and clinicians to study wheelchair-based PAs such as propulsion and transfers in community settings to help prevent shoulder pain and injuries in wheelchair users.

6.0 USABILITY TESTING OF PAMS

6.1 INTRODUCTION

Physical activity monitors can play a key role in assisting consumers who use manual wheelchairs to perform optimal physical activity (PA) and lead a healthy lifestyle. However, to our knowledge, there is no technology available on the market capable to estimate PA levels in consumers who use wheelchairs. As discussed in the earlier chapters we developed the Physical Activity Monitoring System (PAMS) to make PA monitoring technology accessible to manual wheelchair users (MWU) [88, 119, 120]. In this chapter we explore aspects of participatory action design research by involving consumers (end-users) in the development of PAMS [118, 155]. Specifically, we implemented a user-centered design process to obtain the consumers' feedback about this prototype technology prior to developing a market prototype [156]. This usability study allows us to understand the needs of our consumers, their perception of our technology and to identify existing barriers in the way of this technology's acceptance. The usability testing of PAMS through a focus group of end-users increases the possibility of knowledge translation and is critical to the success of converting this device into a consumer product [157].

The purpose of this study was to evaluate the usability of PAMS in a small sample of manual wheelchair users (MWUs). The study measured the usability aspects of PAMS by evaluating the ease of use, learnability, effectiveness of PAMS (outcomes), and the users' attitudes and experiences (satisfaction) [156, 158-160]. The usability testing of PAMS evaluated securing and using the PAMS sensing devices, and interacting with the PAMS smartphone application (PAMS app). The evaluation of securing and using the PAMS sensing devices involved observing how the participants placed the accelerometer in an armband, how they wore the armband on their upper arm, and how they secured the gyroscope based wheel rotation monitor's holder to the spokes of their wheelchairs. The accelerometer and wheel rotation monitor collect acceleration and angular velocity information from the upper arm and the wheelchair's wheel, respectively, prior to sending it to an android-based smartphone. The android-based smartphone analyzes and provides the user with feedback regarding their PA levels. The PAMS app requires the user to start the communication between the sensors and the smartphone. The PAMS app also asks the user to provide their demographic parameters such as age, gender, weight and height to accurately estimate PA levels such as energy expenditure. Furthermore, the app applies machines learning algorithms to the sensor and the demographic data to estimate PA levels and displays the PA information on the phone's touchscreen. Evaluating the use of the PAMS app included studying the users' interaction with the smartphone, collecting their expectations about the device and their interpretation of the feedback data. In addition, we wanted to study from the consumers' perspective additional aspects related to PAMS' usability and possible applications, which we might have overlooked.

6.2 METHODS

The study was approved by the Institutional Review Board of the University of Pittsburgh. The study was conducted at the Human Engineering Research Laboratories (HERL), University of Pittsburgh. The study was designed in collaboration with clinicians and researchers who work with persons who use wheelchairs.

6.2.1 Participants

Six persons with spinal cord injury (SCI) took part in the study. Participants were included if they met the following inclusion criteria: 18-65 years of age, used a manual wheelchair as their primary means of mobility (> 80% of their ambulation), had a diagnosis of SCI, and had experience using a computer. Participants were excluded from the study if they were unable to tolerate sitting for two hours and had active pelvic or thigh wounds (pressure ulcers). The study did not exclude MWUs who had taken part in the earlier study of PAMS as they have not interacted with the technology and the population size of MWUs from the Pittsburgh region is small. Previous research has shown that about five users are sufficient to explain 80-85% of the problems associated with usability studies [156, 161].

6.2.2 Instrumentation

The usability testing evaluated PAMS, a device composed of an accelerometer (wocket) worn on the upper arm and a gyroscope based wheel rotation monitor (G-WRM) secured to the wheelchair wheel, and the PAMS smartphone application (PAMS app). The PAMS application is a software service implemented on an Android-based smartphone, which wirelessly collects data from PAMS devices, analyzes the data and provides users with a brief PA summary in near-real-time. The PAMS app utilizes classification and energy expenditure (EE) estimation algorithms to detect the user's current activity and estimate their EE used to track the user's PA levels. The preliminary classification algorithm implemented here was developed on 25 participants in a laboratory environment and could detect wheelchair-based PAs such as resting, arm-ergometry, darts, deskwork, folding clothes, wheelchair propulsion, external pushing, resistance band, and basketball. The PAMS app displays the following information: distance travelled, speed travelled, EE in calories and duration of moderate intensity activities such as propulsion and arm-ergometry. Prior to using the device, users have to select a particular sensor set on the PAMS app in order to ensure they choose the recharged wocket while the second wocket is recharging.

6.2.3 Usability Protocol Design

We used a formative testing method with the goal of diagnosing and fixing problems to evaluate the usability of PAMS [156]. The testing started with collecting baseline information related to the participants' current PA levels, exercises they perform, methods they use to track PAs, use of smartphones, and food and PA balance. We also asked them questions related to PA Stages of Change Model, commonly asked by researchers or clinicians prior to any PA intervention towards a healthy lifestyle [162].

Users evaluated PAMS by going through the following steps: getting familiar with the technology, securing the G-WRM to the spokes of the wheelchair, wearing the armband, interacting with the PAMS smartphone app and using PAMS while performing five wheelchair based PAs. The evaluation of the ease of use and learnability of PAMS was performed through a System Usability Scale (SUS) [156, 160] adapted to this study with 7 point Likert scale responses [163]. Furthermore, the Technology Acceptance Model (TAM) was modified to suit PAMS and PA monitoring in wheelchair users compared to TAM being used to measure perceived usefulness of a tool or software that people use for their jobs [159]. We also asked the participants open-ended questions about their experience using PAMS and whether they would recommend this device to their friends.

6.2.4 Procedures

The study evaluated the usability of PAMS and the PAMS app on an Android based Nexus smartphone. Before testing, the investigator explained to each participant the purpose and overall procedure of the study. After signing the informed consent, participants filled in two questionnaires. The first questionnaire (Part I) included questions on demographics (e.g., gender, ethnicity, age, injury level, and time of injury), wheelchair information (e.g., brand and model), physical activity information, and the user's prior experience with smartphones (Appendix D). The second questionnaire (Part II) was exploratory and included questions on physical activity stages of change, and food and physical activity balance. The five stages of change are: stage 1 (pre-contemplation) during which the person has not yet acknowledged that there is a problem with their PA behavior that needs to be changed, stage 2 (contemplation) during which the person acknowledges the existence of a problem but is not yet ready to make a change, stage 3 (preparation) during which the person is getting ready to change their PA behavior, stage 4 (decision/action) during which the person is undergoing a change in behavior, and stage 5 (maintenance) in which the person maintains an earlier implemented behavior change [162, 164].

Before starting the interaction with PAMS, a brief orientation and demonstration on how to use PAMS and the PAMS app was provided to each participant with the help of a 10-minute long video and a manual. The video had the following subsections: 1) introduction, 2) using the PAMS app, 3) entering the demographic information in the PAMS app on the smartphone, 4) wearing the wocket on the upper arm, 5) securing the G-WRM and its holder to the spokes of the wheelchair wheel, and 6) performing a propulsion task while wearing PAMS. If after watching the video participants still had doubts about how to use PAMS and the PAMS app, they could refer to the manual and ask any additional questions to the investigator. The manual had similar subsections to the video and included pictures and text explaining how to use PAMS and the PAMS app. An additional section incorporated in the manual was the recharging section, explaining how to recharge PAMS and the smartphone. Participants reviewed the video and the manual prior to performing a number of tasks and evaluating PAMS and the PAMS app using a think aloud method. These tasks included: 1) using the PAMS app, 2) entering demographic information such as age, gender, height and weight in the PAMS app on the phone, 3) wearing the wocket on the upper arm, 4) securing the G-WRM and its holder to the wheelchair wheel, 5) performing five PAs for two minutes each while using PAMS. The evaluation process was recorded on video and audio, and we used this recorded data as reference methods for our data analysis. Using the PAMS app involved: switching on the phone, selecting the right set of sensors, waiting for the sensors to communicate with the phone, locking the screen, and going back to the application. Securing the G-WRM and its holder involved securing the holder to the spokes with four zip ties. During this procedure the participants could choose to remain in their wheelchair or transfer to a mat table. If the participants had limited function, they could ask the investigator to assist with securing the holder to the wheel's spokes. After securing PAMS, the participants answered a subsection of a questionnaire (Part III) related to the securement of PAMS. Following this, the participants performed five wheelchair related PAs for two minutes each to evaluate the PAMS's performance. The wheelchair related PAs the participants could choose from included wheelchair propulsion, being pushed by an investigator, reading, arm-ergometry, deskwork, and resistance band.

Investigators probed participants to talk if silences continued for several seconds. Neutral cues such as “keep talking” or “what are your thoughts” encouraged subjects to think aloud but did not bias the data by adding external ideas to the internal process of participants’ train of thought. Once the think aloud process was completed for each task, investigators asked follow-up questions (Part III) regarding the evaluation of PAMS. Then, participants completed a customized usability questionnaire that included the SUS and the TAM to gather user feedback on the overall usability, ease of use, and perceived usefulness of PAMS. At the end of the evaluation process, users participated in an interview with open-ended questions (Part III). The interview explored how users envisioned the features and application of this system beyond the current capabilities and use of PAMS and the PAMS app. For example, the investigators asked participants whether they were satisfied with how the PAMS app displayed information regarding the users’ PA.

6.2.5 Data Analysis

We used descriptive statistics to analyze the data obtained from the three questionnaires. We performed quantitative data analysis by assessing success rates, error rates, and frequency of specific problems [156, 165]. Qualitative data analysis was performed by analyzing the video data for evaluation of PAMS, problems experienced, comments, and answers to open-ended questions. We used the video content analysis to identify common themes in the transcripts from both usability testing and in depth interviews. In addition, we assessed whether demographic variables such as level of injury had an impact on using the PAMS technology.

6.3 RESULTS

6.3.1 Demographics

Five male MWUs and one female MWU with SCI participated in this study. The mean (SD) age of the participants was 30.7 (11.2) years, weight of 78.8 (13.4) kg, and height of 1.7 (0.1) m. The injury level of the participants varied from C7 to T12, with one participant having injuries at or above T3 and five participants having injuries at or below T4. Three of the six participants had a complete SCI. Three of the participants were of Caucasian ethnicity, while the other three were of African American ethnicity. The number of years participants had used a manual wheelchair was 9.8 (8.3) years. Self-reported PA indicated that five participants performed some form of regular PA and one performed no regular PA. Four of the participants reported to be non-smokers. The perceived nutritional levels reported by participants varied from good to excellent with two for good, three for very good and one for excellent. Moreover, two participants also indicated they followed specific dietary plans. The perceived fitness level reported by participants varied from very good to fair with three for very good, two for good, and one for fair. Five of the six participants reported they had performed some form of PAs and exercise during the last month other than wheelchair propulsion. The PAs performed included weights, wheelchair basketball, sled hockey, arm-ergometry, resistance band, using other gym equipment, swimming and wheelchair rugby. Further, based on the participants' responses to the PA stages of change questionnaire we found that participants were at stage 2 (contemplation: N=1), stage 4 (decision/action: N=1) and stage 5 (maintenance: N=4) phases of the readiness towards regular PA [162].

6.3.2 Smartphone Use

The smartphone use questionnaire (Appendix D) indicated that five participants had smartphones (two: iPhones, two: Android based phones, and one: flip phone) out of which four had touchscreens. Table 29 shows the responses to the remaining questions on the smartphone use questionnaire.

Table 29: Responses of the participants to the smartphone use questionnaire.

Question	Response (N)
Do you have a smartphone?	Yes (5) No (1) • I tried but found it difficult to use; • I do not need other features except calls
How long have you been using a smart phone?	1-2 years (1) 2-3 years (1) 3 years or longer (3)
Please state your average hours of smart phone use per day?	Less than 1 hour (1) 2-4 hours (3) 4-6 hours (1)
When you use your smart phone, what functions do you usually use?	Browsing internet Entertaining yourself (listening music, watching movie, etc.) Accessing social networking site (Facebook, Tweeter, etc.) Accessing email Text messaging
On a scale of 1-5 (1 being low and 5 being high), how fluent do you regard yourself as a smart phone user?	Median: 5 Mean: 4.4
On a scale of 1-5, how essential is a smart phone to you?	Median: 4 Mean: 3.4
On a scale of 1-5, how satisfied are you with your current smart phone?	Median: 3 Mean: 3.2
In your opinion, what do you miss from your smart phone?	Simplicity of the operation (2), Bigger screen size (1); Faster processor (1), Bigger button or keyboard size (1)
Do you have a smartphone? If no please explain:	I' tried but found it difficult to use; I do not need other features except calls

6.3.3 Food and Physical Activity Balance

The food and physical activity balance part of the questionnaire (Appendix E) indicated that four participants did not keep an account of the calories consumed, while one participant tracked it on a regular basis and one tracked it occasionally. Five of the six participants did not track their wheelchair propulsion and the remaining participant tracked it with a Global Positioning System (GPS) application on his phone. Five of the six participants tracked their other types of PAs by tracking the time duration of their physical activity (N=4) and tracking the number of repetitions or sets of resistance exercises they performed (N=4). Four of the five participants who tracked their PA were satisfied with their current method of tracking PA with one of the participants neither satisfied nor unsatisfied with the current method of tracking. Two participants had suggestions on how to maintain a balance between nutrition and PA by: a) limiting the amount of high fat food consumption (P7) and b) exercising caution toward eating habits and exercising every day (P11). Four of the participants had the following suggestions on how to measure the PA of wheelchair users: using a timer, using a GPS, tracking the number of transfers to and from the car, and using a specific PA plan adapted to different age and activity level groups.

6.3.4 Securement of the Physical Activity Monitor System

Participants' responses to the ease of securing the G-WRM holder, i.e. a permanent securement, to the spokes of the wheelchair wheel varied from very easy to difficult with one for very easy, one for easy, three for neutral and one for difficult. Two participants (one who chose neutral and the other who selected difficult) indicated that it would be easy if they were to transfer to another surface or bed before securing the G-WRM holder to their wheelchair. However, all participants indicated that it was very easy to plug the G-WRM in and out of the holder, once this holder had been secured to the spokes of the wheelchair. The median (mean ± SD) satisfaction ratings (with 5 as high and 1 as low) for the dimensions (size and weight) of the G-WRM, the dimensions (size and weight) of the wocket, and the comfort of wearing the wocket were 4.5 (4.5±0.5), 5 (4.7±0.5), 5 (5.0±0.0), respectively.

6.3.5 Evaluation of a Physical Activity Monitor System

The evaluation of PAMS was collected through questionnaires including Evaluation of PAMS, System Usability Scale, Technology Acceptance Model, and open-ended questions. Table 30 shows the responses for the general evaluation of PAMS. Table 3 shows the responses to the overall System Usability Scale and Technology Acceptance Model. The final score for the SUS measured was a mean ± SD of 94±7 indicating that PAMS has a very high usability and learnability (A) [160, 166]. Furthermore, the responses of the participants to the modified TAM had a median range from 4.5 to 7 and mean range from 4.5 to 6.5 indicating that PAMS was useful [159].

Table 30: Responses to the Evaluation of a Physical Activity Monitor System questionnaire.

Question	Response (N) and comments
Do you think the information provided by PAMS is helpful to you?	Yes (6): • It can help me monitor my miles and speed. • I like knowing the distance I travel even when I am simply doing my daily activities. Track burning calories. • Allows the user to track activity in a way that they can use to better their physical activity. • I think this would be a great device in my daily activity as an athlete to stay healthy. • Helps show my activity level • To better know the condition; monitor my weight; going to gym; losing weight
Are you satisfied with the way the information was presented on the smartphone application?	Yes (5) • The application is very easy to understand and to work • Simple, and effective. Gives good data. • Information given in the application is very useful. • Very good as it provides calorie information No (1) • I would like the measuring tools in a form I ‘am used to seeing in my everyday life such as miles. Suggestion (1) • English conversion/option
Do you wish to see any other physical activity information that is not provided by the PAMS?	Yes (3) • Heart rate, timer, or time • I would like to know the amount of energy used while transfering from Wheelchair to car; I would like some monitoring of body fat composition to see how much body fat I burn while exercising on any of my ADLs. • Propulsion No (3) • Really touches upon useful data.
Do you think the PAMS may help you change your physical activity levels?	Very likely (2) • I would work harder to increase the speed Definitely (3) • The PAMS would allow to evaluate my work out on a daily basis. Neutral (1) • Not change but track easier for activity and calories burned

Table 31: Responses to the overall System Usability Scale and Technology Acceptance Model.

Overall Usability Questionnaire: System Usability Scale		
Question	**Median**	**Mean ± SD**
1. I think that I would like to use this system frequently.	7	6.5 ± 0.8
2. I found the system unnecessarily complex.	1	1.2 ± 0.4
3. I thought the system was easy to use.	7	7.0 ± 0.0
4. I think that I would need the support of another person to be able to use this system.	1	1.8 ± 1.6
5. I found the various functions in this system were well integrated.	7	6.8 ± 0.4
6. I thought there was too much inconsistency in this system.	1	1.2 ± 0.4
7. I would imagine that most people would learn to use this system very quickly.	7	6.7 ± 0.5
8. I found the system very cumbersome or burdensome to use.	1	1.2 ± 0.4
9. I felt very confident using the system.	7	6.8 ± 0.4
10. I needed to learn a lot of things before I could get going with this system.	1	2.0 ± 2.4
Overall Usability Questionnaire: Technology Acceptance Model		
Question	**Median**	**Mean ± SD**
1. Using PAMS gives me greater control over my physical activity levels.	7	5.7 ± 2.4
2. Using PAMS improves my physical activity levels.	6	5.7 ± 1.4
3. Using PAMS allows me to be physically active than would otherwise be possible.	4.5	4.5 ± 2.1
4. Using PAMS makes it easier to do my regular physical activity.	5.5	5.0 ± 2.4
5. Overall, I find this product useful in achieving my regular physical activity.	7	6.5 ± 0.8

Table 32: Performance rates in terms of success rate, error rate and frequency of problems.

Task	Success Rate	Error Rate	Frequency of problem
Using the PAMS app	100	0	0
Entering demographic information	100	0	0
Wearing the wocket	100	0	0
Securing the G-WRM Holder	70	30	3
Placing the G-WRM in it's holder	100	0	0
Software failure	80	20	1
Delay in data (synchronizing)	10	90	6
Classification of correct PA	50	50	25

6.3.6 Qualitative Data Analysis

The qualitative data analysis is included in Table 5. The data analysis has been split into major categories with appropriate subsections for each category. The subsections included general findings, positive findings, negative findings, suggestions, and recommendations (possible solutions).

Table 33: Qualitative analysis from the transcripts obtained from video and audio recordings of the usability study.

1.	**Food Tracking Methods** **a. General Findings** Only two of the six participants tracked their food. **Comments** P11: “Actually yeah, I just got, I’ve just been more self-aware and self-conscious of what I’ve been eating in the last 3 months, about what I put in, how I prepare my food and what I eat. So in the least 3 months it’s been yogurt free and water in one meal a day. I am conscious about how I prepare that meal. No fried food, baked fish, steamed vegetables, No white rice, brown –wheat rice. That type of thing. But I’m not actually counting. But they say you don’t put no more portions than as big as your hand on your plate.” P10: “sometimes I have used MyFitnessPal to track calories”
2.	**Current PA tracking methods** **a. General Findings** Only one of the participants tracked his wheelchair based PA using a GPS-based application on his phone. The application showed speed, distance, and duration. **Comments** P8: “because I use my phone, and I have like I guess it’s just the GPS or whatever. So I turn it on whenever I do laps, or go for rides” P10: “From the questionnaire, may be one can use a bike computer but I have never tried it.” P11: “you do have to be conscious about what you eat and exercise on a daily basis. Because you know gravity is not nice when you are sitting down. You see what I’m saying? And that’s what’s happening”
3.	**Need of PA tracking by the consumers** **a. General Findings** Two of the participants indicated a need for some type of PA tracking monitor before being introduced to PAMS. **Comments** P8: “how many times did that wheel spin and how many differences, I mean how many times the disk would spin compared to this one.” P8: “you know like there’s the apps on the phone, but they’re not really specific to wheelchair users.” P10: “not really. I mean, you know I’ve looked at all the basic ones that you use for recording for an able bodied person” P10: “I am interested to see how much distance I covered” P10: “MyFitnessPal cannot track my physical activity.”
4.	**Food Tracking Methods** **a. General Findings** Only two of the six participants tracked their food. **Comments** P11: “Actually yeah, I just got, I’ve just been more self-aware and self-conscious of what I’ve been eating in the last 3 months, about what I put in, how I prepare my food and what I eat. So in the least 3 months it’s been yogurt free and water in one meal a day. I am conscious about how I prepare that meal. No fried food, baked fish, steamed vegetables, No white rice, brown –wheat rice. That type of thing. But I’m not actually counting. But they say you don’t put no more portions than as big as your hand on your plate.” P10: “sometimes I have used MyFitnessPal to track calories”

Table 33 (continued)

5.	**Current PA tracking methods** **a. General Findings** Only one of the participants tracked his wheelchair based PA using a GPS-based application on his phone. The application showed speed, distance, and duration. **Comments** P8: "because I use my phone, and I have like I guess it's just the GPS or whatever. So I turn it on whenever I do laps, or go for rides" P10: "From the questionnaire, may be one can use a bike computer but I have never tried it." P11: "you do have to be conscious about what you eat and exercise on a daily basis. Because you know gravity is not nice when you are sitting down. You see what I'm saying? And that's what's happening"
6.	**Need of PA tracking by the consumers** **a. General Findings** Two of the participants indicated a need for some type of PA tracking monitor before being introduced to PAMS. **Comments** P8: "how many times did that wheel spin and how many differences, I mean how many times the disk would spin compared to this one." P8: "you know like there's the apps on the phone, but they're not really specific to wheelchair users." P10: "not really. I mean, you know I've looked at all the basic ones that you use for recording for an able bodied person" P10: "I am interested to see how much distance I covered" P10: "MyFitnessPal cannot track my physical activity."
7.	**Orientation and demonstration of PAMS: Video (Appendix H)** **a. Positive Findings** The user's liked that the video was short and informative. The video explained PAMS to both the non-smartphone and Smartphone users. The video explained PAMS in more detail to non-smartphone users. **Comments** P6: "That's very detailed man." P8: "Like the video, I really like how the video was short, it was sweet. It was bang, bang, bang. There was not a bunch of extra stuff to confuse you." **b. Negative Findings** The G-WRM placement was not clear; three of the six participants had to either look at that part of the video carefully or asked further questions. **Comments** P6: "I had to watch it again" **c. Recommendation** Animation to show how the G-WRM holder goes between the spokes of the wheelchair and the buckle is facing out.
8.	**Manual for PAMS** **a. Positive Findings** The participants found that the PAMS Manual was self-explanatory with useful pictures (Appendix G).

Table 33 (continued)

	Comments P8: "it's very simplified. You know not everybody is going to be good with technology. So, especially if you get somebody a little older that's trying maybe [t]o get back into doing some physical activity. You don't throw out the stuff at them to confuse them, and they lose the whole idea of what they're doing."
9.	**Application on Smartphone** **a. Positive Findings** The application was very easy to use. **Comment** P7: "very easy. I was listening, but I was not watching." P7: "experience with smarphones. I like the whole idea that is touch screen. I mean, touch screen makes it easier for a person to find things." P6: "it's really easy to work." P8 "It's to a point that it's easy to read, there's not a bunch of stuff you don't need there. I like how you can adjust it to your height and weight and stuff. It's your phone, or the app, it's not just to anybody. It's more specific. It kind of understands what one is doing while you're using it." P9: "P: It's really easy. Very easy. I think even somebody who is not using an iphone on a regular basis nowadays would be able to figure that out." P9: "it looks awesome. I like it a lot. I think this looks fantastic." ***Function of resetting a particular Parameter for a session:*** P9: "It makes it really easy, the whole screen like that Reset that easily by the touch without having to set everything. **b. Negative Findings** Even though there was a scroll bar to input, height weight and age, it was not fast enough for one of the participant. Using a touchscreen was difficult for P11 as she had minimal prior experience with smartphones. For example, she repeatedly held an icon rather than feather touch it. **Comments** ***Inputting Demographic Data*** P10: "so one suggestion I can give for the demographic area here, cause this was sitting down at 140 pounds, and I am 210, I had to sit there and hit the button forever to go up. Instead of being able to push it and scroll down faster" ***Smartphone*** P8: "It's very simple. I mean, if somebody doesn't have a basic knowledge of the smartphone I can understand it being a little confusing you know cause they look at a screen and they're like: there's no buttons." **c. Suggestion** P7: "Include injury level to make it specific to wheelchair users. " P7: "Like the pause button: to continue the exercise session" **d. Observation** ***Sensor Connection*** There was a delay between selecting the wocket set and then the sensors connecting to the app through bluetooth (coming ON). One of the participants (P10) tried "Reconnect" as the sensors didn't connect to the app immediately. ***Learning while using the PAMS for the first time (+ve)*** P10 pressed the reconnect when the sensors didn't come on in less than 5 secs. We had not even told him there was that function available.

Table 33 (continued)

	e. Recommendations ***Sensor Connection*** Show a message asking them to wait till the sensors come ON with a large message for at least a few seconds. Software wise we should not let them reconnect unless a sufficient amount of time has not passed. ***Touchscreen usage*** Change the time to open an App from the home screen for this person. Provide some training to use smartphone. ***Session Recording*** Design the application that user can have sessions that he can separately workout compared to the continuous tracking. The consumer should be able to stop the session if one wants to take a short break during their workout. ***Choice of Sensor Set (Green vs. Red Set)*** The OK button on choosing the wocket set should disappear immediately after chosen as two of the participants pressed it more than once as they thought it did not register their selection.
10.	**Information by Application** **a. Positive Findings** The information provided about Calories, Duration of PA, Distance travelled and speed were specific and appropriate. **Comments** P6: "definitely I think it's really good information I could use. Pushing miles would be good for me at a practice so I know how many miles I push a day. Yeah, cause we push a lot at practice in the University. So yeah. I would like to know myself. Yeah." P6: "Yeah, like speed. I want to see like if I start pushing fast, one day then work out for a month or so, then see if the speed would increase, if I get faster" P7: "Yeah, I kind of like the actual calories, in my understanding how many calories I am putting in, I like to know how many I am burning." P8: "Does this thing continuously read [estimate] your calories even while sitting there? That's pretty cool." P8: "It's very simplified so that it can help you keep track of like your activities. Especially like somebody that's maybe on a diet, and trying to really regulate their calorie burning and intake, it would allow them to, without doing excessive workout, they can keep track of their calories while they are like, you know maybe at work, or doing something at desk or something, and then they can get in there with some other physical activity too, and then it will monitor all that over a widespread as to just like not knowing, you know, it's very helpful, I think so" P9: "It's good. Everybody wants to know distance travelled, calories burned. Especially distance travelled. Everybody I interact with is like: I did so many miles today." P9: "Calorie burn is a bonus. You guys have touched it all." P11: "Well what is showing, yeah, very good. Yes, it is Calories, distance... No, cause those are your basics. I mean there could be more, but that's satisfying." ***When the application showed that the participant was performing arm-ergometry:*** P11: "I need that type of data in my life"

Table 33 (continued)

	b. Negative Findings The application did not present the distance travelled and the speed in a form the participants were familiar with. **Comments** ***Units for Information displayed*** P7: "I would prefer it in miles per hour. More something that I am accustomed to see it. I can picture" P10: "Maybe, it would be good to also have English conversions." **c. Recommendation** Allow users to choose English (mph and miles) and metric units (m/s and meters or kilometers).
11.	**Securement of G-WRM holder and G-WRM** **a. Positive Findings** Three of the participants found it really easy to place the G-WRM holder, which is a onetime installation on their wheelchairs. All the participants could easily place and remove the G-WRM in and out of the G-WRM holder. **Comments** P9: "I think the device where it is now, of mounting it on your chair, It's a lightweight, it's easy to slip in, it's a very compact device. I did not do an even great job of even securing it to the spokes very well but it did not move around too much it seemed. It seemed it stayed there just like that. Very easy to use, popping it back out the case there, it did not like jump on me, it smoothly came out and rested." P8: "It's very simple" P8: "It's perfect. ...I Have a couple more spokes than others do, I thought it might be a problem but it was fine, You did a good job designing that piece." P9: "I could sit on and do it, but I would rather transfer. I would get out of the chair and make myself more comfortable to look at it. I think I would do a better job at placing it out of the chair, especially the first piece." **b. Negative Findings** Two of the participants had difficulty to attach the G-WRM holder to their wheelchair while sitting on the wheelchair, as they did not have trunk control. **Comments** ***Putting the G-WRM holder*** P6: "If I transfer I can put the datalogger" P7: "difficult to put datalogger sitting on the chair" **c. Suggestion** Need to come up with a different design for the G-WRM holder for wheels that have really close spokes. Pinching the G-WRM's buckle to pull it out could be difficult for someone who has high level injury (P10). However, pushing it or having a clip to pull it out would be easier for persons with tetraplegia. **Comments** P9: "In some cases spokes very close." P7: "Give good directions of getting out of the chair" P9: "I think you can always ask someone to help you when you're putting that on. It's very easy.." P10: "Use long zip ties." P10: "There are only so many wheel types, you should just make 3-D models that just go right on,"

Table 33 (continued)

12.	**Securement of Armband** **a. Positive Findings** P6: “will forget it on the arm; easy to wear wocket” P8: “I actually cannot recognize this thing is on me anymore.” P8: “It’s simple to wear” P9: “The armband is easy to use, lightweight, not much to it around your arm that makes it difficult to propel the chair or anything, ….” **b. Suggestion** **Comment** P10: “You can have gasket or a rubber ring so that the armband does not slip down my hand” **c. Recommendation** Need to have armbands of various lengths to accommodate consumers with various upper arm circumferences. The armband length can be increased by increasing the length of Velcro loops until the Velcro hook.
13.	**Suggestion for improvement of PAMS** **a. Negative Findings** **Comments** P6: “Classification was not right as it was not picking the right thing.” P7: “remove the classification altogether” P9: “I know you are still working on the algorithms. But I think it’s neat that it’s picking up a little bit of wheelchair propulsion, deskwork, slow down. I know it will be better.” P9: “I could see people getting frustrated if the technology is not reliable: Oh, I’ve been there and pushed and pushed and pushed...” **b. Suggestions** **Comments** ***Weather or Waterproofing*** P8: “the wocket – are these waterproof?” **Impact Sports** P10: “Test these in rugby chairs” **c. Recommendations** ***Classification and PA detection*** We have to make sure that the algorithms can correctly detect the wheelchair based activities. We will Incorporate the classification algorithms and extensively validate their performance. Also we need to ensure that the data from the G-WRM and wocket are time synchronized prior to classification. ***Weather or Waterproofing*** We need to design a waterproof version of the G-WRM as the consumers may face rain, and snow while using G-WRM in the community settings.
14.	**Usefulness of PAMS** **a. Positive Findings** All the participants thought that PAMS is useful in tracking PA and in many cases help them achieve their PA goals. **Comments** P7: “I think PAMS again will help, definitely help the athletes training. You know our wheelchair users did our training in various sports. I think it would be imp for them to know what other physical activity, what impact physical activity is having on their body. I think that’s good.”

Table 33 (continued)

P9: "I think this device would be very helpful to me in my daily activity for sure. Just as somebody who is conscious of his health and tries to stay as healthy as possible, I think this would be very helpful in monitoring my activities, set better goals for myself, monitor my daily activity better." P8: "Nailed it on the head" P9: "I think it would definitely change my PA level, cause it would allow me to see what I do and perfect it better. My PA doing exactly the mileage I want to do, or getting more. Out of it each day, from speed, calories burned, definitely allow me to change my work out, make it better and better as I got familiar with." P9: "It's an easy application, easy to put on the chair, easy to use on the phone. Most people, a lot of people now have, even they might not have a smartphone, they are learning the touch screen technologies through just your regular phone now has a touch screen. It's very common to everybody, you know, at the bank or anywhere else, it's there, at the grocery store. Everybody is familiar with that technology a little bit, so it's very easy to use, not too many different screens to change to, you just put in your information and it gives you the information you are getting out." P9: "Overall, I am very satisfied with the technology, so I would definitely push on others, my friends and others who play sports or not play sports, to try this device on a regular basis." P10: I think it will be nice to integrate or allow MyFitnessPal app to be able to get data from this device as MyFitnessPal tells me what to eat and how much calorie I have to burn on a daily basis to reach my goal. P10: "If you can sync it with a computer, let me see what my lazy days are. That's what it comes down to." Investigator: Once you reach the goal, would you still keep – the things that you're doing, using, or would you drop the diet and PA? P11: "but for a lot of people it's not easier to maintain. Right. But no, I would still use the device to maintain, to maintain. Because I would want to see, I would want to know that I'm not falling of." P11: "But if I had this right now, and I have it, and I could take it home, now whatever I'm doing with the resistance bands, or the exercises being for the physical therapy . If they could tell me that I'm actually physically doing something, and I'm helping, oh, you would be surprised. That's encouraging, you know. Same difference as they say, well if you're not good about going to the gym, take a friend with you and... And me, I don't have nobody that I know. I do, some of my friends go to gym after work, which is not convenient for me at the time." ***Monitoring*** P8: "I would use it everyday" P11: "To better know what condition I am, to monitor my calories, my weight, and since I go to the gym, that would be a good idea, for, you know, for losing weight, burning calories or fat or so, that would really help, cause yeah, it would be a helpful thing for somebody in my position. Yes, that really would" P11: "Definitely, because I would be more interested in how the distance, calories etc. you know what I mean? That would even motivate me. Cause I would know. Cause if you see something, in a written, or you know you are losing calories or fat in your body, that makes you even striving harder, vs not seeing it…." ***Investigator: So you think that constant positive feedback, even if it does not show yet in the mirror, it would be the thing to keep you going?*** P11: "Yes, because not only the outer work is showing, the inner, that you're losing. Because that inner you would eventually see it on the outside. A lot of people would like this. Even walking, not just wheelchair users. Because you know, it still don't matter, people that walk don't have a lot of discipline." **b. Suggestion** **Clinical tool for new users** P8: "The only thing that I really think it could use, we were talking about how it could do the propulsion to distance rate [Show distances covered per propulsion push]."

Table 33 (continued)

15.	**Technology Acceptance Model** Three of the participants (P7, P10 and P11) indicated that the system will not make them more active or will not make it easier to attain their desired PA. From triangulation of observation, qualitative and quantitative data we found that if the participant was an athlete or was very active they were more likely to report that PAMS will make them more active or will make it easier for them to do PA. However, P11 also reported that information provided by PAMS would encourage her to perform PA. **a. Positive findings** **Comments** ***Motivation*** P8. "Yeah, definitely, it helps to have an actual push. Cause when you do it on your own you're just like: yeah, I guess it's fine" P11: "encouraging information" **b. Negative findings** **Comments** ***Will the system make me more active?*** P7: ": No, I think the person already buying it is already going in that route. You are not going to get nobody to say this is going and say oh this is going to make me more active." P10: "I like this for tracking sense, to know what my calories are burned, you know being able to see my distances is nice, but it's not that it makes it easier, or it would change anything for me. For other people who are maybe told ok, you need to become more active, it's a good way for a doctor also to sit there and say – ok, try and burn an extra 500 calories." ***Motivation*** P7: "Do I think it would help motivate people to be Physically active? No, I don't think it would motivate people to be physically active." P7: "I don't think it will motivate me to do more PA" P11: "It is not the motive for doing the act. It would be in the middle somewhere" P11: "no, that would not make it easier, no. In the middle. Cause you would do it anyway. It just keeps track."
16.	**Market for tools to track PA from Consumers Perspective** **a. General Findings** **Comments** P7: "I don't know anything else on the market right now. Not that I'm looking. But I, out of the top of my head, I don't know anything like that on the market for wheelchair users." P8: "you know like there are these apps on the phone, but they're not really specific to wheelchair users." P11: "it's encouraging. It's, what do I want to say...I'm impressed, I like it, it's encouraging, it will motivate me a lot to do what I need to do, as for physical activities. But you are asking me my overall feeling about it? I like it, I like it. I would use it if it was on the market." **b. Suggestion** P7 indicated that we should market this technology to Nursing Homes and also provided a marketing tip. **Comments** P7: "How about for a few, for one hour a day you do everything without having no one push you around. That might happen." ***Marketing tip*** P7: "Here is a device that can help you monitor your PA to improve your life expectancy. Who does not want to live forever?"

Table 33 (continued)

17.	**Social networks** **a. General Findings** Consumer's perspective on using PAMS along with social networks. **Comments** P7: "Facebook will help with competing with others" P8: "Would you be able to share that data on Facebook? If so that would be cool." P9: "I think this is, in this time and age the social networks and technology this is a fantastic device to have for a wheelchair user, you know, for all levels of exercise and anything they want to do. I think this could really help a lot of people get out there and do a little bit more when they have something showing them what they're doing on a regular basis. Just going outside and about. And I think it would be fun, knowing a lot people with disabilities, the idea of a Facebook and all that. Somebody who is not even an athlete to somebody who's a friend and showing them what I did to someone else who doesn't maybe play sports. See what they try to do. It could really enhance other peoples' lives, and how us, who are trying, to enhance newer wheelchair users, showing them the things that can be done out there." P10: "if you can connect it to social network, then it will be really good for team coaching."
18.	**Wish list of suggestions for future PAMS** **a. General Findings** **Comments** ***Holder for Smartphone*** P6 and P8: Leg band for holding the phone while exercising or a band to hold the smartphone on the person or the wheelchair ***PAMS for Pushrim-Activated Power-Assist Wheelchairs (PAPAW)*** P11 recently got a PAPAW to prevent her upper arm from injury and pain. We will have to adapt the algorithms to take this technology into consideration. ***Timer and Seconds Counter*** P6: "yeah, because, sometimes it's all about the breaks." ***Surface Roughness*** P8: "Surface roughness" ***Heart Rate*** P6: "include heart rate" ***Transfers to car*** P7: "the amount of times a manual wheelchair user transfers from chair to vehicle/car." ***Fat content*** P7: if it can show fat content P11: "Showing that I am burning fat" ***PAMS for Aqua therapy*** Based on what P11 told us that she performs a lot of Aqua therapy for PT

Table 33 (continued)

19.	**Other Qualitative Questions** **a. General Findings** **Comments** ***Why no smartphone*** P11: "I tried but I found it's too difficult. I did not need all these features.." **Difference in perspective:** P11: "Is not, and that's where, all my discipline has to come in. Because I don't like the way I look."

6.4 DISCUSSION

Five of the six participants reported they performed some form of regular PA which is significantly above the US average for MWUs (13-16%) [73, 74]. Some possible explanations for this anomaly are: self-reporting, our inability to measure the participants' PA levels in the community, and the fact that the majority of the participants who responded to the flyer and the recruitment were self-opted and happened to be physically active. Future studies should specifically sample wheelchair users who are not physically active and resemble the average PA levels among MWUs in the US. However, the demographics related to the SCI with respect to the level of injury and the completeness of injury was reasonably represented. Regarding the use of weight management techniques, three participants understood the importance of cooking and eating habits [108]. One participant specifically stated she was very conscious of her food selection, a second participant claimed he tracked calories on a regular basis, and a third one monitored his calorie intake infrequently. The participants' interest in tracking their calories suggests a possible development for the PAMs app, namely incorporating aspects of behavior monitoring techniques and other education components to motivate individuals to pay attention to the food they consume [107, 108, 130]. One of the participants (P10) suggested that if we allowed MyFitnessPal, an app with food tracking capability, to access the PA information from the PAMS app this function would assist him to better balance his food and PA.

On the technology front the baseline questionnaire data indicated that most of the MWUs (N=5) in this study had a smartphone and could use this technology fluently. This indicates that the telecommunication technology used by MWUs is similar to the general population (91% of adults in US have a cellphone with 56% of adults having a smartphone) allowing us to use the smartphone as a feedback device for monitoring PA levels for MWUs [167]. Four of the six participants reported they used the time duration of performed PAs to track their total amount of PA. In addition, one of the participants regularly uses a GPS-based smartphone app to track his propulsion activity. Based on the SUS, TAM scores and the qualitative data analysis we found that PAMS was easy to use and participants rated the system high for satisfaction, usability and learnability. Further, five of the six participants indicated they would use PAMS on a daily basis if available on the market. As none of the participants in this study population were at stage 1 (pre-contemplation) of the PA Stages of Change model, i.e. not yet acknowledging that there was a problem with their PA behavior that needed to be changed, this might have biased the users' satisfaction with PAMS. This device fulfills a need all participants already had. [162, 164]. In addition to the PA stage of change bias we identified a technology bias, as most of the participants used on a daily basis their smartphones, a major component of PAMS. The usability study's observations and recommendations for designing the next version of PAMS are included in Table 5.

The usability study allowed us to identify some key problems we plan to address during our next iteration in the development of PAMS: a better method for securing the G-WRM holder and the G-WRM, improved PA detection and classification, and providing additional wheelchair movement information.

6.4.1 Securing the G-WRM holder and the G-WRM

From this research, we concluded that the current design of the G-WRM holder works for the majority of the manual wheelchair users who use wheels with less spokes (spokes that are at least 2 inches apart at the rim). However, we need to redesign the G-WRM holder and the G-WRM in order to successfully secure the G-WRM on wheels with more spokes (closer than 2 inches at the rim) or on wheels that do not have spokes without any obstruction to the user. One of the participants (P6) had problems with securing the G-WRM on the wheel because he had an older model of the wheelchair wheel with more spokes. Some of the design options are using the hub of the wheel or using other types of attachments such as Velcro to hold the device. Four of the participants indicated that the video and manual should clearly instruct them to transfer out of the wheelchair before securing the G-WRM holder, as this step was necessary for an easy and successful securement of the G-WRM holder. One of the participants also expressed the concern that persons with tetraplegia missing the ability to pinch might not be able to use the buckle design to place and remove the G-WRM in its holder. A possible design solution is adding to the G-WRM and its holder a push-release engagement, which would allow the user to push in to either lock an unlocked device or release a previously secured device from the holder. The G-WRM also requires an additional clip to help people with little finger dexterity to hold the G-WRM; these users could hold the G-WRM by the clip rather than clasping the whole device.

6.4.2 PA detection and classification

One major problem that needs to be immediately addressed is the imprecise working of the classification algorithm. The problem resulted due to two reasons: a) use of preliminary classification algorithms developed in a laboratory environment to detect wheelchair based PAs; and b) problems related to data synchronization between the G-WRM and the wocket. To address the first set of problems we plan to use the two level classification algorithms we have developed recently, which first classify PAs based on wheelchair movement and then appropriately detect PAs such as resting, arm-ergometry, other sedentary PAs, PAs that may involve small amounts of wheelchair movement, wheelchair propulsion, caretaker pushing and basketball (Chapter 5). For the second part of the problem we require the firmware developer to set the wocket's frequency for sending data at 1Hz, an alteration of the current rate of 40Hz. Additionally, the Android programmer should perform rigorous tests to ensure a correct alignment of the data prior to applying the classification algorithms. The data management on the PAMS app side should use appropriate software framework to process data from external sensors. Moreover, some classification errors shown by the Android-based smartphone indicate the presence of a delay in obtaining the data from one of the sensing devices. The firmware and PAMS app developers should fix this delay, probably caused by a Bluetooth protocol issue.

6.4.3 Wheelchair Movement Information

Even though the classification algorithm did not always detect correctly all wheelchair-based PAs, the participants were very satisfied with the wheelchair movement information in terms of distance and speed. The video analysis for a random sample of participants (N=2) confirmed the accuracy of the distance and speed information, which was consistent with the validation based study [120]. A minor adjustment we need to incorporate in the PAMS app is offering users the ability to input their wheelchair wheel diameter rather than always using the default value of 0.61 m (~24 inches), applicable to the majority of the wheelchairs. As our participants expressed the desire to measure the speed and distance in mph and mile, we will modify the app to give users the option of choosing between the metric and the US/Imperial system.

6.4.4 Usefulness of PAMS

To our knowledge, there have been no studies performed on evaluating the usability of PA monitors among wheelchair users. The overall usability analysis of PAMS showed that all participants were very satisfied with PAMS and found the information provided by PAMS effective towards monitoring their PA. The majority of participants enjoyed interacting with the interface and indicated they would continue to use this device even after meeting their PA level goals. In addition, the triangulation analysis revealed that participants who reported they were athletes (more active on a regular basis) indicated that PAMS would encourage them to be physically more active than participants who were not athletes. One participant (P8) also suggested that PAMS could be used as a clinical tool for new wheelchair users. The results of this study are very encouraging and allow us to reduce or remove barriers that limit translating the PAMS technology into a consumer product.

One of the limitations of this study is the small sample size (N=6) of participants. In future we plan to perform multiple usability studies to iteratively incorporate user feedback in the design and development of PAMS as a consumer product [156, 161]. We also plan to perform rigorous tests in the laboratory to evaluate the battery recharging and use of PAMS for one to two weeks prior to performing a longitudinal study of PAMS in community settings. The software and the device development teams should also perform content analysis of recorded videos to guide further developments and refinement of PAMS and the PAMS app.

6.5 CONCLUSION

PAMS can play a crucial role in informing consumers who use wheelchairs about their PA levels. The study indicated that participants were very satisfied with PAMS and were ready to use it on a daily basis if available on the market. After incorporating the modifications mentioned in this study and performing some more laboratory tests, PAMS will be ready for longitudinal testing among MWUs in community settings.

7.0 DISCUSSION AND RECOMMENDATIONS FOR FUTURE WORK

7.1 INTRODUCTION

For the past two decades, extensive research has been performed on utilizing activity monitors in the ambulatory population without disabilities. However, only limited research has been performed in wheelchair users, a population which faces a number of additional challenges including environmental barriers, physiological changes and mobility limitations. Therefore, our research evaluated and developed algorithms for existing activity monitors and developed new physical activity monitors especially for wheelchair users. Physical activity monitors for manual wheelchair users can play a crucial role in understanding their current PA patterns in the community, providing them with information regarding their PA levels, and motivating them to lead a healthy lifestyle. Optimal PA levels in MWUs can reduce physical health problems, and improve the psychological well-being and quality of life. However, caution needs to be exercised when using activity monitors for this population. On one hand we want to increase their PA level but on the other we want to avoid increasing the risk of upper arm pain and injury.

7.2 RESEARCH STUDIES PERFORMED

Our approach began with the development and evaluation of new models for SenseWear, an off-the-shelf activity monitor, designed for the general population without disabilities. The EE estimation algorithms indicated that activity specific models estimated EE better than a general model, which led us to develop and evaluate classification models to detect resting, wheelchair propulsion, arm-ergometry, and deskwork. The results indicated that the average EE estimation error using the activity-specific EE prediction models for these four wheelchair-related activities post classification (accuracy: 96.3%) was 5.3±21.5%. The high classification accuracy and low EE estimation errors suggest that the SenseWear can assist researchers and clinicians to classify and estimate the EE for the four activities tested in this study among MWUs with SCI.

Based on previous research conducted at HERL and the studies discussed above, we found that wheelchair mobility characteristics are crucial in studying PA patterns in MWUs. This insight motivated us to develop and evaluate a gyroscope based wheel rotation monitor (G-WRM) as a component of a newly developed Physical Activity Monitor System (PAMS). PAMS consists of a G-WRM, which tracks wheelchair mobility, and an accelerometer, which tracks upper arm movement. We tested PAMS in 45 MWUs with SCI in structured (HERL) and semi-structured (NVWG) environments and we also tested a subsection of this population (N=20) a second time, in their home environments. We classified the PAs into resting, arm-ergometry, other sedentary activities, activities involving some wheelchair movement, propulsion, basketball and caretaker pushing. The EE estimation results (error: -9.8%) and the classification results (accuracy: 89.3%) indicated that PAMS can track wheelchair-based activities in laboratory and home environments. Furthermore, we evaluated the usability of PAMS in six MWUs with SCI. The usability study indicated that users were very satisfied with PAMS and would use this device if it were available on the market. We used participatory action design concepts to evaluate this newly developed technology and hope that the results of this study will reduce the barriers of transforming PAMS into a market product.

7.3 ALIGNMENT WITH THE PURPOSE OF THE REHABILITATION ACT AND NIDRR'S MISSION

The research projects discussed in this dissertation assist persons with severe disabilities and therefore are closely aligned with the first priority of the Rehabilitation Act of 1973: serving individuals with severe disability [168]. Our work is also closely aligned with the National Institute of Disability and Rehabilitation Research's (NIDRR's) mission and interests, in that it involves "developing rehabilitation technology" which increases health and function and quality of life among "individuals with the most significant disabilities" [168, 169]. We developed a physical activity monitor system that is "engineered to meet the special needs of individuals with disabilities," is easily usable by consumers in future, and is therefore aligned with Sections 204.(a)(2)(B)(iv). We provide PA level feedback to consumers, researchers and clinicians through "existing telecommunications systems" (smart phone), matching the goal of Section 204. (a)(7); in future, consumers will share this physical activity information with their friends and family through social networks to encourage healthier lifestyles. Moreover, we believe that our work will increase knowledge of and improve methods in the rehabilitation of individuals with severe disabilities by assisting therapists and rehabilitation professionals to evaluate the efficacy of physical rehabilitation programs, matching the goal of Section 204. (a) (2)(B)(vi).

As per the NIDRR's Long-Range Plan for Fiscal Years 2010-14, improvements in health and function are critical antecedents to improve employment for persons with disabilities [169]. This work concentrated on the individual level of NIDRR's units of analysis for employment research and tried to address components of objectives 1.2 and 1.4 under the research and development goals [169]. A physical activity monitor system that quantifies a manual wheelchair user's upper extremity usage can indicate good arm function (Strategy 1.4.1), which is important to maintain mobility needed for employment [169]. Increased mobility helps MWUs live independently and participate in their community. Additionally, an increase in PA levels in MWUs can reduce secondary health conditions (Strategy 1.2.1), such as pain, fatigue, weight gain, muscle wasting, pressure ulcers and deconditioning, which also have an impact on work attendance and performance [169].

7.4 CONTRIBUTIONS

The contributions of our research are the following: we proved that off-the-shelf activity monitors cannot be directly used in MWUs, we explored collaborations with the industry (BodyMedia Inc.), we developed an activity monitor specific for wheelchair users (both hardware and software) which provides a comprehensive summary of PAs, consumers evaluated PAMS prototype and liked it, and we are currently exploring commercialization partners through Small Business Innovation Research grants. During this research we developed and evaluated algorithms for an off-the-shelf activity monitor and for a newly built physical activity monitoring system specifically developed for MWUs with SCI. We used data from a single multi-sensor based SenseWear activity monitor and multiple sensors based PAMS to quantify PAs in MWUs with an SCI. We provided real-time feedback to our participants about their PA levels in terms of distance, speed, EE and duration of moderate intensity PAs through an Android-based smartphone in MWUs with SCI. Furthermore, we validated PAMS through testing done both in laboratory and home environments.

7.5 ACCURACY OR ERROR ESTIMATION IN ACTIVITY MONITORS

A number of studies evaluated the validity of physical activity monitors in ambulatory population without disabilities by measuring the accuracy, namely the complement of error (Accuracy = 100% - Error%). Some studies reported very high accuracies (>90%), others reported high to medium level accuracies (>70%) and a third group reported low accuracies. In this section we discuss the accuracy of activity monitors in terms of the EE error estimation compared to a criterion. The EE error estimation can be divided into at least three parts a) error due to certain types of PAs where the device over/underestimates the EE, b) average error over a session including several PAs or extending over an entire day (24 hours), during which the device combines the over and under estimation of the EE, and c) error in a group of participants, for certain specific PAs or over a session, where the error is a combination of over and under estimation of EE within and between the participants. All these errors are important as they impact the performance of the device in a) specific interventions such as aerobic exercises or strengthening exercise, b) over a session or a 24 hour day, and c) in new participants who were not involved in the modeling phase of the algorithms. Researchers should consider the advantages and disadvantages of various errors discussed here prior to developing activity monitors to assess performance in a specific PA or to estimate the overall EE. Along these lines, athletes can use activity monitors towards improving their performance in a specific PA or regular consumers can use activity monitors in modifying their overall EE in order to maintain or decrease their weight.

Even though developers of activity monitors need to control the EE error types, the performance of an activity monitor is also determined by its ability to quantify most of the PAs at a reasonable cost and ease of use. Additionally, developers need to consider the consistency of the device, a feature which impacts the wheelchair users' ability to track PA patterns on a day-to-day basis. In other words, a reasonably accurate (>80%) and reliable activity monitor that tracks multiple types of wheelchair based PAs may be more beneficial than a very accurate (>90%) device which identifies a smaller number of PAs. A device that can work with multiple PAs might be able to pick and show the relative difference of PA levels performed on a regular basis within the same person allowing users to maintain or increase their PA levels. Another important aspect is that the performance of the activity monitor may change slightly in an individual who progresses from a sedentary to an active PA behavior meeting the regular PA quota. The energy expended in this person may be reduced slightly as they might become more efficient in performing the same PA. In this case the change in demographic variables, such as weight and fat content (based on skinfold measure), measured on a regular or monthly basis may be able to better predict the EE.

7.6 FUTURE RESEARCH AVENUES

The three studies performed here identified two solutions: SenseWear and PAMS. Both devices perform activity monitoring in various wheelchair-based PAs among MWUs with SCI. In addition, these studies stimulated our interest towards a number of new avenues of research in the field of activity monitoring among persons with disabilities. This section is divided into immediate or near future priorities and long term priorities.

7.6.1 Near Future Priorities

7.6.1.1 Estimation of PA in METs

Another way of approaching the PA quantification is to estimate the PA data in terms of METs, which is independent of the subject parameters [18, 70]. The PA estimation in terms of METs can then be used to estimate EE in wheelchair users. MET values can also be used to identify the duration of PA in light, medium and vigorous PAs.

7.6.1.2 Algorithms

Our research group will perform studies to evaluate various machine learning and traditional statistical algorithms to detect and estimate PA levels for various wheelchair-based PAs. We will also implement simple decision based algorithms to mimic common sense approach to prevent errors from applying machine learning algorithms on data that has not been previously dealt with. This will reduce frustration among researchers and consumers when tracking PA in community settings.

7.6.1.3 Longitudinal Evaluation of PAMS in Community

Based on the models and the technology developed here we will ensure the reliability and robustness of our device through multiple laboratory-based tests. Then we plan to perform a longitudinal study of one to four weeks. Future studies should compare the PA level estimation from PAMS with criterion measures such as doubly labeled water [93].

7.6.1.4 Monitoring Upper Arm Movements and Exercise Interventions

The publication Preservation of Upper Limb Function Following Spinal Cord Injury, a clinical practice guideline for health-care professionals, indicates that wheelchair users are at high risk of shoulder pain, rotator cuff injuries and carpal tunnel syndrome due to improper technique and overuse of upper extremities during wheelchair propulsion and transfers [134]. To address this problem we need to study the use of PAMS in monitoring propulsion and transfers. Based on our research we identified characteristic features of upper arm movement that may play a crucial role in objectifying and detecting upper arm movement during propulsion and transfers. We plan to modify PAMS so that it can be used as a clinical tool to train new wheelchair users in community settings.

Future research should develop and evaluate PAMS to estimate PAs that involve larger muscles in wheelchair users such as rowing, handcycling, tennis, and basketball. Further, this device can help evaluate the effectiveness of exercise based intervention programs to improve health and function among wheelchair users [59, 62, 65].

7.6.2 Long term priorities

7.6.2.1 Monitoring Wheelchair Use in Community Settings

Upcoming research should evaluate whether G-WRM, a key component of PAMS, can track manual wheelchair use in the community settings over several months. Monitoring assistive technology use in community settings will permit evidence based practice in wheelchair usage and prescription [117, 118].

7.6.2.2 Extending PAMS to Wheelchair users with Other disabilities

Research should be performed to develop algorithms for PAMS to estimate PA in persons with other disabilities such as multiple sclerosis, cerebral palsy, and amputees. This also involves identifying how PAMS can monitor PA in power wheelchair users.

7.6.2.3 Making PA tracking Fun

Future research should investigate how to make the interaction between users and the PAMS app enticing. If users were motivated to use PAMS consistently, on a daily basis, this would increase their adherence to a healthy lifestyle. Aspects of Human Computer Interaction such as games, incorporation of social networks and virtual buddies could motivate users to attain and maintain their PA levels. The creation of virtual buddies can take into account a number of parameters such as interviews, personal goals and customizing the physical activity monitor for each individual. Self-monitoring along with social support can play a crucial role in improving the quality of life of wheelchair users.

APPENDIX A

FEATURES USED FOR CLASSIFICATION AND REGRESSION EQUATIONS AND THEIR DESCRIPTION.

Table 34: Features used for classification and regression equations and their description.

Feature	**Description of a feature**
mean_x_rtUArm	Mean of acceleration in one axis
stdev_x_rtUArm	Standard deviation of acceleration in one axis
rms_x_rtUArm	Root mean square of acceleration in one axis
mad_med_x_rtUArm	Mean absolute deviation with respect to median in one axis
zcr_x_rtUArm	Zero cross rate in one axis
mcr_x_rtUArm	Mean cross rate in one axis
ampl_x_rtUArm	Amplitude in one axis
energy_x_rtUArm	Energy content of one axis acceleration
entropy_x_rtUArm	Entropy content of one axis acceleration
corr_x_xyz_rtUArm	Correlation between acceleration of an axis with the resultant acceleration
corr_x_yrtUArm	Correlation between acceleration of two axes
TotalPower_x_rtUArm	Total power for frequencies in the range of 0.3-15 Hz
1DomFreq_x_rtUArm	Dominant frequency content in the range of 0.3-15 Hz
1DomFreqPwr_x_rtUArm	Dominant frequency content's Power
2DomFreq_x_rtUArm	2nd dominant frequency content in the range of 0.3-15 Hz
2DomFreqPwr_x_rtUArm	2nd dominant frequency content's Power
3DomFreq_x_rtUArm	3rd dominant frequency content in the range of 0.6-2.5 Hz
3DomFreqPwr_x_rtUArm	3rd dominant frequency content's Power
Ratio1DomFreq_w_Pwr_x_rtUArm	Ratio of dominant frequency's power with total power
NumPeaks_x_rtUArm	Number of peaks
mad_mean_x_rtUArm	Mean absolute deviation with respect to mean

Table 34 (continued)

dist_axis_x_rtUArm	Difference between acceleration's of two of the axes
var_x_rtUArm	Variance in acceleration
energy_WO_dcComp_x_rtUArm	Energy without the DC component in one axis
entropy_WO_dcComp_x_rtUArm	Entropy without the DC component in one axis
var_hist_x_rtUArm	Variance of six minutes or less of acceleration in one axis
stdev_hist_x_rtUArm	Standard deviation of six minutes or less of acceleration in one axis
backtrend_x_rtUArm	Back trend of one axis acceleration
freqRatio_hist_x_rtUArm	Ratio of dominant frequency of the current and the past minute
XMAD*YMAD	Multiplication of mean absolute deviation in two axes
XMAD+YMAD	Sum of mean absolute deviation in two axes
Weight	Weight of the person
Height	Height of the person
Age	Age of the person
is_male	Gender of the person
WeightPlusWheelchair	Weight of the person and their wheelchair
is_parapelgia	Does the person have paraplegia or tetraplegia
Completeness	Completeness of injury
XMAD*Height	Mean absolute deviation multiplied by height
XMADDivHeight	Mean absolute deviation divided by height
XMAD*HeightSqrt	Mean absolute deviation multiplied by square root of height
XMAD*HeightSq	Mean absolute deviation multiplied by square of height
HeightDivXMAD	Height divided by mean absolute deviation
MassPow0.75	Mass to the power of 0.75
HeightSqRoot	Square root of height
HeightSquare	Square of height
HB_BMR	Harris-Benedict basal metabolic rate
Mufflin_BMR	Mufflin basal metabolic rate
WHO_RMR	World Health Organization resting metabolic rate
LeanBodyMass	Lean body mass
WHORMR_div_HBBMR	World Health Organization resting metabolic rate divided by HB_BMR
WHORMR_div_mass	World Health Organization resting metabolic rate divided by mass
WHORMR_div_LBM	World Health Organization resting metabolic rate divided by lean body mass

APPENDIX B

CLASSIFICATION PERFORMANCE OF NAÏVE BAYES, DECISION TREE AND SUPPORT VECTOR MACHINE ALGORITHMS USING 80-20CV.

Phase I: Classification performance of Naïve Bayes, Decision Tree and Support Vector Machine algorithms using 10-fold cross validation on the 80% of subjects' data used for training and testing on the 20% of subjects' data not used for training. The algorithms classified the PAs into wheelchair based PAs that involve moving continuously for most of the time, PAs that may require moving in the wheelchair and stationary activities Table 35.

Table 35: Phase I: Classification performance of Naïve Bayes, Decision Tree and Support Vector Machine algorithms using 80-20CV.

Device	Training Accuracy	Testing Accuracy	Features	Model
PAMS-Arm	0.9299	0.970179	mean_v_G-WRM, mcr_v_G-WRM	NB
PAMS-Arm	0.9350	0.902584	mean_v_G-WRM, mcr_v_G-WRM	J48
PAMS-Arm	0.9356	0.980119	rms_v_G-WRM, mcr_v_G-WRM	SVM
PAMS-Wrist	0.9299	0.970179	mean_v_G-WRM, mcr_v_G-WRM	NB
PAMS-Wrist	0.9350	0.902584	mean_v_G-WRM, mcr_v_G-WRM	J48
PAMS-Wrist	0.9356	0.980119	rms_v_G-WRM, mcr_v_G-WRM	SVM
G-WRM	0.9299	0.970179	mean_v_G-WRM, mcr_v_G-WRM	NB
G-WRM	0.9350	0.902584	mean_v_G-WRM, mcr_v_G-WRM	J48
G-WRM	0.9356	0.980119	rms_v_G-WRM, mcr_v_G-WRM	SVM
Arm Wocket	0.7157	0.765408	stdev_xyz_rtUArm, corr_y_xyz_rtUArm	NB
Arm Wocket	0.7870	0.787276	Ratio1DomFreq_w_Pwr_xyz_rtUArm, mad_med_xyz_rtUArm	J48
Arm Wocket	0.7256	0.765408	stdev_xyz_rtUArm, corr_y_zrtUArm	SVM
Wrist Wocket	0.7737	0.876740	mean_x_rtWrist, mad_med_xyz_rtWrist	NB
Wrist Wocket	0.8074	0.793241	mean_x_rtWrist, entropy_WO_dcComp_xyz_rtWrist	J48
Wrist Wocket	0.7680	0.829026	mean_x_rtWrist, ampl_y_rtWrist	SVM

Phase II: Classification performance of Naïve Bayes, Decision Tree and Support Vector Machine algorithms using 10-fold cross validation on the 80% of subjects' data used for training and testing on the 20% of subjects' data not used for training. The algorithms classified the Moving (M) PAs into wheelchair propulsion, caretaker pushing, and basketball Table 36. The algorithms classified the Non-Moving (NM) PAs into resting, arm-ergometry, other activities.

Table 36: Phase II: Classification performance of Naïve Bayes, Decision Tree and Support Vector Machine algorithms using 80-20CV.

Device	M/ NM	Training Accuracy	Testing Accuracy	Features	Model
PAMS-Arm	M	0.9501	0.9434	2DomFreqPwr_y_rtUArm, ampl_z_rtUArm, energy_v_G-WRM	NB
PAMS-Arm	NM	0.8423	0.8315	mcr_xyz_rtUArm, corr_y_xyz_rtUArm, zcr_z_rtUArm	NB
PAMS-Arm	M	0.9151	0.9612	Ratio1DomFreq_w_Pwr_y_rtUArm, 3DomFreqPwr_y_rtUArm, rms_x_rtUArm	J48
PAMS-Arm	NM	0.8678	0.8495	2DomFreqPwr_xyz_rtUArm, stdev_z_rtUArm, ampl_xyz_rtUArm	J48
PAMS-Arm	M	0.9557	0.9340	stdev_y_rtUArm, ampl_y_rtUArm, entropy_v_G-WRM	SVM
PAMS-Arm	NM	0.8561	0.8602	mcr_xyz_rtUArm, mcr_z_rtUArm, ampl_z_rtUArm	SVM
PAMS-Wrist	M	0.9677	0.9009	mcr_xyz_rtWrist, ampl_x_rtWrist, dist_axis_z_rtWrist	NB
PAMS-Wrist	NM	0.8655	0.8351	mcr_xyz_rtWrist, mean_x_rtWrist, dist_axis_z_rtWrist	NB
PAMS-Wrist	M	0.9713	0.9387	Ratio1DomFreq_w_Pwr_xyz_rtWrist, mean_x_rtWrist, 3DomFreqPwr_xyz_rtWrist	J48
PAMS-Wrist	NM	0.9032	0.8638	3DomFreqPwr_xyz_rtWrist, mean_x_rtWrist, 1DomFreqPwr_xyz_rtWrist	J48
PAMS-Wrist	M	0.9234	0.8396	entropy_WO_dcComp_xyz_rtWrist, NumPeaks_x_rtWrist, corr_z_xrtWrist	SVM
PAMS-Wrist	NM	0.8821	0.8315	NumPeaks_x_rtWrist, ampl_z_rtWrist, backtrend_x_rtWrist	SVM
G-WRM	M	0.8873	0.8019	3DomFreqPwr_v_G-WRM, freqRatio_hist_v_G-WRM, zcr_v_G-WRM	NB
G-WRM	NM	0.6197	0.5018	rms_v_G-WRM, zcr_v_G-WRM, entropy_v_G-WRM	NB
G-WRM	M	0.9206	0.8774	3DomFreqPwr_v_G-WRM, mcr_v_G-WRM, entropy_v_G-WRM	J48
G-WRM	NM	0.6203	0.2437	2DomFreq_v_G-WRM' 'zcr_v_G-WRM mcr_v_G-WRM	J48
G-WRM	M	0.8079	0.7453	ampl_v_G-WRM, 3DomFreqPwr_v_G-WRM, entropy_v_G-WRM	SVM
G-WRM	NM	0.6197	0.5018	stdev_v_G-WRM, rms_v_G-WRM, mad_med_v_G-WRM	SVM
Arm Wocket	M	0.9501	0.9293	2DomFreqPwr_y_rtUArm, ampl_z_rtUArm, TotalPower_y_rtUArm	NB
Arm Wocket	NM	0.8423	0.8315	mcr_xyz_rtUArm' 'corr_y_xyz_rtUArm' 'zcr_z_rtUArm'	NB
Arm Wocket	M	0.9612	0.9151	Ratio1DomFreq_w_Pwr_y_rtUArm, 3DomFreqPwr_y_rtUArm, rms_x_rtUArm	J48
Arm Wocket	NM	0.8678	0.8495	2DomFreqPwr_xyz_rtUArm' 'stdev_z_rtUArm' ampl_xyz_rtUArm'	J48
Arm Wocket	M	0.9308	0.8585	stdev_y_rtUArm, ampl_y_rtUArm, 2DomFreqPwr_xyz_rtUArm	SVM
Arm Wocket	NM	0.8561	0.8602	mcr_xyz_rtUArm, mcr_z_rtUArm, ampl_z_rtUArm	SVM

Table 36 (continued)

Arm Wocket	M	0.9501	0.9293	2DomFreqPwr_y_rtUArm, ampl_z_rtUArm, TotalPower_y_rtUArm	NB
Arm Wocket	NM	0.8423	0.8315	mcr_xyz_rtUArm' 'corr_y_xyz_rtUArm' 'zcr_z_rtUArm'	NB
Arm Wocket	M	0.9612	0.9151	Ratio1DomFreq_w_Pwr_y_rtUArm, 3DomFreqPwr_y_rtUArm, rms_x_rtUArm	J48
Arm Wocket	NM	0.8678	0.8495	2DomFreqPwr_xyz_rtUArm' 'stdev_z_rtUArm' ampl_xyz_rtUArm'	J48
Arm Wocket	M	0.9308	0.8585	stdev_y_rtUArm, ampl_y_rtUArm, 2DomFreqPwr_xyz_rtUArm	SVM
Arm Wocket	NM	0.8561	0.8602	mcr_xyz_rtUArm, mcr_z_rtUArm, ampl_z_rtUArm	SVM
Wrist Wocket	M	0.9677	0.9009	mcr_xyz_rtWrist, ampl_x_rtWrist, dist_axis_z_rtWrist	NB
Wrist Wocket	NM	0.8655	0.8351	mcr_xyz_rtWrist, mean_x_rtWrist, dist_axis_z_rtWrist	NB
Wrist Wocket	M	0.9713	0.9387	Ratio1DomFreq_w_Pwr_xyz_rtWrist, mean_x_rtWrist 3DomFreqPwr_xyz_rtWrist	J48
Wrist Wocket	NM	0.9032	0.8638	3DomFreqPwr_xyz_rtWrist, mean_x_rtWrist, 1DomFreqPwr_xyz_rtWrist	J48
Wrist Wocket	M	0.9234	0.8396	entropy_WO_dcComp_xyz_rtWrist, NumPeaks_x_rtWrist, corr_z_xrtWrist	SVM
Wrist Wocket	NM	0.8821	0.8315	NumPeaks_x_rtWrist, ampl_z_rtWrist, backtrend_x_rtWrist'	SVM

APPENDIX C

FEATURES CHOSEN BY REGRESSION ANALYSIS USING 80-20CV TO ESTIMATE EE FOR VARIOUS WHEELCHAIR-RELATED PAS.

Table 37: Features chosen by regression analysis using 80-20CV to estimate EE for various wheelchair-related PAS.

Device	Activity	Training MAE %	Testing MAE %	Features
PAMS-Arm	Resting	-7.05	-5.32	LeanBodyMass, mean_v_G-WRM, entropy_WO_dcComp_z_rtUArm, 1DomFreq_x_rtUArm, rms_z_rtUArm
PAMS-Arm	Arm-ergometry	-14.44	-1.66	backtrend_xyz_rtUArm, Ratio1DomFreq_w_Pwr_xyz_rtUArm, entropy_WO_dcComp_y_rtUArm, NumPeaks_z_rtUArm, energy_v_G-WRM
PAMS-Arm	OA Not moving	-10.14	-11.86	ZMAD*HeightSqrt, is_male, stdev_z_rtUArm, stdev_hist_z_rtUArm, 1DomFreqPwr_x_rtUArm
PAMS-Arm	May be moving	-5.99	-7.27	mad_mean_x_rtUArm, LeanBodyMass, stdev_hist_x_rtUArm, 2DomFreqPwr_y_rtUArm, mad_med_x_rtUArm
PAMS-Arm	Propulsion	-7.50	-11.66	Ratio1DomFreq_w_Pwr_xyz_rtUArm, 2DomFreqPwr_xyz_rtUArm, MassPow0.75, freqRatio_hist_v_G-WRM,, 1DomFreqPwr_v_G-WRM,
PAMS-Arm	Caretaker pushing	-6.66	-0.96	LeanBodyMass, energy_WO_dcComp_z_rtUArm, entropy_x_rtUArm, mcr_z_rtUArm, entropy_WO_dcComp_y_rtUArm
PAMS-Arm	Basketball	-1.87	-15.64	backtrend_v_G-WRM, LeanBodyMass, mad_med_xyz_rtUArm, 2DomFreqPwr_x_rtUArm, entropy_WO_dcComp_xyz_rtUArm
PAMS-Wrist	Resting	-6.82	-6.94	LeanBodyMass, dist_axis_x_rtWrist, freqRatio_hist_xyz_rtWrist, mcr_xyz_rtWrist, zcr_x_rtWrist
PAMS-Wrist	Arm-ergometry	-7.69	5.34	XMAD+YMAD, mean_v_G-WRM, NumPeaks_x_rtWrist, freqRatio_hist_x_rtWrist, energy_WO_dcComp_x_rtWrist
PAMS-Wrist	OA Not moving	-9.73	-12.61	NumPeaks_y_rtWrist, is_male, TotalPower_y_rtWrist, stdev_hist_xyz_rtWrist, entropy_y_rtWrist
PAMS-Wrist	May be moving	-6.57	-1.50	LeanBodyMass, ampl_y_rtWrist, stdev_hist_z_rtWrist, WHORMR_div_LBM, WHO_RMR

Table 37 (continued)

PAMS-Wrist	Propulsion	-5.16	-7.81	3DomFreqPwr_v_G-WRM, backtrend_v_G-WRM, MassPow0.75, corr_y_xyz_rtWrist, TotalPower_xyz_rtWrist
PAMS-Wrist	Caretaker pushing	-7.45	-4.77	LeanBodyMass, 2DomFreqPwr_z_rtWrist, stdev_hist_v_G-WRM, corr_x_xyz_rtWrist, 1DomFreq_z_rtWrist
PAMS-Wrist	Basketball	-1.91	-20.14	backtrend_v_G-WRM, NumPeaks_xyz_rtWrist, NumPeaks_v_G-WRM, Mufflin_BMR, 2DomFreqPwr_x_rtWrist
G-WRM	Resting	-7.00	-5.35	LeanBodyMass, mean_v_G-WRM, 3DomFreq_v_G-WRM, 2DomFreq_v_G-WRM, HB_BMR
G-WRM	Arm-ergometry	-18.30	-7.58	freqRatio_hist_v_G-WRM, entropy_WO_dcComp_v_G-WRM, Ratio1DomFreq_w_Pwr_v_G-WRM, '2DomFreq_v_G-WRM, 'HeightSquare'
G-WRM	OA Not moving	-12.10	-11.32	LeanBodyMass, Ratio1DomFreq_w_Pwr_v_G-WRM, HeightSqRoot, 2DomFreq_v_G-WRM, 3DomFreq_v_G-WRM
G-WRM	May be moving	-7.23	0.24	LeanBodyMass, Completeness, WHORMR_div_LBM, WHO_RMR, stdev_hist_v_G-WRM
G-WRM	Propulsion	-6.31	-15.95	3DomFreqPwr_v_G-WRM, backtrend_v_G-WRM, MassPow0.75, 3DomFreq_v_G-WRM, ampl_v_G-WRM
G-WRM	Caretaker pushing	-7.38	-6.39	LeanBodyMass, stdev_hist_v_G-WRM, Age, WHORMR_div_mass, WHORMR_div_LBM
G-WRM	Basketball	-1.70	-18.46	backtrend_v_G-WRM, LeanBodyMass, NumPeaks_v_G-WRM, freqRatio_hist_v_G-WRM, Ratio1DomFreq_w_Pwr_v_G-WRM
Arm-Wocket	Resting	-6.92	-6.82	LeanBodyMass, HeightDivZMAD, energy_xyz_rtUArm, ZMAD+XMAD, HeightSquare
Arm-Wocket	Arm-ergometry	-16.08	-6.14	backtrend_xyz_rtUArm, Ratio1DomFreq_w_Pwr_xyz_rtUArm, entropy_WO_dcComp_y_rtUArm, NumPeaks_z_rtUArm, 1DomFreqPwr_z_rtUArm
Arm-Wocket	OA Not moving	-10.14	-11.86	ZMAD*HeightSqrt, is_male, stdev_z_rtUArm, stdev_hist_z_rtUArm, 1DomFreqPwr_x_rtUArm
Arm-Wocket	May be moving	-5.99	-7.28	mad_mean_x_rtUArm, LeanBodyMass, stdev_hist_x_rtUArm, 2DomFreqPwr_y_rtUArm, mad_med_x_rtUArm
Arm-Wocket	Propulsion	-8.99	-14.32	Ratio1DomFreq_w_Pwr_xyz_rtUArm, 2DomFreqPwr_xyz_rtUArm, MassPow0.75, freqRatio_hist_x_rtUArm, NumPeaks_z_rtUArm
Arm-Wocket	Caretaker pushing	-6.66	-0.96	LeanBodyMass, energy_WO_dcComp_z_rtUArm, entropy_x_rtUArm, mcr_z_rtUArm, entropy_WO_dcComp_y_rtUArm
Arm-Wocket	Basketball	-2.70	-28.81	mad_med_xyz_rtUArm, LeanBodyMass, ZMAD*Height, entropy_WO_dcComp_x_rtUArm, ampl_z_rtUArm
Wrist-Wocket	Resting	-6.82	-6.94	LeanBodyMass, dist_axis_x_rtWrist, freqRatio_hist_xyz_rtWrist, mcr_xyz_rtWrist, zcr_x_rtWrist
Wrist-Wocket	Arm-ergometry	-9.05	-31.61	XMAD+YMAD, freqRatio_hist_x_rtWrist, energy_x_rtWrist, Ratio1DomFreq_w_Pwr_y_rtWrist, is_parapelgia
Wrist-Wocket	OA Not moving	-9.73	-12.61	NumPeaks_y_rtWrist, is_male, TotalPower_y_rtWrist, stdev_hist_xyz_rtWrist, entropy_y_rtWrist
Wrist-Wocket	May be moving	-6.57	-1.50	LeanBodyMass, ampl_y_rtWrist, stdev_hist_z_rtWrist, WHORMR_div_LBM, WHO_RMR
Wrist-Wocket	Propulsion	-10.95	-16.47	entropy_WO_dcComp_xyz_rtWrist, freqRatio_hist_x_rtWrist, is_male, is_parapelgia, 1DomFreq_xyz_rtWrist

Table 37 (continued)

Wrist-Wocket	Caretaker pushing	-7.21	-5.66	LeanBodyMass, 2DomFreqPwr_z_rtWrist, corr_z_xyz_rtWrist, HeightSquare, WHORMR_div_LBM
Wrist-Wocket	Basketball	-5.13	-33.12	NumPeaks_xyz_rtWrist, backtrend_xyz_rtWrist, mcr_z_rtWrist, 1DomFreqPwr_y_rtWrist, corr_y_xyz_rtWrist

APPENDIX D

PHYSICAL ACTIVITY MEASUREMENT

IN MANUAL WHEELCHAIR USERS WITH SCI – PART I

Part I: Demographics and Basic Information

Date: ___/___/______

Gender: ❑ Male (1) ❑ Female (0)

Age: ______

Body weight: _______lbs

Height:_______feet _______inches

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 ☐ Pride
☐ Everest and Jennings ☐ Sunrise/Quickie
☐ Kuschall ☐ TiLite/TiSport
☐ Otto Bock ☐ Other (please specify): ______________________

Manual Wheelchair Model: __________________

Diameter of your wheelchair's wheel in inches: __________________

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

Which is your dominant hand? ❑ Right ❑ Left

Are you an athlete? ❑ Yes ❑ No

Do you smoke? ❑ Yes ❑ No

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 follow any specific dietary intake plan? ❑ Yes ❑ No

In general how do you feel about your nutritional habits?

- ❑ Excellent
- ❑ Very good
- ❑ Good
- ❑ Fair
- ❑ Poor

Physical Activity Information

1. What is the approximate distance you propel your wheelchair on a typical day?

- ❑ ______miles per day
- ❑ ______miles per week (include weekdays and weekends)
- ❑ Don't know/Not sure

2. During the past month, other than your regular job and propelling your wheelchair, did you participate in any physical activities or exercises? (Check all that apply)

Activity Type	**Check (✓)**	**Frequency (number of times per week)**	**Average duration of each exercise session (minutes)**
Handcycling			
Wheelchair Basketball			
Wheelchair Tennis			
Wheelchair Rugby			
Arm-ergometry			
Swimming			
Weights			
Resistance Band			
Sled Hockey			
Other:			
Other:			
Other:			

3. In general, how do you rate your fitness level?

- ❑ Excellent
- ❑ Very good
- ❑ Good
- ❑ Fair
- ❑ Poor

Smart Phone Use Information

1. **Do you have a smart phone (i.e., a phone that can access internet)?**

   ❑ If no, please provide a reason (check all that apply, and skip the rest of questions from the Smart Phone Use Information questionnaire)

   - ❑ Cost
   - ❑ I've tried, but I found it difficult to use
   - ❑ I do not need other features except calls.
   - ❑ Other, please specify _________

   ❑ Yes (check all that apply):

   - ❑ IPhone
   - ❑ Blackberry
   - ❑ Motorola android
   - ❑ HTC android
   - ❑ Samsung galaxy
   - ❑ Other, please specify _________

2. **Does your phone have touch screen capability?**

   ❑ Yes

   - ❑ Very easy to use
   - ❑ Somewhat easy to use
   - ❑ A little difficult to use
   - ❑ Difficult to use

   ❑ No

3. **How long have you been using a smart phone?**

   ❑ Less than a month
   ❑ 1-6 month
   ❑ 6 month – a year
   ❑ 1-2 year
   ❑ 2-3 year
   ❑ More than 3 years

4. **What provider that you're using right now for your smart phone?**

   ❑ Verizon ❑ AT&T
   ❑ T-Mobile ❑ Sprint
   ❑ Virgin ❑ Cricket
   ❑ Other, please specify___________________

5. Please state your average hours of smart phone use per day (including phone calls, internet browsing, email etc.)?

- ❑ Less than 1 hour
- ❑ 1-2 hours
- ❑ 2-4 hours
- ❑ 4-6 hours
- ❑ More than 6 hours

6. When you use your smart phone, what functions do you usually use? (Choose all that apply)

- ❑ Browsing internet
- ❑ Entertaining yourself (listening music, watching movie, etc.)
- ❑ Accessing social networking site (Facebook, Tweeter, etc.)
- ❑ Accessing email
- ❑ Text messaging
- ❑ Other, please specify ____________________

7. On a scale of 1-5 (1 being low and 5 being high), how fluent do you regard yourself as a smart phone user?

1 2 3 4 5

8. On a scale of 1-5 (1 being low and 5 being high), how essential is a smart phone to you?

1 2 3 4 5

9. On a scale of 1-5 (1 being low and 5 being high), how satisfied are you with your current smart phone?

1 2 3 4 5

10. In your opinion, what do you miss from your smart phone (check all that apply)?

- ❑ Bigger screen size
- ❑ Bigger button or keyboard size
- ❑ Bigger font size
- ❑ Simplicity of the operation
- ❑ None of the above
- ❑ Other, please specify_______

APPENDIX E

PHYSICAL ACTIVITY MEASUREMENT IN MANUAL WHEELCHAIR USERS WITH SCI – PART II

Part II: Exploratory Questionnaire

Physical Activity Stages of Change

"Physical activity or exercise includes activities such as continuously propelling your wheelchair for half a mile, propelling your wheelchair at a faster pace, handcycling, wheelchair basketball, wheelchair tennis, wheelchair rugby, arm-ergometry, swimming, weights, resistance band or any other activity in which the exertion is at least as intense as these activities."

1. **I am currently physically active.**
   a. Yes
   b. No

2. **I intend to become more physically active in the next six months.**
   a. Yes
   b. No

"For activity to be regular, it must add up to a total of 30 minutes or more per day and be done at least five days per week. For example, you could perform one 30-minute exercise session or perform three 10-minute exercise sessions for a total of 30 minutes."

3. **I currently engage in regular physical activity.**
   a. Yes
   b. No

4. **I have been regularly physically active for the past six months.**
   a. Yes
   b. No

<u>Food and Physical Activity Balance</u>

How do you balance food (nutrition) and physical activity (energy expenditure)?

1. **Do you keep an account of the calories of food you eat or consume over a day?**

   a. Yes (check all that apply ✓)
      ❑ By recording or logging your meals (food label or nutrition facts)
      ❑ By using an online weight management or calorie consumption tool
      ❑ Other. Explain _________________

   b. No

2. **Do you track the amount of wheelchair propulsion on a daily basis?**

   a. Yes (check all that apply ✓)
      ❑ Track the distance travelled by counting the number of blocks
      ❑ Track the distance travelled by bike pedometer
      ❑ Track the time duration of wheelchair propulsion
      ❑ Other. Explain _________________

   b. No [Go to Question 4 below]

3. **Are you satisfied with the current way of measuring the amount of wheelchair propulsion?**

   a. Very satisfied
   b. Satisfied
   c. Neither satisfied nor dissatisfied
   d. Dissatisfied
   e. Very dissatisfied

4. **Do you track the amount of physical activity you perform (other than wheelchair propulsion)?**

   a. Yes (check all that apply ✓)
      ❑ Track the time duration of your physical activity
      ❑ Track the number of repetitions or sets for resistance exercises
      ❑ Track your pulse (example: heart rate)
      ❑ Other. Explain _________________

   b. No [Go to Question 6 below]

5. **Are you satisfied with the current way of measuring physical activity?**

    a. Very satisfied
    b. Satisfied
    c. Neither satisfied nor dissatisfied
    d. Dissatisfied
    e. Very dissatisfied

6. **Do you have other methods to maintain a balance between nutrition and physical activity?**

    a. Yes. Explain _________________
    b. No

7. **Do you have any suggestion on how physical activity of wheelchair users should be measured?**

    a. Yes. Explain _________________
    b. No

APPENDIX F

PHYSICAL ACTIVITY MEASUREMENT IN MANUAL WHEELCHAIR USERS WITH SCI – PART III

<u>Part III: Usability Testing of PAMS</u>

<u>Securement of a Physical Activity Monitor System</u>

1. **In general, what do you think about the securement of the physical activity monitor system.**

   a. Very easy
   b. Easy
   c. Neutral
   d. Difficult
   e. Very difficult

   Explain ___________________

2. **How satisfied are you with**

   a. the dimensions (size and weight) of the wheel rotation monitor?

Not satisfied at all	Not very satisfied	More or less satisfied	Quite Satisfied	Very Satisfied
1	2	3	4	5

   b. the dimensions (size and weight) of the wocket?

Not satisfied at all	Not very satisfied	More or less satisfied	Quite Satisfied	Very Satisfied
1	2	3	4	5

c. how comfortable is the Wocket to wear?

Not satisfied at all	Not very satisfied	More or less satisfied	Quite Satisfied	Very Satisfied
1	2	3	4	5

Evaluation of a Physical Activity Monitor System

1. **Do you think the information provided by PAMS is helpful to you?**

   Explain _________________

2. **Are you satisfied with the way the information was presented on the smartphone application?**

   Explain _________________

3. **Do you wish to see any other physical activity information that is not provided by the PAMS?**

   a. Yes. Explain _________________
   b. No

4. **Do you think the PAMS may help you change your physical activity levels?**

   a. Definitely
   b. Very likely
   c. Likely
   d. Neutral
   e. Unlikely
   f. Very unlikely
   g. Not sure at this point

   Explain _________________

Overall Usability Questionnaire: System Usability Scale

1. I think that I would like to use this system frequently.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

2. I found the system unnecessarily complex.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

3. I thought the system was easy to use.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

4. I think that I would need the support of another person to be able to use this system.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

5. I found the various functions in this system were well integrated.

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

6. **I thought there was too much inconsistency in this system.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

7. **I would imagine that most people would learn to use this system very quickly.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

8. **I found the system very cumbersome or burdensome to use.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

9. **I felt very confident using the system.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

10. **I needed to learn a lot of things before I could get going with this system.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

<u>Overall Usability Questionnaire: Technology Acceptance Model</u>

1. **Using PAMS gives me greater control over my physical activity levels.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

2. **Using PAMS improves my physical activity levels.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

3. **Using PAMS allows me to be physically active than would otherwise be possible.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

4. **Using PAMS makes it easier to do my regular physical activity.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

5. **Overall, I find this product useful in achieving my regular physical activity.**

Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
O	O	O	O	O	O	O

Open Ended Questions

1. **What are your overall impressions about the PAMS?**

   Explain ___________________

2. **Would you recommend the PAMS to a friend?**

   a. Definitely will recommend
   b. Might consider recommending
   c. Will not recommend
   d. Not sure at this point

3. **Do you have any comments or suggestions to improve the PAMS?**

   Explain ___________________

APPENDIX G

PAMS INSTRUCTION MANUAL

PAMS

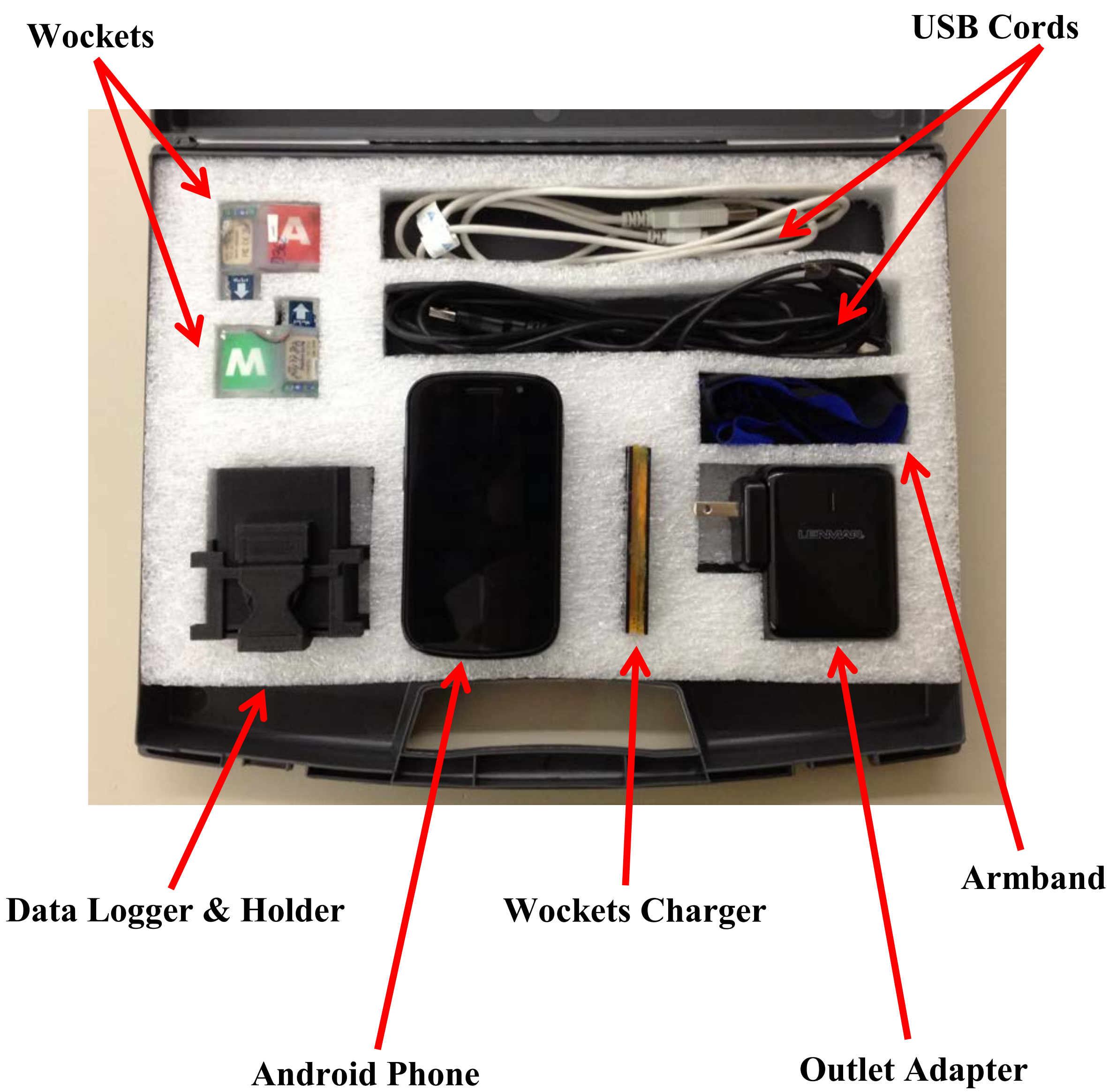
Instruction Manual

Last Revised 5/23/2013

Authors: Natthasit Wongsirikul, Shivayogi Vishwanath Hiremath

Briefcase Overview

Inventory



Connecting Devices to Phone

Data Logger

Wocket

Android

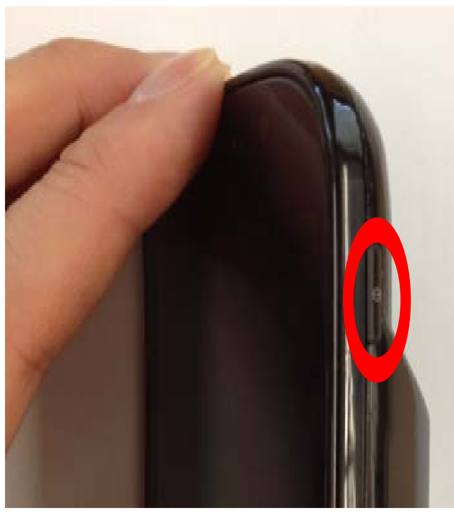
Phone

In order for the app to work, both the Data Logger and one Wocket has to be connected to the mobile phone via Bluetooth.

<u>Manual Instruction on Connecting Devices to Phone</u>

<u>Turning the phone On/Off</u>

The power switch is on the right side of the phone



To turn on, press and hold onto the button until phone turn on
The first thing you will see is the screen lock. To deactivate it, touch the lock then drag it to the right.

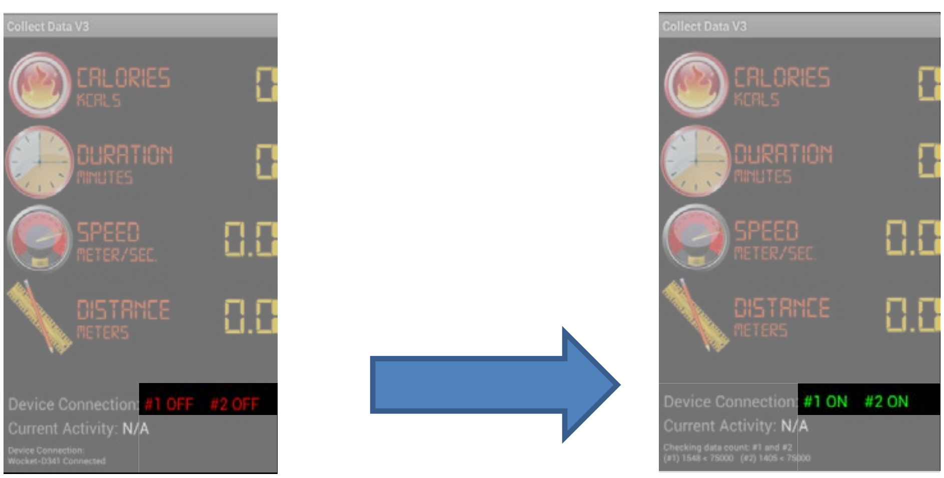
Note: Screen Locking

The power switch also works as a screen-locker. The phone will go into a screen lock mode if you press on the power button. This mode is a protective feature that prevents the device from responding to touch or gestures while not in use. It also helps save powers. Even though the screen is off, the phone and the apps are still running in the background.

<u>Connecting Devices to Phone</u>

When you turn on the phone and unlock the screen, the first thing you will see is the app screen asking you to select a wocket set.

Select the wocket set that matches the wocket color you are using. Tap to select.
Then tap Ok to run the App.
The following screen will appear. Wait until both device #1 and device #2 connections are established.



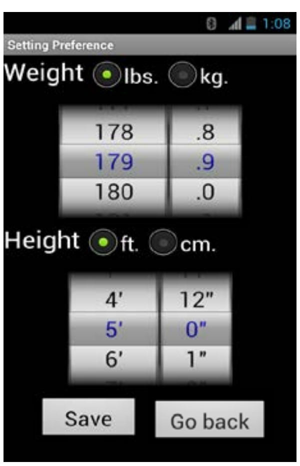
Both devices are not connected Both devices are connected

Entering Demographic Information

Once devices are connected, you have to enter your demographic information into the phone so as to get accurate results. On the bottom of the phone, tap on the menu

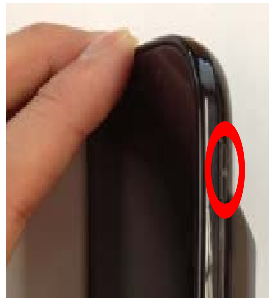
The app's menu will pop up on the screen. Select "Demographic Info." and the following screen will appear. You can leave this screen by selecting "Back to main screen".

You will need to enter your weight, height, gender, and age into the phone. After you have input the correct information, hit "Save" then "Go Back" to return to the previous menu.



<u>Screen Locking</u>

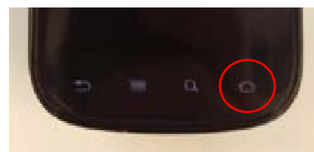
After you are sure that the app is running properly, you can screen lock the phone by just pressing the power switch on the right side. The phone's screen will turn off but the app is still running.



<u>Returning to the Home Screen</u>

In the case when you accidentally tap on something, that brings you to somewhere on the phone that you did not intend or the app quits expectedly, you can navigate your way back to the app by following this method.

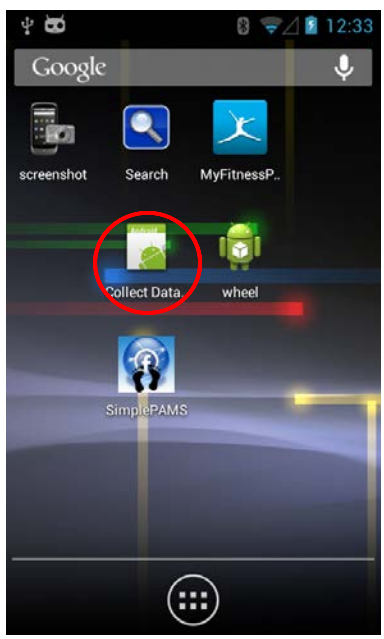
On the bottom of the phone, tap the home button



No matter where you are on the phone, if you tap the Home button you will always go to the main screen.

Tap on the Collect Data App 

and it will take you back to the app page



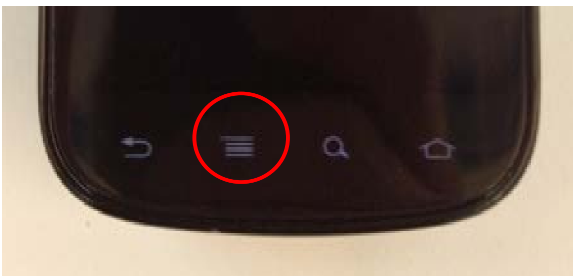
Swapping Wocket

Swapping Wocket

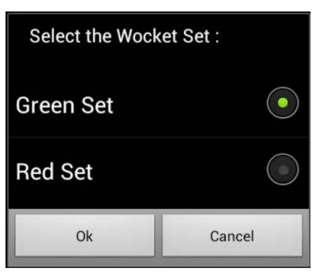
In the case where the wocket you are using is running out of battery or ran out of battery, you will want to switch it with another fully charged wocket. You will need to change the connection between the phone and the new wocket.

On the bottom of the phone, tap on the menu button.

Then the following Menu will appear.
Tap on "Reconnect"



The app will then take you back to the start where you can select the Wocket Set based on color.



Select the appropriate color set then tap Ok to establish new device to phone connection.

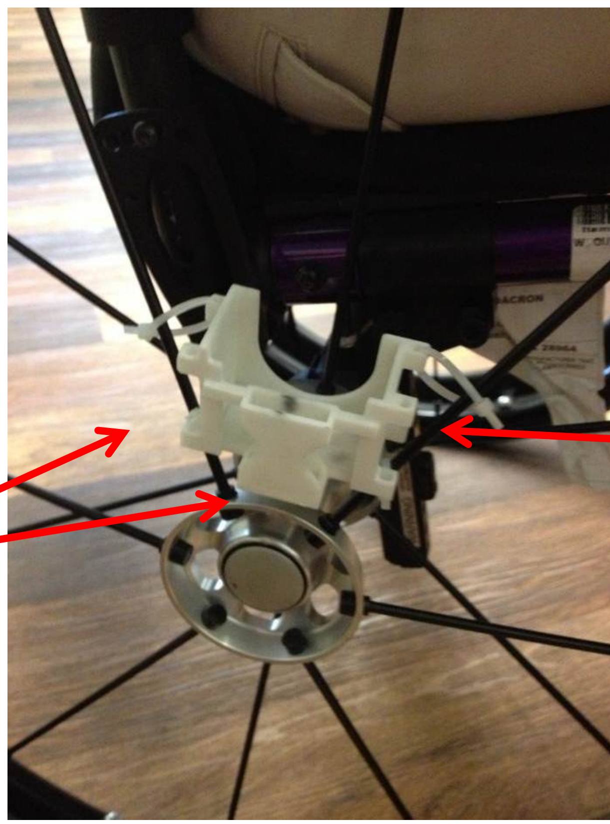
Putting on the Devices

Putting on the Devices

Wocket: Place the wocket into the armband pouch. Then wear the armband.

Data Logger

The Data Logger comes with its Holder. First, you or an assistant will put the Data Logger Holder onto the wheel by attaching it to the spokes using zip ties. Example is shown below

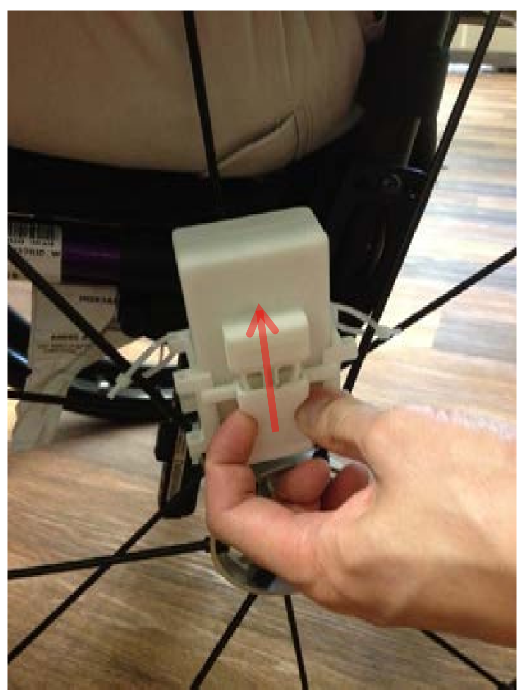


Data Logger Holder

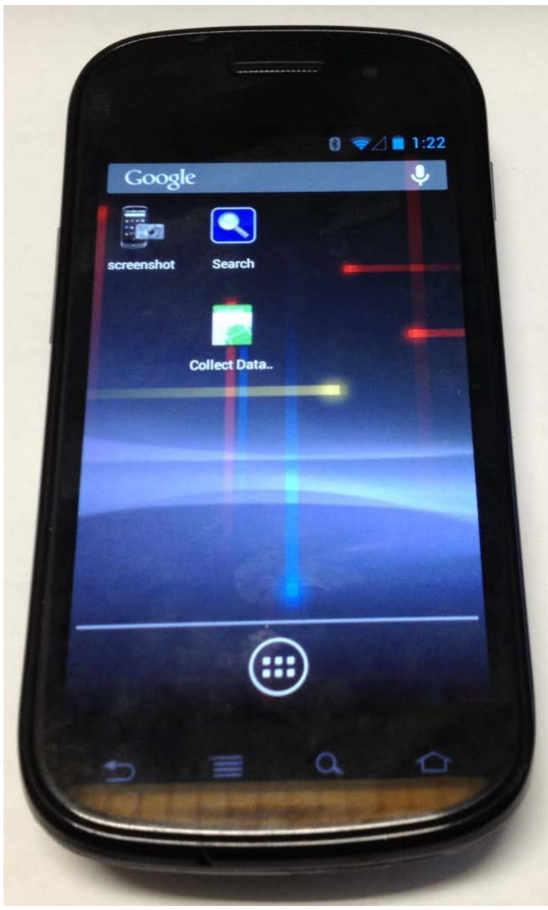
Ziptie

Once the Data Logger Holder is secured to the wheel, you can put the Data Logger into its holder by just inserting it in.

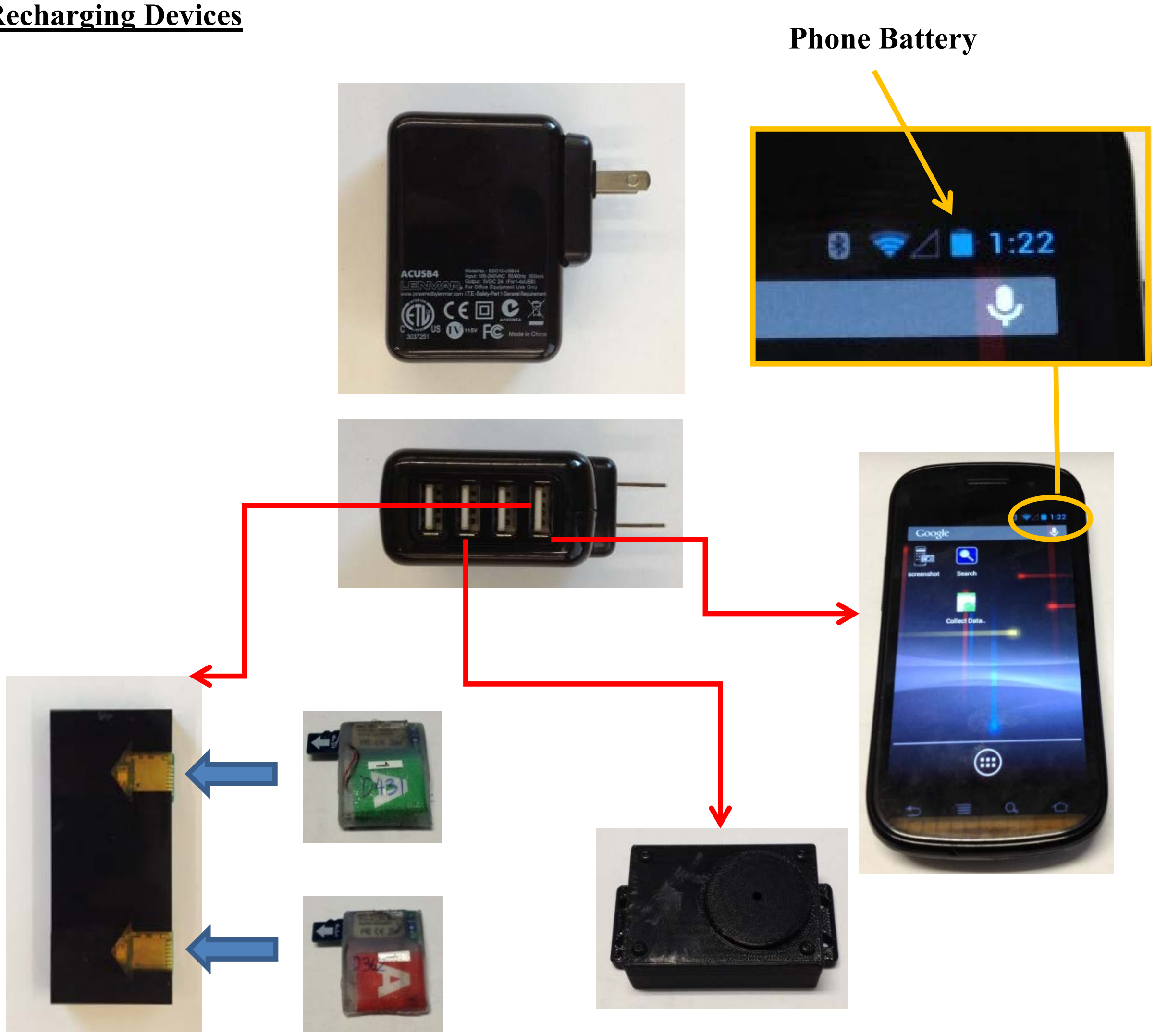
To release the Data Logger from its Holder, squeeze the buckle on the side to release like so. Then pull the Data Logger out.



<u>Recharging Devices</u>



Recharging Devices



Orange light indicates wocket is charging. Green light indicates wocket is fully charged. When the wocket is not being used, leave it in the charger. The wocket is always on, only when it is in the charger that it is off.

APPENDIX H

BRIEF ORIENTATION AND DEMONSTRATION VIDEO OF PAMS

Brief orientation and demonstration video of PAMS is included as an attachment to the dissertation.

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