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Measurement of Energy Expenditure During Laboratory and Field Activities

Scott E. Crouter
University of Tennessee, Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Scott E. Crouter entitled "Measurement of Energy Expenditure During Laboratory and Field Activities." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Education.

David R. Bassett, Jr., Major Professor

We have read this dissertation and recommend its acceptance:

Edward T. Howley, Dixie L. Thompson, James W. Bailey

Accepted for the Council:
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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MEASUREMENT OF ENERGY EXPENDITURE DURING LABORATORY AND FIELD ACTIVITIES

A Dissertation

Presented for the

Doctor of Philosophy Degree

The University of Tennessee, Knoxville

Scott E. Crouter

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ABSTRACT

This dissertation was designed to examine the validity of heart rate (HR) and motion sensors for estimating energy expenditure (EE) during activities ranging from sedentary behaviors to vigorous exercise. A secondary purpose was to devise new ways to improve on current methods of estimating EE. Specific aims of the dissertation were: (1) to examine the use of pedometers to measure steps taken, distance traveled, and EE during treadmill walking at various speeds; (2) Examine the use of a Polar HR monitor to estimate EE during treadmill running, stationary cycling, and rowing; (3) compare the current Actigraph regression equations (relating counts$\cdot$min^{-1} to EE) against three newer devices (Actiheart, Actical, and AMP-331) during sedentary, light, moderate, and vigorous intensity activities; and (4) development of a new 2-regression model to estimate EE using the Actigraph accelerometer.

For the first aim, 10 participants performed treadmill walking for five minutes at five speeds while wearing two pedometers of different brands (10 pedometer brands were tested) on the right and left hip. Simultaneously oxygen consumption (VO_2) was measured and actual steps were counted using a hand tally counter. Six of the 10 pedometers were within ± 3% of actual steps at 80 m$\cdot$min^{-1} and faster. Most pedometers were within ± 10% of actual distance at 80 m$\cdot$min^{-1}, but they overestimate distance at slower speeds, and underestimate distance at faster speeds. Most pedometers gave estimates of gross EE within ± 30% of measured EE across all speeds. In general, pedometers are most accurate for assessing steps, less accurate for assessing distance, and even less accurate for assessing kcals.

In the second aim, 10 males and 10 females performed a maximal treadmill test. On a separate day they performed treadmill, cycle, and rowing exercise for 10 minutes at three different intensities. During each trial EE was estimated using two Polar S410 HR monitors (one with predicted VO_{2max} and HR_{max} (PHRM) and one with actual VO_{2max} and HR_{max} (AHRM), input into the watch). Simultaneously, EE was measured by indirect calorimetry (IC). For males there were no differences among the mean values of EE for the AHRM, PHRM and IC for any exercise mode ($P \geq 0.05$). In females, the AHRM significantly improved the estimate of EE compared to the PHRM ($P < 0.05$), but it still overestimated mean EE on the treadmill and cycle ($P < 0.05$). The Polar S410 HR monitor provides the best estimate of EE when the actual VO_{2max} and HR_{max} are used.

For the third aim, 48 participants performed various activities ranging from sedentary pursuits to vigorous exercise. The activities were split into three routines of six activities and each participant performed one routine. During each routine an Actigraph (right hip), Actical (left hip), Actiheart (chest), and AMP-331 (right ankle) were worn. Simultaneously, EE was measured by IC. The Actiheart HR algorithm was not significantly different from measured EE for any of the 18 activities ($P \geq 0.05$). The Actiheart combined HR and activity algorithm was only significantly different from measured EE for vacuuming and ascending/descending stairs ($P < 0.05$). All remaining prediction equations, for the devices examined, over- or underestimated EE for at least seven activities. The Actiheart HR algorithm provided the best estimate of EE over a wide range of activities. The Actical and Actigraph tended to overestimate walking and sedentary activities and underestimate most other activities.

For the fourth aim, 48 participants performed various activities (sedentary, light, moderate, and vigorous intensities) that were split into three routines of six activities. Each participant performed one routine. During each test the participants wore an Actigraph accelerometer and EE was measured by IC. Forty-five tests were randomly selected for the development of the new equation, and 15 tests were used to cross-validate the new equation and compare against existing equations. For each activity the coefficient of variation (CV) of the counts per 10 seconds was calculated to determine if the activity was walking/running, or some other activity. If the CV $\leq$ 10 then a walking/running regression equation (relating counts·min^{-1} to METs) was used, while if the CV > 10 a lifestyle/leisure time physical activity (LTPA) regression was used. The new 2-regression model explained 73% of the variance in EE for walking/running, and 83.8% of the variance in EE for lifestyle/LTPA and it was within ± 0.84 METs of measured METs for each of the 17 activities performed ($P \geq 0.05$). The new 2-regression model is a more accurate prediction of EE then the currently published regression equations using the Actigraph accelerometer.

TABLE OF CONTENTS

LIST OF TABLES

TABLE PAGE

Part III: Validity of 10 Electronic Pedometers for Measuring Steps, Distance, and Energy Cost

Part IV: Accuracy of Polar S410 Heart Rate Monitor to Estimate Energy Cost of Exercise

Part V: Validity of Heart Rate and Accelerometry for the Measurement of Energy Expenditure

Part VI: A Novel Method for Using Accelerometer Data to Predict Energy Expenditure

LIST OF FIGURES

FIGURE **PAGE**

Introduction

Part III: Validity of 10 Electronic Pedometers for Measuring Steps, Distance, and Energy Cost

Part IV: Accuracy of Polar S410 Heart Rate Monitor to Estimate Energy Cost of Exercise

Part V: Validity of Heart Rate and Accelerometry for the Measurement of Energy Expenditure

Part VI: A Novel Method for Using Accelerometer Data to Predict Energy Expenditure

NOMENCLATURE

$beasts \cdot min^{-1}$	beats per minute
cm	centimeter
$counts \cdot min^{-1}$	counts per minute
$d \cdot wk^{-1}$	days per week
h	hour
in	inch
km	kilometer
kcal	kilocalorie
$kcals \cdot day^{-1}$	kilocalorie per day
$kcals \cdot kg^{-1} \cdot min^{-1}$	kilocalorie per kilogram body weight per minute
$kcals \cdot min^{-1}$	kilocalorie per minute
$kcals \cdot week^{-1}$	kilocalorie per week
kg	kilogram
$kg \cdot m^{-2}$	kilograms per meter squared
$km \cdot hr^{-1}$	kilometers per hour
L	liters
$l \cdot min^{-1}$	liters per minute
m	meter
m^2	meters squared
$m \cdot s^{-2}$	meter per second squared
MET	resting metabolic equivalent
min	minute
mm	millimeter
$ml \cdot kg^{-1} \cdot min^{-1}$	millimeter per kilogram body mass per minute
$m \cdot min^{-1}$	meters per minute
mph	miles per hour
rpm	revolutions per minute
$steps \cdot min^{-1}$	steps per minute
$strokes \cdot min^{-1}$	strokes per minute

LIST OF ABREVIATIONS

ACSM	American College of Sports Medicine
AEE	activity energy expenditure
BMI	body mass index
BMR	basal metabolic rate
CDC	Centers for Disease Control and Prevention
CV	coefficient of variation
DLW	doubly labeled water
EE	energy expenditure
ECG	electrocardiogram
HR	heart rate
HRaS	heart rate above sleeping
HR_{max}	maximal heart rate
Hz	hertz
LTPA	leisure time physical activity
PA	physical activity
PAEE	physical activity energy expenditure
PAI	physical activity intensity
PAL	physical activity level
PAR	physical activity ratio
PAR-Q	Physical Activity Readiness Questionnaire
RMR	resting metabolic rate
RT3	RT3 Research Tracker
SD	standard deviation
SEE	standard error of the estimate
SVO_2	oxygen consumption relative to body mass raised to the power of 0.75
TDEE	total daily energy expenditure
TEF	thermic effect of feeding
TriTrac	TriTrac-R3D accelerometer
VO_2	oxygen uptake
VO_{2max}	maximal oxygen consumption
VO_{2peak}	peak oxygen consumption
yr	year
yrs	years

PART I

INTRODUCTION

There is substantial evidence that supports the importance of physical activity for preventing chronic diseases. The American College of Sports Medicine (ACSM) and the Centers for Disease Control and Prevention (CDC) have recommended that all Americans should accumulate a minimum of 30 minutes of moderate-intensity physical activity on most, preferably all days of the week (21). This should be considered a starting point for Americans rather than a maximal amount needed. Unfortunately, most adults are not reaching this minimal recommendation, with nearly a quarter of Americans not performing any leisure time physical activity (LTPA) at all (5). Of additional importance is that an estimated 65.7% of US adults are overweight or obese (based on BMI) and among children and adolescents the prevalence of those overweight is 16% (based on norm tables) (13). Obesity has become a major public health concern and physical inactivity is a major contributor to obesity (18).

In free-living individuals, obtaining an accurate assessment of physical activity related energy expenditure is difficult. For an average-sized person, the current ACSM/CDC recommendation translates into expending a minimum of 150 $kcals \cdot day^{-1}$ or 1000 $kcals \cdot week^{-1}$ (32). Various techniques have been developed in an effort to estimate both physical activity related energy expenditure and 24 hour energy expenditure. Such methods include recall questionnaires, activity logs, motion sensors that detect bodily movement, heart rate (HR), and doubly labeled water (DLW). Essentially there are two main primary outcomes from these methods: (1) total daily energy expenditure (TDEE), and (2) physical activity-related energy expenditure (PAEE). TDEE is composed of three components: (1) resting metabolic rate (RMR), (2) thermic effect of feeding (TEF), and (3) PAEE. For most individuals RMR contributes 60-70% to the TDEE (23), while the

TEF contributes 10-15% (26), and PAEE contributes the remaining 15-30%. PAEE is the main component of TDEE that is associated with chronic diseases and is also the most variable among individuals. Therefore, it is important that we have accurate tools for assessing PAEE.

Questionnaires and activity logs are commonly used to estimate energy expenditure because of the ease with which they can be administered to large groups of individuals. However, a major drawback is that they rely on the participant's ability to recall and accurately record the activities performed, which can result in significant errors occurring for the estimation of energy expenditure. In general, questionnaires are useful for recalling structured activities, but fail in their estimation of light- to moderate-intensity activities (19). Therefore, researchers are interested in developing more accurate, objective methods of quantifying physical activity.

DLW is considered the "gold standard" for measuring 24-hour energy expenditure, but its applications are limited. DLW relies on the use of stable isotopes (deuterium and O_2^{18}), but they are in limited supply and are very expensive (> $500 per participant). The equipment needed (i.e. gas isotope ratio mass spectrometer) is also a limiting factor due to the cost and expertise needed to perform the analysis. In addition, DLW cannot distinguish bouts of activity or the intensity at which they are performed; thus, it only gives information on TDEE.

In an effort to more accurately assess the amount of physical activity performed during the day researchers have used various motion sensors (e.g. accelerometers and pedometers) and attempted to use them to predict energy expenditure. Pedometers are low cost devices that provide a measure of ambulatory physical activity. In general, these devices provide an accurate measure of steps taken at normal walking speeds ($\geq$ 80 m·min^{-1}), but under-count at slower walking speeds ($\leq$ 67 m·min^{-1}) (1, 8, 25). In addition, they fail to provide an accurate estimate of TDEE (15) and have only modest correlations with energy expenditure assessed by indirect calorimetry during moderate-intensity lifestyle activities (r = 0.493 – 0.580) (2). Furthermore, most pedometers cannot record the intensity, duration, or frequency of activity bouts.

Accelerometers are devices that measure the magnitude of acceleration and deceleration of the body, which enables researchers to distinguish between activities of different intensities. Uniaxial accelerometers measure acceleration in one plane (vertical), where as biaxial or triaxial accelerometers measure acceleration in two or three planes, thus providing more information about body movements. Accelerometers also have the ability to store data and track the duration and frequency of activity bouts, as well as being non-invasive, which makes them a popular choice among researchers.

In laboratory settings accelerometers show promise for the estimation of energy expenditure. Most researchers find a strong linear relationship between counts·min^{-1} during activities such as treadmill walking/running on flat surfaces and actual energy expenditure measured by direct or indirect calorimetry (11, 20, 31, 33). Unfortunately, when accelerometers are used in free-living populations, they fail to accurately detect the additional energy expenditure associated with various lifestyle activities, specifically upper body movement, walking up grades, carrying or lifting objects, and activities such as cycling where there is no displacement of the hip (2, 14, 34). Since physical activity plays an important role in preventing chronic disease it is important that we have accurate tools to assess physical activity. In addition, we need to improve how these devices are used for the assessment of PAEE during a variety of activities.

HR has also been examined as a method for estimating free-living energy expenditure. Several investigators have shown HR to be a good estimate of energy expenditure during structured activities and over a 24-hour period in a room calorimeter (6, 7, 9, 10, 16, 22, 27, 30). HR has the advantage of being a physiological measure that has a linear relationship with oxygen consumption during dynamic activities involving large muscle groups. However, there are numerous factors that affect an individual's HR including environmental factors, gender, training status, hydration level, and stress levels. HR also is limited in its ability to accurately estimate energy expenditure during sedentary and light activities. This has led investigators to develop methods that employ the combined use of HR and motion data to get a better estimate of energy expenditure during various activities. In general, the combined HR + motion sensor technique shows promise and appears to improve the estimate of energy expenditure during laboratory and free-living conditions (3, 4, 12, 17, 24, 28, 29). However, it is limited in its use due to the need to construct individual HR-VO_2 curves on each participant for both leg and arm activity. In addition, data analysis is extremely time-consuming which currently limits its use in studies involving a large number of participants.

Statement of the Problem

Currently there are numerous devices on the market to predict energy expenditure, but they all have limitations in their ability to estimate the energy expenditure of individual physical activities, as well as 24-hour energy expenditure. Currently, there are numerous prediction equations relating accelerometer counts·min^{-1} to energy expenditure, which makes it difficult to compare values across studies. In addition, they all rely on a linear relationship between activity counts and energy expenditure during a limited amount of activities (i.e. walking/running or moderate-intensity lifestyle activities), which limits the generalizability of these equations to free-living conditions. Therefore, it is necessary that we compare the current methods available to estimate energy expenditure and improve on these methods so a more accurate estimation of energy expenditure can be obtained.

Statement of Purpose

The purpose of this dissertation is to examine the validity of HR and motion sensors for estimating energy expenditure and to devise new ways to improve on current methods that are currently in use. The first study (Part III) examines the use of pedometers to measure steps taken, distance traveled, and energy expenditure during treadmill walking at various speeds. The second study (Part IV) examines the use of a Polar HR monitor to estimate energy expenditure during treadmill running, stationary cycling, and rowing. The third study (Part V) compares the current Actigraph regression equations (relating counts·min^{-1} to energy expenditure) against three newer devices (Actiheart, Actical, and AMP-331) during sedentary, light, moderate, and vigorous intensity activities. The fourth study (Part VI) describes the development of a new 2-regression model to estimate energy expenditure using the Actigraph accelerometer.

Significance of these Studies

With the advent of new physical activity monitoring devices it is critical that these devices are validated against a well-accepted criterion measure (e.g. indirect calorimetery) and compared against current devices so researchers know which methods work best. In addition, in the current validation study a wide range of activities were used (sedentary, light, moderate, and vigorous intensity) in order to obtain a better understanding of where the devices work and where they fail.

The development of the new 2-regression model for the prediction of energy expenditure enables a researcher to distinguish between walking, running, and other activities that are performed through the day. In addition, it provides a much closer estimate of energy expenditure across a wide range of activities.

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PART II

REVIEW OF LITERATURE

Physical Activity Assessment

Various methods for the assessment of physical activity include subjective and objective measures. Subjective measures include physical activity questionnaires, physical activity diaries, and interviews either by phone or in person. Objective measures include heart rate (HR) monitoring, oxygen consumption, and bodily movement by motion sensors. While subjective measures are an important aspect of physical activity assessment they are beyond the scope of this review, which will focus on objective measures of physical activity.

Doubly Labeled Water

For the assessment of total daily energy expenditure (TDEE) doubly labeled water (DLW) is generally accepted as the "gold standard". Briefly, for the measurement of DLW, an individual is first given a solution containing deuterium (^{2}H) and oxygen-18 (^{18}O) ($^{2}H_2{}^{18}O$). Following equilibration, a urine sample is taken to determine the levels of ^{2}H and ^{18}O in the system. After a 7 to 14 day measurement period a second urine sample of ^{2}H and ^{18}O is taken to examine the decrease in these isotopes over the measurement period. During the measurement period the ^{2}H will decrease due to H_2O turnover, while the ^{18}O will decrease due to both H_2O turnover and CO_2 production. TDEE can then be calculated by the difference in the rates of ^{2}H and the ^{18}O disappearance. Lifson et al. (48) was the first to develop this technique using rodent models in the 1955. It was not until the early 1980s that Schoeller and van Santen (70) introduced this technique for use in humans. Schoeller and van Santen (70) examined the use of DLW in four adults versus energy intake over a 14 day period. All meals during the measurement period were prepared by the Clinical Research Center kitchen. Energy expenditure was calculated by taking the sum of the dietary intake and the change in body stores. The average energy expenditure by DLW overestimated energy intake by 2.1 ± 5.6% (-5.8 to 7.1%), which was not significantly different.

DeLany et al. (20) validated the DLW technique for measuring energy expenditure in 36 soldiers. Eighteen soldiers were assigned to a light ration group and 18 soldiers were placed in a ready-to-eat group. Only nine of the participants in each group had their energy expenditure measured by DLW. The light ration group received 1980 kcals·day^{-1}, while the ready to eat ration contained 4,020 kcals·day^{-1}. Each was supplied with the appropriate meals before heading into the field. For the 18 soldiers who took DLW, their mean energy expenditure was 5% higher than that measured by energy intake/balance method, which was not significant.

DLW has been used in numerous studies (6, 29, 45, 49, 64, 71, 74, 89) as a "gold standard" for the measurement of energy expenditure. The advantage of using DLW over a technique such as a whole room calorimeter is that DLW can be done in free-living participants without constraining them to a single room. However, it should be noted that DLW has its limitations. The DLW technique is usually performed over 1-3 weeks and provides a measure of the average TDEE, hence the type, intensity, and duration of activities cannot be determined. To get an estimate of PAEE using DLW, the RMR and TEF are subtracted from the TDEE, which is shown by the following equation: PAEE = TDEE (0.9) – RMR, where TDEE x 0.10 accounts for TEF. Alternatively, the TDEE can be expressed as a multiple of the daily resting energy expenditure which indicates the overall daily physical activity level (PAL). Another major limitation to using DLW is that it is very expensive (> $500 per subject) and sophisticated and expensive equipment is necessary for analysis.

Motion Sensors

Pedometers

Electronic pedometers are a popular means for estimating physical activity. Originally developed hundreds of years ago, its main function was to measure plots of land. It was not until recently that researchers began using pedometers for monitoring physical activity (78). Most pedometers are worn at the midline of the thigh on the waist, while some are secured to the ankle or wrist with a strap. Early pedometers with mechanical mechanisms were unreliable and generally considered to be unacceptable for research (30, 40, 84). Kemper and Verschuur (40) examined the validity of a Russian and German mechanical pedometer in 58 boys (age: 12-18 yrs). They had the participants walk at 2, 4, and 6 $km \cdot hr^{-1}$ for 5, 4, and 4 minutes, respectively on a treadmill. In addition, they also ran at 6, 8, 10, and 14 $km \cdot hr^{-1}$ for 3, 3, 3, and 2 minutes, respectively on a treadmill. For the German pedometer, it underestimated actual steps by 66% ± 35.6% at 2 $km \cdot hr^{-1}$ and overestimated steps by 7.1% ± 33.3% and 6.9% ± 11.4% at 4 and 6 $km \cdot hr^{-1}$, respectively. The Russian pedometer underestimated steps by 88.8% ± 19.7% and 13.9% ± 33.9% at 2 and 4 $km \cdot hr^{-1}$, respectively, while overestimating actual steps by 10.2% ± 8.1% at 6 $km \cdot hr^{-1}$. Both pedometers overestimated actual steps taken at the running speeds, with the German pedometer overestimating by 3.4% ± 9.8%, 0.6% ± 9.5%, and 8.6% ± 8.1% at speeds of 8, 10, and 14 $km \cdot hr^{-1}$, respectively. The Russian pedometer overestimated actual steps by 3.9% ± 6.4%, 3.7% ± 3.4%, and 9.0% ± 8.6% at speeds of 8, 10, and 14 $km \cdot hr^{-1}$, respectively. This study showed the inaccuracies associated with the mechanical pedometers, especially at slower walking speeds. Interestingly, these researchers believed the pedometer would be a good training tool for cardiovascular endurance exercise and so it was thought that it would be best if the pedometer did not register slow walking speeds at all, due to these steps having a minor importance as a training stimulus.

With time the pedometer has evolved into a more sophisticated device, capable of recording steps, distance, and energy expenditure. The newer electronic pedometers are generally mounted on the waist and have either a spring-suspended lever arm mechanism or a piezo-electric accelerometer mechanism. The horizontal spring-suspended lever arm moves up and down in response to the hip's vertical accelerations. This movement opens and closes an electrical circuit; the lever arm makes an electrical contact and a step is registered. For this pedometer to work correctly it must be placed in a vertical plane, perpendicular to the ground. The piezo-electric accelerometer mechanism has a horizontal cantilevered beam with a weight on the end, which compresses a piezo-electric crystal when subjected to acceleration. This generates voltage proportional to the acceleration and the voltage oscillations are used to record steps. Thus, this mechanism could be less susceptible to errors that occur due to tilt.

Several studies have shown these newer electronic pedometers to be accurate and reliable for measuring steps taken (3, 18, 38, 68, 69), but their accuracy is not as great for measuring distance and energy expenditure (3, 18, 38). In 1996, Bassett et al. (3) examined the accuracy and reliability of five electronic pedometers for measuring steps taken and distance walked. In the first part of the study 20 participants walked a 4.88 km sidewalk course while wearing the same brand of pedometer on the left and right hip. This was repeated for each pedometer for a total of five trials. They found that there was a significant difference among pedometers for measuring distance ($P < 0.05$), with the Yamax Digiwalker DW-500 and Accusplit Fitness Walker giving closer estimates of distance than the other pedometers. In addition, the Yamax Digiwalker DW-500 showed close agreement between the left and right hips for measuring steps taken, recording 100.6% and 100.7% of actual steps, respectively. In the same study the effects of treadmill walking speed on pedometer accuracy to count steps was also examined. This was accomplished by having 10 participants walk at 54, 67, 80, 94, and 107 $m \cdot min^{-1}$ for five minutes at each speed. The Yamax Digiwalker DW-500 was shown to be more accurate than the other pedometers for recording steps taken and distance traveled at the slower walking speeds (54-80 $m \cdot min^{-1}$) while at speeds greater than 80 $m \cdot min^{-1}$ all pedometers showed close agreement.

Since all of the pedometers examined by Bassett el al. (3) are no longer manufactured, Crouter et al. (18) examined the validity of 10 currently available electronic pedometers for measuring steps taken, distance traveled, and energy expenditure. They had 10 participants walk on a treadmill at 54, 67, 80, 94, and 107 $m \cdot min^{-1}$ for 5 minute stages. Eight of the pedometers displayed an estimate of energy expenditure, therefore during those walking trials energy expenditure was measured by indirect calorimetry. One pedometer was worn on the right side and a second pedometer of a different brand was worn on the left side at each speed, then the pedometers were switched and the participants performed a second trial. Most pedometers showed good agreement between the left and right side, having intraclass correlation coefficients greater than 0.81. The Oregon Scientific and Sportline 345 were the exceptions with correlation coefficients of 0.76 and 0.57, respectively. Most of the pedometers underestimated steps at 54 $m \cdot min^{-1}$, but there accuracy improved at the faster speeds. At 80 $m \cdot min^{-1}$ and faster, six of the models (Yamasa Skeleton, Omron, Yamax Digiwalker SW-701, Kenz Lifecorder, New Lifestyles NL-2000, and Walk4Life LS 2525) were within ± 1% of actual steps taken. Of the six pedometers that measured distance traveled, most were within ± 10% at 80 $m \cdot min^{-1}$, but overestimated distance at slower speeds and underestimated distance at faster speeds. Two (Kenz Lifecorder and New Lifestyles NL-2000) of the eight pedometers that measured energy expenditure displayed both net and gross energy expenditure, while the other six pedometers were assumed to display gross energy expenditure. Seven of the eight pedometers were accurate to within ± 30% of actual gross energy expenditure at all speeds. The authors concluded that pedometers are most accurate for step counting, less accurate for assessing distance, and less accurate still for assessing energy expenditure.

Some investigators have attempted to examine the validity of pedometers under free-living conditions. Bassett et al. (4) examined the validity of motion sensors for measuring energy expenditure during 28 activities. Eighty-one participants performed one to nine activities for 15 minutes each. During each activity, energy expenditure was measured by indirect calorimetry using a Cosmed K4b^2 and one pedometer (Yamax Digiwalker SW-701) and three other motions sensors were worn. The pedometer tended to overestimate the energy cost of over-ground walking by approximately 1 MET, but underestimated most other moderate-intensity lifestyle activities by approximately 1

MET. The pedometer also showed a modest correlation between the displayed energy expenditure and indirect calorimetry ($r = 0.49$). The mean error score (indirect calorimetry minus pedometer) showed that the pedometer underestimated all 28 activities by 1.1 METs with a 95% confidence interval of ± 3.0 METs.

Leenders et al. (45) examined different methods of measuring physical activity versus DLW in 13 females. They had participants wear a Yamax Digiwalker-500 pedometer along with two other motion sensors for seven days, while TDEE was measured by DLW. Over the 7-day period the Yamax pedometer underestimated actual energy expenditure by 59% (-497 $kcals \cdot day^{-1}$). This study highlights the fact that pedometers may by useful for use in large studies to estimate steps, but not to determine their PAEE.

Recently, pedometers have been developed that are designed to be worn on the ankle. Ankle-mounted pedometers have been shown to be superior at detecting steps at slower walking speeds (< 80 $m \cdot min^{-1}$), which is important when trying to obtain an accurate estimate of steps taken over a 24-hour period (38). During the day, much time is spent in light activity such as washing dishes, cooking, or light cleaning, which may not be entirely detected by a waist-mounted pedometer. The StepWatch 3 (Cymatech Inc., Seattle, WA) had been shown to be nearly 100% accurate on the treadmill at speeds ranging from 26.8 $m \cdot min^{-1}$ to 107 $m \cdot min^{-1}$. In addition, it detected an extra 1367 to 1843 steps over a 24-hour period versus a Yamax SW-701 and a New Lifestyles NL-2000 waist-mounted pedometers, respectively, while another ankle-mounted pedometer the AMP-331 detected 2185 fewer steps than the StepWatch 3 (38). When trying to get an accurate estimate of 24-hour energy expenditure it is important to be able to track all activities. Ankle-mounted pedometers, specifically the StepWatch 3, appear to have the ability to track light activities performed throughout the day, where other devices may fail.

The electronic pedometer is a valuable tool for researchers to help assess the amount of physical activity that individuals are obtaining. They do have some limitations such as not being able to detect vertical work, upper body activities or when an individual is carrying or pushing an object. In addition, pedometers are not capable of detecting the "pattern" of physical activity (i.e. intensity, frequency, duration), as the more expensive piezo-electric accelerometers can. Furthermore, there is growing evidence that the spring-levered pedometers may be susceptible to errors that occur due to being tilted or factors related to obesity (i.e. increased waist circumference) (17, 53).

Accelerometers

Currently there are several commercially available accelerometers such as the Caltrac (Hemokinetics, Madison, WI), the Actigraph accelerometer (Manufacturing Technology, Fort Walton Beach, FL) (formerly called the Manufacturing Technology Inc. (MTI) Actigraph accelerometer, or the Computer Science Application (CSA) accelerometer), the Actical and Actiwatch (Minimitter, Sunriver, OR), the Tracmor, (Maastricht, The Nethlerlands) and the Tritrac-R3D accelerometer (Hemokinetics, Madison, WI). Accelerometers are devices that measure the magnitude of acceleration and deceleration of the body, which enables the researcher to distinguish between activities of different intensities. Uniaxial accelerometers measure acceleration in one plane (vertical) while biaxial or triaxial accelerometers measure acceleration in two or three planes, thus being able to capture a greater amount of movements. In addition, accelerometers have the ability to store data and track the frequency of exercise, as well as being non-invasive which makes them a popular choice among researchers.

Caltrac

The Caltrac, which uses a uniaxial accelerometer, was one of the first commercially available accelerometers. The Caltrac has a major limitation in that it cannot store minute-by-minute data, so only total activity during a certain period can be examined. The original algorithm used by the Caltrac to estimate energy expenditure was developed by Montoye et al. (54). They had 21 participants (age: 20-60 yrs) perform flat and graded walking/running on a treadmill, bench stepping, knee bends, and floor touches for 4 minutes each, while wearing a Caltrac. During the fourth minute of each activity, oxygen consumption was measured using a Beckman Metabolic Cart. They hypothesized that the Caltrac would not be able to detect the increased energy cost of graded walking and running, which was correct, but due to the inclusion of these activities into the regression equation the algorithm developed overestimated the cost of walking and running on a flat surface.

Since Montoye et al. (54) developed the original algorithm to estimate energy expenditure using the Caltrac, other investigators have confirmed their findings that the Caltrac overestimates walking (2, 9, 26, 32, 37, 58, 59, 67, 80) and cannot detect the increased energy cost associated with graded walking and running (26, 54, 79). For example, Haymes and Byrnes (32) placed the Caltrac on twenty one participants during treadmill walking and running. Each participant walked at 2, 3, 4, and 5 mph at a 0%

grade and ran at 4, 5, 6, 7, and 8 mph at a 0% grade. Each speed was performed for four minutes and gas exchange measurements were measured by indirect calorimetry. During brisk walking and slow jogging the Caltrac was found to overestimate energy expenditure by 20-40%. An additional finding was that the Caltrac was not able to detect increases in running speeds from 5 to 8 mph.

Bray et al. (9) used a respiratory chamber to examine 40 girls (age: 10-16 yrs) over a 24-hour period. While in the respiratory chamber the participants wore two Caltrac accelerometers, one on each hip, and performed normal sedentary activities and two 20 minute bouts on a cycle ergometer. During the 24-hour period the Caltrac significantly underestimated energy expenditure by 6.8% to 30.4%.

While the literature suggests that the Caltrac is reliable (54, 59, 67), it significantly overestimates energy expenditure during walking and running on a flat surface, while underestimating energy expenditure over a 24-hour period. Thus, the Caltrac does not seem to be a suitable device for use by researchers to measure energy expenditure.

Actigraph

The Actigraph accelerometer is the most widely used accelerometer in physical activity research. The Actigraph is small (2.0 x 1.6 x 0.6 in) and lightweight (1.5 ounces) and can be attached at the waist, wrist, or ankle using velcro straps. The Actigraph uses a uniaxial accelerometer, which can measure accelerations in the range of 0.05 to 2 G's and a band limited frequency of 0.25 to 2.5 Hz. These values correspond to the range where most human activities are performed. An 8-bit analog-to-digital converter samples at a rate of 10 Hz and then summed for the specified time period (epoch). If a one minute epoch is used the Actigraph can store 22 days worth of data, which is downloaded to a personal computer via a reader interface unit.

Numerous studies have examined the validity and reliability of the Actigraph in both laboratory and field settings (4, 23, 27, 34, 36, 41, 52, 57, 81, 83, 85, 88). The first published study using the Actigraph accelerometer (model 5032) was performed by Janz in 1994 (36). This study examined the validity of the Actigraph to assess physical activity in 31 children (age: 7-15 yrs). Each child in the study wore an Actigraph accelerometer and HR monitor for three consecutive days. In addition, they completed a physical activity diary at the end of each day. It was found that the correlation between the average movement counts from the Actigraph and the average net HR for each of the three days were $r = 0.70$, 0.51, and 0.55, respectively. The relationship between average movement counts and minutes spent at $\geq 60\%$ of HR reserve was also found to be high for each of the three days; $r = 0.72$, 0.61, and 0.60, respectively. Because of the high correlation coefficients between the Actigraph counts and the HR variables, it was concluded that the Actigraph accelerometer is a valid, objective method to monitor children's physical activity.

Melanson and Freedson (52) were one of the first to examine the validity of the Actigraph accelerometer (model 5032) under laboratory conditions. They had 15 males (age: 21 ± 1.0 yrs) and 13 females (age: 21 ± 1.1 yrs) walk at 4.8 and 6.4 $km \cdot hr^{-1}$ and run at 8.1 $km \cdot hr^{-1}$ on a treadmill for eight minutes at each speed, while wearing an Actigraph at the hip, ankle, and wrist. In addition, at each speed, data were collected at 0%, 3%, and 6% grades. Simultaneously energy expenditure was measured by indirect calorimetery. While the Actigraph was able to detect changes in speed, it was not able to detect changes in treadmill grade. The correlation between measured energy expenditure and Actigraph counts from the ankle, hip, and wrist were $r = 0.66$, 0.80, and 0.81, respectively (all, $P < 0.01$). Twenty-one participants were selected at random to be used for the development of prediction equations for energy expenditure, which was then cross-validated on the remaining seven participants. The best one predictor model, which included wrist counts and body mass had a mean difference (predicted minus actual) for the cross-validation group of 0.21 $kcals \cdot min^{-1}$. Overall, the model that best predicted energy expenditure included the ankle, hip, and wrist counts plus body mass. This resulted in a mean difference of 0.02 $kcals \cdot min^{-1}$, but there were large individual differences ranging from -2.86 to +3.86 $kcals \cdot min^{-1}$.

Trost et al. (83) examined the validity of the Actigraph in 30 children (age: 10-14 yrs) during treadmill walking and running. Each participant walked at 3 and 4 mph and ran at 6 mph at a 0% grade for 5 minutes at each speed. Indirect calorimetry was used to determine energy expenditure. While performing the walking and running the participant wore an Actigraph on both the left and right hips, which were found to give similar activity counts and had an intraclass reliability coefficient between the two Actigraph devices of 0.87 across all speeds. The activity counts were also highly correlated with energy expenditure ($kcals \cdot min^{-1}$), $r = 0.87$ ($P < 0.01$). Twenty participants were randomly selected to be used for the development of a prediction equation, with the remaining 10 participants set aside for a cross-validation of the new equation. For the group of 10, the mean energy expenditure from the new prediction equation was not significantly different from the actual energy expenditure for all speeds combined. The mean difference was

0.01 kcals$\cdot$min^{-1}, but there was a trend for overestimation of energy expenditure at the slowest speed and underestimation of energy expenditure at the fastest speed. Specifically, at 3, 4, and 6 mph the mean differences were +0.46, -0.02, and -0.41 kcals$\cdot$min^{-1}, respectively. While it appears that the Actigraph is a valid device for estimating energy expenditure in children, it was most accurate at 4 mph, which most likely is greater than normal walking speeds for children.

Currently, the most widely used regression equations for estimating energy expenditure (kcals$\cdot$min^{-1} and METs) in adults is the Actigraph regressions developed by Freedson et al. (27). Their study also computed cut-points that would relate Actigraph activity counts to the intensity of the activity. This allowed researchers to estimate how much time was spent performing light, moderate, and vigorous intensity activities. Freedson et al. (27) had 25 males (age: 24.8 ± 4.2 yrs) and 25 females (age: 22.9 ± 3.8 yrs) walk at 4.8 and 6.4 km$\cdot$hr^{-1} and run at 9.7 km$\cdot$hr^{-1} on a treadmill for six minutes at each speed. The participants wore an Actigraph accelerometer (model 7164) on the right hip for all trials. Simultaneously, energy expenditure was measured using indirect calorimetry. The authors first developed an algorithm to predict MET level based off the counts$\cdot$min^{-1} from the Actigraph accelerometer; METs = 1.439008 + (0.000795 * counts$\cdot$min^{-1}). This equation was then used to determine cut points (for counts$\cdot$min^{-1}) corresponding to various MET levels; light activity (< 3.0 METs) corresponds to less than 1952 counts$\cdot$min^{-1}, moderate activity (3.0 – 5.99 METs) corresponds to 1952 – 5724 counts$\cdot$min^{-1}, hard activity (6.0 – 8.99 METs) corresponds to 5725 – 9498 counts$\cdot$min^{-1}, and very hard activity (> 8.99 METS) corresponds to greater than 9498 counts$\cdot$min^{-1}. The development of the prediction equation for energy expenditure (kcals$\cdot$min^{-1}) used a random sample of 35 of the participants, which was then cross-validated in the remaining 15 participants. Mean differences (measured minus predicted) for energy expenditure were -0.19, -0.46, and 0.12 $kcals \cdot min^{-1}$ at 4.8, 6.4, and 9.7 $km \cdot hr^{-1}$, respectively, which were not significantly different.

In 2000 Hendelman et al. (34) published one of the first studies examining the use of an Actigraph accelerometer to predict energy expenditure in moderate-intensity lifestyle activities. They had 25 participants (age: 40.8 ± 7.2 yrs) perform three test sessions consisting of various activities. In session one, the participants walked at four self-selected speeds (leisurely, comfortable, moderate, and brisk) on in indoor track. Each walking bout lasted approximately 5 minutes. In session two, they played two holes of golf using a pull cart. In session three, they performed the following activities for 5 minutes each; 1) washing windows, 2) dusting, 3) vacuuming, 4) lawn mowing (using a gas powered push mower), and 5) planting shrubs. During all sessions the participants wore an Actigraph accelerometer (model 7164) on the left hip and a TEEM100 Aerosport portable gas analyzer was simultaneously worn for the measurement of energy expenditure. Regression analysis was performed on the walking only data, and on all the data combined, to develop equations for the prediction of METs based on the $counts \cdot min^{-1}$. These equations were then used to determine intensity cut points for light (1.9 – 2.99 METs), moderate (3.0 – 5.99 METs), and hard (6.0 – 8.99 METs). The walking cut points were 2191, 6893, and 11596 $counts \cdot min^{-1}$ for light, moderate, and hard activity, respectively, which were similar to that reported by Freedson el al. (27). The cut points for all the data combined were 191, 7526, and 14861 $counts \cdot min^{-1}$ for light, moderate, and hard activities, respectively. They also developed individual regression equation for each participant based on the accelerometer and energy expenditure during the walking activity. This was then applied to the accelerometer data from the remaining activities and it was found that the Actigraph underestimated the energy expenditure of moderate-intensity lifestyle activities by 30.5-56.8%.

In 2000, Swartz et al. (81) also examined the use of an Actigraph accelerometer (model 7164) in a field setting. They developed intensity cut points for moderate-intensity lifestyle activities and added an Actigraph accelerometer to the wrist to see if there was an improvement in the estimation of energy expenditure by using both the hip and wrist accelerometer counts. Seventy participants (age: 41 ± 15 yrs, BMI: 26.0 ± 5.4 $kg \cdot m^{-2}$) performed one to six activities, within one or more of the following categories; yard work, occupation, housework, family care, conditioning, and recreation. In all there were a total of 28 activities, with 12 participants performing each activity. Each activity was performed for 15 minutes. A Cosmed $K4b^2$ was used to measure energy expenditure during all activities. In addition, the participants wore an Actigraph accelerometer on the right anterior axillary line at waist level and one on the dominant wrist. Based on the equation developed to predict METs from hip $counts \cdot min^{-1}$ the intensity cut points were 574, 4945, and 9317 for light (1.1-3 METs), moderate (3-5.9 METs) and hard (≥ 6 METs), respectively. It was also found that the regression equations developed for the wrist, hip, and wrist plus hip accelerometer counts accounted for 3.3%, 31.7% and 34.3% of the variation in MET level of the activities performed, respectively. Although the addition of the wrist data to the hip data explained significantly more of the variability in the MET level, it was only a 2.6% improvement. The authors concluded that this small improvement was outweighed by the additional time needed to analyze the data and the extra cost needed for the accelerometer placed on the wrist.

Bassett et al. (4) examined the validity of the Actigraph accelerometer (model 7164) to estimate energy expenditure during moderate-intensity lifestyle activities. The Actigraph accelerometer was worn on the right hip. Simultaneously, a Cosmed $K4b^2$ portable metabolic unit was used to measure energy expenditure. The Actigraph MET values were calculated based on three commonly used equations; 1) manufacture's equation (CSA1), which gives an estimate of net EE (15) 2) Freedson's equation (CSA2), which uses counts per minute and was developed from a study using treadmill walking and running (27), and 3) Hendelman's equation (CSA3), which is based on lifestyle activities performed in the field (34). A total of 28 activities were performed which fell under the categories of yard work, occupation, housework, family care, conditioning, and recreation. Activities were performed for 15 minute periods. Reported mean error scores (indirect calorimetry – device) for all activities combined were: CSA1, 0.97 METs, CSA2, 0.47 METs, and CSA3, 0.05 METs. Across all 28 activities, the equations predict METs fairly well, but there were large variations for individual activities. For example, the equations overestimated walking, but significantly underestimated activities that are predominantly arm activities or had a large upper body component such as pushing/carrying objects, lifting objects, hill climbing, lawn mowing, raking leaves, and washing windows.

Leenders et al. (45) examined the use of an Actigraph accelerometer (model 7164) to assess free-living physical activity versus DLW. Thirteen women wore an Actigraph accelerometer for seven days while actual energy expenditure was determined by DLW. The Actigraph data was collected in one minute epochs and the equation of Freedson et al. (27) was used to estimated energy expenditure ($kcals \cdot min^{-1}$). In this group of females it was found that the Actigraph underestimated PAEE by 59%. This study highlighted the fact that it is difficult to account for all types of activities performed during the day using a device placed on the hip. This was an important finding because it highlighted the fact that laboratory based equations do not necessarily work in a field setting, suggesting that further work was needed to enhance the validity of accelerometer based prediction models in the field.

Recently, King et al. (41) examined the validity of an Actigraph accelerometer (model 7164) during treadmill exercise in 21 healthy adults. Participants wore an Actigraph on their left and right hips while walking on a treadmill at 53, 80, and 107 $m \cdot min^{-1}$ and running at 134, 161, 188, and 214 $m \cdot min^{-1}$. Each speed was maintained for 10 minutes and energy expenditure was measured by indirect calorimetry (Parvomedics TrueMax 2400). Energy expenditure for the Actigraph was calculated using both the manufacturer's equation and the equation developed by Freedson et al. (27). There were no significant differences between the left and right devices at any speed. For the Actigraph, there was a significant effect of speed on activity counts, the manufacturer's estimate of total energy expenditure, and Freedson's equation of estimated total energy expenditure (all, $P < 0.001$). A steady increase in counts occurred as speeds increased from 54 to 161 $m \cdot min^{-1}$, however there was a leveling off or slight drop in the activity counts between the speeds of 161 and 214 $m \cdot min^{-1}$. Using the manufacturer's equation, the Actigraph was not significantly different from actual energy expenditure at speeds of 80, 107, 161, and 188 $m \cdot min^{-1}$ ($P \geq 0.05$), but it significantly underestimated energy expenditure at 54 and 214 $m \cdot min^{-1}$ ($P < 0.05$), while overestimating energy expenditure at 134 $m \cdot min^{-1}$ ($P < 0.05$). The only difference when using the equation of Freedson et al. (27) is that the Actigraph was similar at 134 $m \cdot min^{-1}$. In addition, the correlation between total energy expenditure and estimated Actigraph energy expenditure ranged from $r = 0.73$ at 54 $m \cdot min^{-1}$ to $r = 0.58$ at 214 $m \cdot min^{-1}$. This study highlights an important limitation of the Actigraph accelerometer; at running speeds above approximately 161 $m \cdot min^{-1}$. At these speeds, the activity counts begin to level off, thus limiting its use for high intensity activities.

Actical

The Actical accelerometer is a small (28 x 27 x 10mm) device that uses an omnidirectional accelerometer and weighs only 17 grams. The Actical is sensitive to movements in the range of 0.5 to 3 Hz. It is capable of storing 45 days worth of data using 1-minute epochs. To date, only a few studies have examined the validity and reliability of the Actical (33, 42, 63, 88).

Klippel and Heil (42) validated the Actical in 12 men and 12 women while performing 9 activities; typing, hand writing, card sorting, floor sweeping, carpet vacuuming, table surface dusting, treadmill walking at 67 and 80.4 $m \cdot min^{-1}$, and treadmill jogging at 120.6 $m \cdot min^{-1}$. All activities were performed in a laboratory and energy expenditure was measured using a VmaxST portable metabolic system. While performing the activities the participants wore an Actical on the non-dominant wrist, on the ankle on the same side of the body as the wrist device, and on the right hip. Prediction equations were developed using the average of the last two minutes of each activity. The prediction equation developed for the Actical when worn at the ankle ($r = 0.77$, SEE = ± 1.4 METs, $P < 0.001$), hip ($r = 0.94$, SEE = ± 0.8 METs, $P < 0.001$) and wrist ($r = 0.90$, SEE = ± 1.0 METs, $P < 0.001$) showed promise for the prediction of METs.

Heil and Klippel (33) also validated the Actical in adolescents and teens using similar methods as Klippel and Heil (42). The children performed the following 9 activities; typing, hand writing, video game playing, floor sweeping, carpet vacuuming, table surface dusting, treadmill walking at 67 and 80.4 $m \cdot min^{-1}$, and treadmill jogging at 120.6 $m \cdot min^{-1}$. In the children they were interested in estimating activity energy expenditure (AEE) (AEE = task energy expenditure minus RMR) in $kcals \cdot kg^{-1} \cdot min^{-1}$, rather than METs as was used in the adults. The equations developed for the ankle ($r = 0.80$, SEE = ± 0.0771, $P < 0.001$), hip ($r = 0.89$, SEE = ± 0.0587, $P < 0.001$), and wrist ($r = 0.89$, SEE = ± 0.0592, $P < 0.001$) all provided a reasonable estimate of AEE.

Recently Puyau et al. (63) examined the validity of the Actical to predict AEE in children. Thirty-two children (age: 7-18 yrs) wore an Actical monitor while performing a 4-hour routine in a room calorimeter. Upon awakening, the children remained still for 30 minutes for the measurement of their basal metabolic rate (BMR). They were then allowed to eat before they played Nintendo for 20 minutes in a sitting position, worked at a computer for 20 minutes while sitting in a chair, continuously dusted the contents of the room calorimeter for 10 minutes, performed aerobic exercises by following a videotape for 12 minutes and practiced free throws from a set distance in a standing position for 10 minutes. They then left the room calorimeter had had their oxygen consumption measured by a SensorMedics 2900 metabolic cart while walking on a treadmill at 2.0

mph for 7 minutes, walking at 3.5-4.0 mph for 7 minutes and running at 4.5-7 mph for 7 minutes. Linear regression analysis was used to develop equations for AEE (energy expenditure minus BMR) and physical activity ratio (PAR) (energy expenditure/BMR). The equations developed accounted for 81% of the variability in AEE and PAR. The authors also sought to determine appropriate cut points for sedentary, light, moderate, and vigorous activity based on AEE and PAR. The activity cut points of 100, 1500, and 6500 counts$\cdot$min^{-1} corresponded to light (AEE, 0.01 kcals$\cdot$kg$^{-1}\cdot$min^{-1} and PAR, 1.5), moderate (AEE, 0.04 kcals$\cdot$kg$^{-1}\cdot$min^{-1} and PAR, 3), and vigorous (AEE, 0.1 kcals$\cdot$kg$^{-1}\cdot$min^{-1} and PAR, 6) activities, respectively.

TriTrac-R3D

The TriTrac-R3D (TriTrac) is a triaxial accelerometer that was developed with the hope of overcoming some of the limitations of uniaxial accelerometers. The TriTrac has three independent sensors in orthogonal axes to detect acceleration in three planes (x, y, z). It is about the size of a deck of cards and weighs 170 grams. The TriTrac can be programmed to record in one second to one minute epochs and can store 7-days worth of data when one minute epochs are used. In addition, it provides an estimate for both activity energy expenditure as well as resting energy expenditure (based on age, gender, height, and weight).

The TriTrac has the potential to be a better predictor of energy expenditure due to its use of three accelerometers, versus a uniaxial accelerometer. Many investigators have examined its validity and reliability to predict energy expenditure (10, 12, 14, 24, 34, 35, 41, 43-45, 51, 72, 75, 85-87). Sherman et al. (72) examined the use of the TriTrac to predict energy expenditure during ambulatory activity. Sixteen participants (age: 24 ± 3 yrs) simultaneously had their energy expenditure measured and predicted by indirect calorimetery and a TriTrac, respectively while at rest (10 minutes pre- and 20 minutes post exercise) and while walking on a treadmill at various speeds at a 0% grade. The speeds were between 40% and 70% of their VO_{2peak} which was measured during an incremental treadmill test on a separate day. Each speed was maintained for 15 minutes. The participants on a separate day walked for 15 minutes on a level soccer field at speeds that produced similar HRs as those obtained during the treadmill walking. There were no significant differences between actual energy expenditure and that estimated by the TriTrac at rest before exercise or any of the treadmill walking speeds, although the TriTrac significantly underestimated energy expenditure post exercise ($P < 0.05$), most likely due to its inability to take into account elevations in energy expenditure due to post exercise oxygen consumption. During the field trial, energy expenditure was predicted based on the HR value and there were no significant differences between the energy expenditure estimated by HR and that given by the TriTrac.

Jakicic et al. (35) examined the accuracy of the TriTrac to estimate energy expenditure during various activities. Twenty participants (age: 21.5 yrs) performed five different exercises on separate days, each lasting 20-30 minutes. The activities were performed for 10 minutes at each intensity and included: treadmill walking (3 mph at 0%, 5%, and 10% grade), treadmill running (5 mph at 0% and 5% grade), cycling (1.5 kg resistance at 50 rpm and 65 rpm), stepping (8 in step height at 20 cycles$\cdot$min^{-1} and 30 cycles$\cdot$min^{-1}), and slideboard (160 cm slide at 17 cycles$\cdot$min^{-1} and 21 cycles$\cdot$min^{-1}). For all activities, the participants wore two TriTrac accelerometers and energy expenditure was measured by indirect calorimetry. The assessment of inter-instrument reliability revealed that there was a significant difference between the devices (worn on the left and right sides) for the prediction of energy expenditure during all activities ($P < 0.05$). The highest correlations between indirect calorimetry and predicted EE from the TriTrac were seen during walking and running ($r = 0.78 – 0.92$, $P < 0.05$). Stepping and slideboard activities had a correlation of $r = 0.54 – 0.81$ ($P < 0.05$). Cycling was the only activity where actual and predicted energy expenditure were not significantly correlated ($r = 0.04 – 0.43$, $P \geq 0.05$). Although the TriTrac energy expenditure was significantly correlated with measured energy expenditure, it significantly underestimated measured energy expenditure for all activities, except treadmill running.

Welk et al. (85) published one of the first studies that examined the TriTrac under both laboratory and field conditions. Fifty-two participants (age: 29 yrs) completed two choreographed routines that included six activities that were performed for six minutes each. Three activities (walking at 80.5 $m \cdot min^{-1}$, walking at 107.3 $m \cdot min^{-1}$, and jogging at 170 $m \cdot min^{-1}$) were performed in both routines to assess the reliability of instruments. The three additional activities in routine 1 included mowing, raking, and shoveling, while the three additional activities in routine 2 were vacuuming, sweeping, and stacking groceries. During the indoor activities a SensorMedics 2900 metabolic cart was used to measure energy expenditure, while during the outdoor activities an Aerosport KB1-C portable metabolic unit was used. Correlations between the treadmill walking/jogging energy expenditure and the TriTrac in routine 1 were $r = 0.93$, while the correlation during routine 2 was $r = 0.92$. The correlation between the energy expenditure for the lifestyle activities and the TriTrac was $r = 0.59$. During the treadmill walking (80.5 and 107.3

$m \cdot min^{-1}$) the TriTrac significantly overestimated the actual METs by approximately 0.5 – 1.0 METs ($P < 0.05$), but during treadmill jogging (170 $m \cdot min^{-1}$) there was not a significant difference between the predicted and actual METs ($P \geq 0.05$). During the lifestyle activities the TriTrac significantly underestimated energy expenditure by 57%, with the largest errors seen during the sweeping and vacuuming tasks. This study highlights the fact that the laboratory equations developed do not always transfer to free-living situations, as was seen with the Actigraph accelerometer.

Leenders et al. (45) examined the use of a TriTrac accelerometer to assess free-living physical activity versus DLW. Thirteen women wore a TriTrac accelerometer for seven days while actual energy expenditure was determined by DLW. In this group of females, the TriTrac underestimated PAEE by 35%. This is an improvement over the Actigraph and Yamax pedometer (which each underestimated by 59%). While the TriTrac accelerometer shows promise for being a better measurement device than uniaxial accelerometers, for predicting energy expenditure, it is still missing a large part of the 24-hour PAEE. In addition, it has the same limitations as other devices worn on the hip such as not being able to take into account activities such as walking up/down a grade, carrying objects such as a briefcase or groceries, and bicycling.

Campbell et al. (10) evaluated the use of a TriTrac accelerometer to measure energy expenditure in females during field activities. Twenty women (age: 20-29 yrs) performed a choreographed routine to simulate daily activities, which consisted of the following: walking on a 400 m asphalt track, jogging on a 400 m asphalt track, stair climbing a flight of 17 stairs without the use of a handrail, walking on an incline of 12 degrees in slope and 32 m long, stationary cycling at a work load of 50 watts, and arm ergometry with no resistance. All activities were performed for five minutes at a self selected speed. During the routine the participants wore a TriTrac accelerometer and energy expenditure was measured using indirect calorimetry (Cosmed K4b^2 portable system). The TriTrac prediction of energy expenditure for walking on an incline and for the total routine were not significantly different from the actual energy expenditure, while it significantly overestimated energy expenditure during level walking and jogging, and underestimated actual energy expenditure during stair climbing, stationary cycling, and arm ergometry. This study highlights that fact that overall the TriTrac may give a reasonable estimate of energy expenditure, but it significantly over- and underestimates individual activities.

Recently, King et al. (41) examined the TriTrac during treadmill exercise in 21 healthy adults. Participants wore a TriTrac on their left and right hips while walking on a treadmill at 53, 80, and 107 $m \cdot min^{-1}$ and running at 134, 161, 188, and 214 $m \cdot min^{-1}$. Each speed was maintained for 10 minutes and energy expenditure was measured by indirect calorimetry (Parvomedics TrueMax 2400). There were no significant differences between the left and right devices at any speed. There was a significant effect of speed on vector magnitude counts, estimated AEE, and estimated total energy expenditure (all, $P < 0.001$). Unlike what is observed with other uniaxial accelerometers, the TriTrac counts continued to increase with each speed, but they did become attenuated at the fastest running speeds (161 to 214 $m \cdot min^{-1}$). However, the TriTrac significantly overestimated actual AEE and total energy expenditure at all walking and running speeds. In addition, the correlation between total energy expenditure and estimated energy expenditure by the TriTrac ranged from r = 0.49 at 54 $m \cdot min^{-1}$ to r = 0.83 at 214 $m \cdot min^{-1}$.

RT3 Research Tracker

The RT3 Research Tracker (RT3) was recently introduced as the replacement to the TriTrac-R3D. The RT3 uses a three-dimensional piezoelectric accelerometer and has the ability to store data in epochs of one second to one minute. When one minute epochs are used, up to 21 days of data can be stored depending on the data collection mode (X, Y, and Z or vector magnitude). The RT3 is much smaller than the TriTrac (2.8 x 2.2 x 1.1 in) and weighs 2.3 ounces. The manufacturer claims that the reliability of the RT3 should be better than the TriTrac due to the use of an integrated triaxial accelerometer that integrates the three vectors into a single chip, versus the TriTrac which uses three independent sensors. In addition, they conduct factory testing to make sure the device conforms to specific standards before being sold.

To date few studies have examined the accuracy and reliability of the RT3 (21, 22, 41, 61, 62, 66). DeVoe et al. (22) compared the RT3 and TriTrac accelerometers under laboratory and field settings. The participants performed a maximal stress test, treadmill walking, and over-ground walking on an outside field while wearing a RT3 and TriTrac in the lumbar region of the back. During the stress test and treadmill walking (slow: 4.8 $km \cdot hr^{-1}$ at 0%, 5%, 10%, and 15% grade; fast walk: 6.4 $km \cdot hr^{-1}$ at 0% grade; and jogging: 9.7 $km \cdot hr^{-1}$ at 0% grade) oxygen consumption was measured by indirect calorimetry. The slow walk, fast walk, and jogging were performed for 6 minutes at each speed and grade. The over-ground walking consisted of three 6 minute bouts at 4.8, 6.4

and 9.7 km·hr^{-1}. During all testing HR was measured using a Polar Vantage XL HR monitor. The main finding was that, on average, the RT3 records higher activity counts than the R3D. In addition, there was less variation in the activity counts for a given activity when using the RT3. However, they both had moderate correlations with oxygen consumption and vector magnitude counts during the treadmill walking and jogging (RT3 $r = 0.57$; TriTrac $r = 0.58$; both $P < 0.001$) and HR and vector magnitude counts (RT3 $r = 0.51$; TriTrac $r = 0.51$; both $P < 0.001$). The lowest correlations were seen during the graded walking, which was seen for both accelerometers.

Powell and Rowlands (62) examined the intermonitor variability of the RT3 during various activities. One female (24 yrs) performed the following six activities: treadmill walking at 4 and 6 km·hr^{-1}, treadmill running at 8 and 10 km·hr^{-1}, and a repeated sit-to-stand activity controlled by a metronome set at 40 beats·min^{-1}. Each activity was performed for 12 minutes and the routine was repeated on a separate day. During the activities eight monitors were secured to the female's waist (four above the left hip and four about the right hip). During locomotor activities the intermonitor coefficient of variation was low (< 6%), but it was higher during the sit-and-stand test (8 – 25%). There were no differences in the vector magnitude, X and Z axes between the first and second trials, although one monitor recorded significantly lower activity counts for the Y axis in trial one versus trial two. There were intermonitor differences evident for the Y and Z axis at 4, 6, 8, and 10 km·hr^{-1}, and for the vector magnitude and X axes at 6, 8, and 10 km·hr^{-1}. In addition, as the intensity of exercise increased, the variability among the monitors also increased. The reliability of the RT3 was shown to be good, but researchers should be aware of the intermonitor variability. Also, the vertical axis appeared to show the least variability and was the most reliable.

Rowlands et al. (66) examined the validity of the RT3 for the assessment of physical activity and determined cut-points for moderate (3-5.99 METs) and vigorous ($\geq$ 6 METs) intensity activity in 19 boys (age: 9.5 ± 0.8 yrs) and 15 men (age: 20.7 ± 1.4 yrs). The participants first sat quietly for 10 minutes while playing a keyboard computer game (boys) or completing a crossword (men). This was followed by walking on a treadmill at 4 and 6 $km \cdot hr^{-1}$ and running at 8 and 10 $km \cdot hr^{-1}$, kicking a soccer ball with an investigator (distance: boys = 2.4 m, men = 3 m), and alternately hopping and jumping on a hopscotch grid. All activities were performed for 4 minutes while wearing both an RT3 and a TriTrac accelerometer. Douglas bags were used for the measurement of oxygen consumption and carbon dioxide production during the last minute of each activity. To account for differences in body size, oxygen consumption was expressed relative to body mass raised to the power of 0.75 (SVO_2). The RT3 accelerometer counts were significantly correlated with SVO_2 for all activities in both the boys and men. The RT3 vector magnitude was a significantly better predictor of SVO_2 than the TriTrac vector magnitude. Analyses between the RT3 and TriTrac showed that the RT3 vertical axis counts were significantly higher during walking at 6 $km \cdot hr^{-1}$, running at 10 $km \cdot hr^{-1}$, and hopscotch ($P < 0.05$), but not during the other activities. For the anteroposterior axis the RT3 counts were significantly higher than the TriTrac for all activities ($P < 0.05$), except sitting and kicking a ball. This study highlighted the point that even though both monitors used are triaxial accelerometers, the activity counts given by each are not always comparable.

King et al. (41) examined the RT3 during treadmill exercise in 21 healthy adults. Participants wore a RT3 on their left and right hips while walking on a treadmill at 53, 80, and 107 $m \cdot min^{-1}$ and running at 134, 161, 188, and 214 $m \cdot min^{-1}$. Each speed was maintained for 10 minutes and energy expenditure was measured by indirect calorimetry (Parvomedics TrueMax 2400). There were no significant differences between the left and right devices at any speed. For the RT3 there was a significant effect of speed on vector magnitude counts, estimated AEE, and estimated total energy expenditure (all, $P < 0.001$). A slight attenuation in the counts occurred only at the fastest running speeds (188 to 214 $m \cdot min^{-1}$). However, the RT3 significantly overestimated measured AEE and total energy expenditure at all walking and running speeds. In addition, the correlation between total energy expenditure and estimated energy expenditure by the RT3 ranged from $r = 0.39$ at 54 $m \cdot min^{-1}$ to $r = 0.685$ at 214 $m \cdot min^{-1}$.

Motion sensors provide a valuable tool for objective monitoring of physical activity however, they have several limitations. In general, accelerometers are limited to ambulatory activities such as level walking and slow running. Accelerometers are not as effective during lifestyle activities and have been shown to be ineffective at predicting the energy cost of activities such as cycling, upper body exercise (if waist-mounted), swimming, rowing, or walking/running up an incline (26, 32, 35, 45, 52, 79, 85). In addition, uniaxial accelerometers cannot detect increases in energy expenditure that occur at running speeds over 9 $km \cdot hr^{-1}$ (8, 32).

Heart Rate

HR is often used to estimate both exercise and free-living energy expenditure. Since HR is linearly related to oxygen uptake (VO_2) for dynamic activities involving large muscle groups (13, 73), it can provide a reasonable estimate of energy expenditure during exercise (11, 25). The use of HR provides a physiological measurement which can provide information on the pattern of activity performed. Several methods have been used to estimate energy expenditure, such as average pulse rate (60), net HR (activity HR minus resting HR) (1), and the use of linear predictions based on HR-VO_2 curves developed on an individual basis in a laboratory setting (5, 31, 47, 49, 50, 56, 65, 77). Of these methods the most common approach is using the linear prediction equations, but there are limitations to its use due to the variability in the HR-VO_2 relationship at low HRs. One method that attempts to reduce the error seen from the HR variability is the Flex HR method.

The Flex HR method is a common method used for predicting 24-hour energy expenditure. The Flex HR method utilizes HR and VO_2 measured at rest (lying, standing, sitting) and during exercise of various intensities to develop HR-VO_2 calibration curves (28). The Flex HR is the average of the highest HR during rest and the lowest HR during light exercise. In a field setting, the assumed resting metabolic rate (1 MET) is used for any value below the Flex HR, while the HR-VO_2 curve is used to estimate energy expenditure for any value above the Flex HR. Ceesay et al. (11) examined the Flex HR method in 20 participants. The HR-VO_2 relationship was determined for lying, sitting, standing, and while performing the following activities: cycle ergometer at 50 rpm and work loads of 25, 50, 75, and 100 watts, stepping at 20 steps$\cdot$min^{-1} on a 225 mm block, and jogging in place at 138 steps·min^{-1}. The jogging in place was excluded from the analysis and to determine the Flex HR they used the mean of the highest HR while standing and the lowest HR during the stepping exercise. The participants then spent 21.5 hours in a room calorimeter, during which time they performed the following activities: cycle ergometer at 50 rpm and a work rate of 50 watts, rowing at 20 strokes·min^{-1} at a work rate of 50 watts, stepping at a rate of 20 steps·min^{-1}, and jogging in place at 138 steps·min^{-1}. Overall, the Flex HR method underestimated actual energy expenditure by 1.2 ± 6.2% with a range of -11.4% to +10.6%. More importantly, during the 21 hours in the calorimeter, only 98 minutes were spent above the Flex HR, meaning 22 minutes of the structured exercise were spent below the Flex HR.

Livingstone et al. (49) examined the estimation of energy expenditure by the Flex HR method versus DLW in free-living individuals. Individual calibration curves were developed for 15 participants using lying, sitting, standing and cycle ergometer exercise. The participants then had their HR monitored for 15 days while actual energy expenditure was measured by DLW. Although in two-thirds of the participants, the Flex HR method gave an energy expenditure value within +10% of DLW, the individual error ranged from -22.2% to +52.1%. This large range in individual scores is similar to that reported in other studies (19, 47, 56, 71).

Another approach for the estimation of energy expenditure has been developed by Polar Electro, Inc. Polar Electro, Inc. is a leading manufacturer of HR monitors and their devices have been shown to be valid devices for the measurement of HR when compared to electrocardiogram (39, 46, 82). In addition, Polar has developed software (OwnCal) that allows an individual to estimate energy expenditure during exercise. The OwnCal software uses inputted user data (gender, age, weight, physical activity status, VO_{2max} and HR_{max}) and exercise HR. In Polar watches such as the S410, the user has the ability to have the watch estimate their VO_{2max} and HR_{max}, or they may input their actual values if known. Under laboratory conditions the OwnCal software has been shown to be an accurate way of estimating exercise energy expenditure during various forms of activities (i.e. treadmill walking/running, cycling, and rowing) in males, when either the estimated VO_{2max} and HR_{max} or their actual values are input into the watch (16). In females, regardless of whether the estimated or actual VO_{2max} and HR_{max} are used, the estimated energy expenditure from the Polar watch significantly overestimates measured energy expenditure. In females, one problem with using the predicted VO_{2max} and HR_{max} is that the Polar watch significantly overestimates VO_{2max} by 10 $ml \cdot kg^{-1} \cdot min^{-1}$. Thus, it produces a greater error in estimated energy expenditure when the predicted maximal values are used. When the actual maximal values are used, there is a significant improvement in the estimate of energy expenditure. In addition, even though there are significant differences in females, the mean estimates of energy expenditure are still acceptable giving values that are within ± 12% of measured energy expenditure, when using the actual VO_{2max} and HR_{max}. (16).

The use of HR for the estimation of energy expenditure has many advantages, it also has several limitations. For example, the Flex HR method is a time consuming method, because of the need to develop individual calibration curves for individuals. In addition, the method has mixed results and has not been shown to always be an accurate method (49, 56, 65, 77). The Polar method is only useful for HRs above 90 $beasts \cdot min^{-1}$ and relies on a proprietary algorithm. In addition, a major drawback to using HR is that factors such as environmental temperature, stress, hydration level, mode of exercise (upper vs. lower body), gender, and training status can affect the estimation of energy expenditure. These factors make it difficult to generalize the HR-VO_2 relationship among individuals, which warrants the need for individualized HR-VO_2 regressions to be developed.

Simultaneous Method: HR + Motion Sensor

Due to the large errors in estimating energy expenditure by a single device some researchers have proposed combining devices such as a motion sensor and HR monitor for a more accurate estimate of energy expenditure (31, 50, 55, 65, 77). From these studies it appears that combining devices to estimate energy expenditure will result in a more accurate assessment of energy expenditure versus using a single device by itself. Haskell et al. (31) was the first to propose the simultaneous use of HR and both upper and lower body motion sensors to help improve the estimate of energy expenditure. They had participants perform activities such as treadmill walking and running (flat and up hill), cycling, arm cranking and stepping in the laboratory while wearing a HR monitor, and motion sensor on the wrist and thigh. Simultaneously energy expenditure was measured by indirect calorimetry. The HR-motion sensor method was highly correlated to measured energy expenditure ($R^2 = 0.89$, SEE 2.3 $ml \cdot kg^{-1} \cdot min^{-1}$), on average. They concluded that the use of separate regressions for upper and lower body activity can improve the estimate of energy expenditure when combined with HR.

Since Haskell et al. (31) most investigators have only examined the simultaneous method in the laboratory and have had good success. Rennie et al. (65) examined the simultaneous method, under controlled conditions in a whole room colorimeter, using a new instrument (HR+M) that they developed for use in their laboratory. Their new device was a single instrument that was worn around the chest and recorded minute-by-minute data for both HR and movement. Prior to starting the experiment they developed individualized HR-VO_2 curves by measuring the participants VO_2 in the lying and seated position, and then at four workloads on a cycle ergometer. They then monitored participants for 12-hours in a room calorimeter and during that time they had the participants perform stepping and cycling exercises at prescribed intervals throughout the time period. They found that the overall mean error of estimating total energy expenditure using the simultaneous method was 0.00% versus whole room calorimetry. In the same study, the use of the Flex HR method produced a mean error of 16.5%. A major limitation to this study is that the device used is not currently available; it was something that they designed in their laboratory.

Brage et al. (8) has also found encouraging results using a branching equation that involves the simultaneous use of accelerometry and HR. They used a whole room calorimeter to monitor participants for 22 hours, of which 12.5 hours were spent awake. During this time, the participants performed cycling, walking, running, and stepping exercise. The participants had their VO_{2peak} measured using a treadmill protocol prior to entering the whole room calorimeter, so individualized HR-VO_2 regression equations could be developed. Additionally, an Actigraph flex point and a Flex HR were determined for each individual. The Actigraph flex point was determined by taking 50% of the mean Actigraph counts$\cdot$min^{-1} while walking at 3 km$\cdot$hr^{-1}. The Flex HR was determined by the following equation: 10 beasts$\cdot$min^{-1} plus the average of the resting HR and the mean HR at 3 km·hr^{-1}. The individual data was also averaged together to get a group HR-VO_2 regression curve. To estimate PAEE they used an algorithm they developed based on Actigraph (placed on the hip) activity counts·min^{-1} and HR (beasts·min^{-1}) (figure 1). The first branch in the algorithm is determined by accelerometer counts·min^{-1}. If the counts·min^{-1} are less than the Actigraph flex point then the right side (NO) of the branch is followed. Conversely, if the counts·min^{-1} is greater then the Actigraph flex point the left side (YES) of the branch is followed. The next step in the branch is determined by HR values and finally the PAEE is calculated based on a combination of HR and Actigraph data. They used the algorithm in figure 1 to estimate PAEE based on both the individual HR-VO_2 relationship and the group HR-VO_2 regression equations. Using the individual HR-VO_2 regressions, they found average estimates of PAEE of -4.4% ± 29.0%. When the group HR-VO_2 regression was used, the average estimate of PAEE was 3.5% ± 20.1 %. Neither of these two methods was significantly different from that measured by the whole room calorimeter. While this study is promising, the method requires individualized HR-VO_2 regression equations to be developed for each individual, as well as a time consuming data analysis to determine energy expenditure.

While there have been several laboratory experiments involving the use of the simultaneous method few have examined its use in a field setting. Strath et al. (76) examined the accuracy of the simultaneous method (HR + motion sensor), an Actigraph accelerometer, HR, and a Yamax SW-701 pedometer to estimate energy expenditure for 14 different activities such as vacuuming, house cleaning, walking, pushing a lawnmower, raking leaves, and stair climbing. While performing the activities an

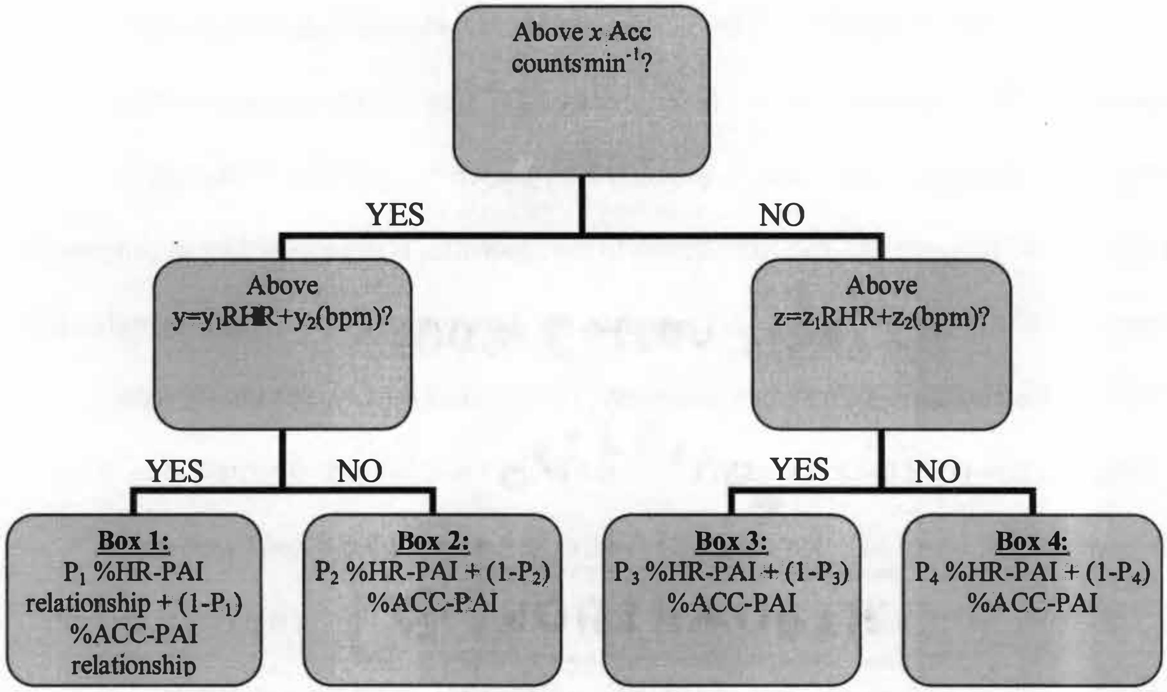

Figure 1. Equation structure for the combination of accelerometry (ACC) and heart rate (HR). All HR values are absolute HR minus resting HR (RHR). All physical activity intensity (PAI) relationships are determined by calibration. Therefore, this study has 2 equation complexes, depending on whether individual or group calibration is used. The equation complexes translate minute-by-minute data into PAI as follows. If Computer Science and Applications (CSA) value is above x, we use box 1 (with P_1) if the HR value is above y; otherwise we use box 2 (with P_2). Similarly, if the CSA value is $\leq x$, we use box 3 (with P_3) if the HR value is above z; otherwise we use box 4 (with P_4). Physical activity energy expenditure (PAEE) is obtained by integrating PAI with respect to time. The parameters x, $y_{1\text{-}2}$, $z_{1\text{-}2}$, and $P_{1\text{-}4}$ are either assumed a priori or can be estimated post hoc by simulation of all possible models, while the standard error between predicted and measured PAEE is minimized. Reprinted from Brage et al (8).

Actigraph accelerometer and Yamax SW-701 pedometer were worn on the hip, a Polar Vantage XL HR monitor was used to collect minute-by-minute HR data and two additional Actigraph accelerometers were worn on the wrist and thigh, which were used in conjunction with HR data for the simultaneous method. Each activity was performed for 15 minutes and actual energy expenditure was measured with a Cosmed $K4b^2$ portable metabolic system. Prior to performing the activities, the participants performed submaximal tests using a treadmill and arm ergometer so individualized HR-VO_2 regression curves could be developed for both leg and arm activity. HR data were used to predict METs based on the individualized HR-VO_2 regression curves obtained from the treadmill test. Data from the motion sensors were used to determine if the activity was performed using arms or legs. To do this, a ratio of the wrist and leg Actigraph counts were taken and if the wrist to leg ratio was greater than 25 if was determined to be arm activity, while if the ratio was less than 25 if was determined to be leg activity. The measured HR was then applied to the specific HR-VO_2 regression line based on the ratio and a MET value was determined for the activity. For each activity an error score was developed (criterion minus device). The mean of the error scores for each device were then used for the analysis. Overall, the simultaneous method was the most accurate and had an R^2 of 0.81 with the Cosmed $K4b^2$. The mean estimates for 13 of 14 activities were within 0.3 METs of measured METs. Lawn mowing was off by 0.7 METs.

In a follow-up study, Strath et al. (77) examined the use of the simultaneous method over a 6-hour period in free-living participants. The simultaneous HR and motion sensor method was compared to actual energy expenditure measured by a Cosmed $K4b^2$ portable metabolic system. The methods used were similar to their previous study (76). Participants wore an Actigraph accelerometers and HR monitor for a 6-hour period, while minute-by-minute VO_2 was continuously measured. Overall, the mean total energy expenditure values for the 6-hr period estimated by the simultaneous method (748 ± 178 MET·min^{-1}) were not different from the measured values from the Cosmed (749 ± 138 MET·min^{-1}). A drawback to the simultaneous method of Strath et al. (76) is that individual HR-VO_2 regressions need to be developed for both arm and leg activity which is very time consuming and also requires the participants to perform submaximal testing prior to the measurement period. In addition, the participants must wear a HR strap the entire time, which can become irritating to the skin and uncomfortable. Lastly, the data analysis is time consuming and requires a large database due to the amount of data collected.

Actiheart

The Actiheart (Minimitter, Suriver, OR) is a relatively new device that combines HR and a movement sensor into a single unit that weighs 10 grams. The device is attached to the chest using ECG electrodes. The main sensor (3.3 cm in diameter) attaches to the sternum and it contains the movement sensor, rechargeable battery, a memory chip, and other electronics. The smaller sensor (5 x 11 x 22 mm) attaches to the midclavicular line, and is connected to the main sensor by a thin wire 100 mm long. The Actiheart can measure acceleration, HR, HR variability, and ECG amplitude. Epoch lengths of 15, 30, or 60 seconds can be chosen to store data and approximately 14 days of data can be stored with a one minute epoch. The Actiheart uses a piezo-electric accelerometer with a frequency range of 1-7 Hz, and a dynamic range of ± 2.5 Gs. The

Actiheart ECG measures in a range of 35 to 255 $beats \cdot min^{-1}$ with a sampling frequency of 128 Hz. To date there is only one published study on the reliability and validity of the Actiheart (7).

Brage et al. (7) examined eight Actiheart units for technical reliability and validity as well as assessed the accuracy of the device to detect walking and running. In the first part of the study, eight Actiheart accelerometers were tested during a controlled mechanical setting. The devices were set to record in 15 second epochs under different controlled conditions (36 different accelerations ranging from 0.1 to 19.7 $m \cdot s^{-2}$). Each frequency was recorded for 2 minutes. At accelerations above 0.7 $m \cdot s^{-2}$ the reliability of the instrument was good with a coefficient of variation (CV) between trials of 0.0% (0-11%), whereas below this point there was considerably more variability (18% (0-245%)). Between instruments CV below 0.5 $m \cdot s^{-2}$ were 89% (40–167%), from 0.5 to 1.0 $m \cdot s^{-2}$ it was 25% (17-33%), and above 1.0 $m \cdot s^{-2}$ the CV was 5.3% (4-14%). Although there is a large variability at lower accelerations, these are probably a small source of error due to human movement being above these values.

In the second part of the study by Brage et al. (7) the Actiheart units were then compared against ECG and a Polar S610 heart rate monitor during treadmill exercise in nine participants. They examined the units for intra- and inter-instrumental reliability for the HR sensor. Again 15 second epochs were used to record simulated HRs with frequencies of 25, 30, 33, 50, 100, 150, 200, and 250 $beats \cdot min^{-1}$. Each frequency was recorded for 2 minutes. The treadmill exercise consisted of 4 minutes of rest, then 4 minutes of walking at 3.2, 4.5, and 5.8 $km \cdot hr^{-1}$, then 4 minutes of running at 8.5, 10.3, and 12.1 $km \cdot hr^{-1}$. The Actiheart did not detect HRs below 25 $beats \cdot min^{-1}$, but was within 1 beats·min^{-1} at HRs between 30 and 250 beats·min^{-1}. In addition, there was less than a 1 beats·min^{-1} difference between the ECG, Actiheart, and Polar S610 HR monitor during the treadmill walking.

The third part of the study by Brage et al. (7) was designed to develop prediction equations to predict physical activity intensity (PAI) during treadmill walking and running. Twenty participants performed treadmill exercise as previously described. During the treadmill exercise indirect calorimeter (Cosmed K4b^2) was used to measure energy expenditure and the Actiheart was set to store data in 15 second epochs. The participants then wore the Actiheart for one night to obtain a sleeping HR measurement. Lastly, they performed a 10 minute step test which consisted of stepping up and down on a 215 mm step, starting at 0.25 Hz in minute one and increasing to 0.625 Hz in minute 10. The Actiheart counts·min^{-1} increased with treadmill speed, but not in a linear manner. The slope of the walking activities was approximately 10 times greater than the slope of the running speeds, indicating that there may be an attenuation in counts·min^{-1} at higher speeds as is seen with other accelerometer devices. The prediction equations developed included models for movement counts only ($R^2 = 0.842$, $P < 0.001$), HR above sleeping HR (HRaS) ($R^2 = 0.903$, $P < 0.001$), Movement plus HRaS ($R^2 = 0.942$, $P < 0.001$), HRaS with the step test ($R^2 = 0.937$, $P < 0.001$), and movement plus HRaS with step test ($R^2 = 0.956$, $P < 0.001$). The combined model using movement plus HRaS with step test was significantly more accurate than any other model ($P < 0.05$). In addition, when absolute HR was substituted for the HRaS there was a significant decrease in the accuracy of the model ($P = 0.011$). While this is only the first study to examine the

Actiheart, it appears to have promise as a potential device to monitor free-living physical activity.

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PART III

VALIDITY OF 10 ELECTRONIC PEDOMETERS FOR MEASURING STEPS, DISTANCE, AND ENERGY COST

This part is a paper by the same name published in *Medicine and Science in Sports and Exercise* in 2003 by Scott E. Crouter, Patrick L. Schneider, Murat Karbulut, and David R. Bassett, Jr.

Crouter, S. E., P. L. Schneider, M. Karabulut, and D. R. Bassett, Jr. Validity of ten electronic pedometers for measuring steps, distance, and energy cost. *Med. Sci. Sports Exerc.*, Vol. 35, No. 8, pp. 1455-1460, 2003.

Abstract

Purpose: This study examined the effects of walking speed on the accuracy and reliability of ten pedometers: Yamasa Skeletone (SK), Sportline 330 (SL330) and 345 (SL345), Omron (OM), Yamax Digi-Walker SW-701 (DW), Kenz Lifecorder (KZ), New Lifestyles 2000 (NL), Oregon Scientific (OR), Freestyle Pacer Pro (FR), and Walk4Life LS 2525 (WL). **Methods:** Ten subjects (33 ±12 yrs) walked on a treadmill at various speeds (54, 67, 80, 94, and 107 $m\cdot min^{-1}$) for five-minute stages. Simultaneously, an investigator determined steps by a hand counter, and energy expenditure (kcal) by indirect calorimetry. Each brand was measured on the right and left side. **Results:** Correlation coefficients between right and left sides exceeded 0.81 for all pedometers except OR (0.76) and SL345 (0.57). Most pedometers underestimated steps at 54 $m\cdot min^{-1}$, but accuracy for step counting improved at faster speeds. At 80 $m\cdot min^{-1}$ and above, six models (SK, OM, DW, KZ, NL and WL) gave mean values that were within ± 1% of actual steps. Six pedometers displayed the distance traveled. Most of them estimated mean distance to within ± 10% at 80 $m\cdot min^{-1}$, but overestimated distance at slower speeds and underestimated distance at faster speeds. Eight pedometers displayed kcals, but except for KZ and NL it is unclear whether this should reflect net or gross kcals. If one assumes they display net kcals, the general trend was an overestimation of kcals at every speed. If one assumes they display gross kcals, then seven of the eight pedometers were accurate to within ± 30% at all speeds. **Conclusion:** In general, pedometers are most accurate for assessing steps, less accurate for assessing distance, and even less accurate for assessing kcals. **Key Words:** ENERGY EXPENDITURE, PHYSICAL ACTIVITY, LOCOMOTION, AND EXERCISE

Introduction

The electronic pedometer is a simple device that can be used to assess physical activity. In recent years a wide variety of new electronic pedometers have been introduced, which makes it necessary to test these new devices for accuracy and reliability. With the phasing out of older analog models, the pedometer has evolved into a device that can also estimate distance traveled and energy expenditure (kcal). Some models have internal clocks and can store information for viewing or downloading to a computer. Concerning principles of operation, electronic pedometers use three basic mechanisms for recording steps. The original and most basic is a spring-suspended horizontal lever arm that moves up and down in response to vertical displacement of the waist. The lever arm opens and closes an electrical circuit with each step and the number of steps are counted (e.g. Yamax Digiwalker SW-701 and Sportline 345). Some newer models have incorporated a glass-enclosed magnetic reed proximity switch (e.g. Omron and Oregon Scientific). The third type has an accelerometer consisting of a horizontal beam and a piezoelectric crystal (e.g. New Lifestyles and Lifecorder); steps are determined from the number of zero-crossings of the instantaneous acceleration vs. time curve.

In 1996 Bassett et al. (1) assessed the accuracy of five electronic pedometers. To date it is the only multi-brand comparison study of electronic pedometers and none of the pedometers they examined are currently available. Bassett et al. found that at a walking speed of 2.0 mph, pedometers underestimated steps by 50-75% but they became more accurate as the walking speed increased. At self-selected walking speeds of 80 - 107 $m \cdot min^{-1}$, the Yamax Digiwalker DW-500 recorded average values for steps and distance that were within 1% of actual. Nelson et al. (9) looked at the validity of the Yamax Digiwalker DW-500 in reporting gross kcal. Nelson et al. showed that at walking speeds of 3 to 4 mph on the treadmill, it provided valid results, but it significantly underestimates gross kcals at 2 mph and below. However, it is possible that the kcal values displayed by pedometers are supposed to reflect net kcal (i.e. - physical activity energy expenditure, above resting).

In recent years, new recommendations have been issued concerning the amount of physical activity that one should perform on a regular basis. The current recommendation from the U.S. Surgeon General is to accumulate at least 30 minutes of moderate-intensity physical activity on most days of the week (16). This is also supported by the Centers for Disease Control and Prevention and the American College of Sports Medicine, which notes that the recommendation can be met by walking 2 miles briskly (10). Studies have shown that 30 minutes of brisk walking is equal to 3,100 – 4000 steps, depending on the age of the population (13, 17, 19), which allows one to quantify a time recommendation in terms of steps taken. Others recommend a different approach to daily physical activity. Hatano advocates taking a total of 10,000 steps per day for cardiovascular disease prevention (7). At the University of Colorado Health

Sciences Center, Hill has developed a program called "Colorado On The Move" and recommends a 2,000-step increase above one's normal step count for prevention of weight gain (8).

Taking into consideration these pedometer recommendations, the increasing use of pedometers in intervention studies, and their potential for surveillance of physical activity, it is important to have valid devices for measurement. Therefore, the purpose of this study was to examine the accuracy and reliability of 10 electronic pedometers for measuring steps taken, distance traveled, and kcals at various treadmill walking speeds.

Methods

Subjects

Five males and five females from the University of Tennessee volunteered to participate in the study. The average (± SD) age and body mass index (BMI) was 33 ± 12 years and 25.7 ± 6.3, respectively. The testing protocol was approved by the University of Tennessee Institutional Review Board prior to the start. Written informed consent was obtained from all subjects prior to testing. Age was recorded, and height and weight were measured in street clothes (without shoes) with a stadiometer and calibrated physician's scale, respectively. Stride length was measured by having the subjects take 20 strides down an indoor hallway at their normal walking speed. The total distance was divided by 20 to compute stride length. This was repeated three times and an average was programmed into the pedometers. Descriptive data of the subjects is presented in Table 1.

Table 1. Physical characteristics of subjects (mean ± SD).

	Men (N = 5)	Women (N = 5)	All Subjects (N = 10)
Age (yr)	34 ± 13	31 ± 13	32 ± 12
Height (cm)	180.9 ± 4.2	162.8 ± 7.3	171.9 ± 11.08
Weight (kg)	84.7 ± 32.6	68.1 ± 10.6	76.4 ± 24.49
BMI ($kg \cdot m^{-2}$)	25.7 ± 8.8	25.7 ± 3.2	25.7 ± 6.25
Stride Length (m)	0.81 ± 0.07	0.78 ± 0.08	0.80 ± 0.07
RMR ($kcals \cdot day^{-1}$)*	2080 ± 502	1659 ± 307	1869 ± 451

* RMR measured by indirect calorimetry.

Protocol

Ten pedometers were examined to determine the effects of walking speed on steps taken, distance traveled, and energy expenditure (kcal): Yamasa Skeletone EM-180 (SK), Sportline 330 (SL330) and 345 (SL345), Omron HJ-105 (OM), Yamax Digi-Walker SW-701 (DW), New Lifestyles NL-2000 (NL), Kenz Lifecorder (KZ), Oregon Scientific PE316CA (OR), Freestyle Pacer Pro (FR), and Walk4Life LS 2525 (WL). Prior to the first trial the subjects received instructions for walking on the treadmill and were allowed time to adapt to walking at the various speeds. The subjects walked at speeds of 54, 67, 80, 94, and 107 $m \cdot min^{-1}$ on a motor driven treadmill (Quinton model Q55XT, Seattle, WA). The treadmill speed and grade were calibrated prior to testing according to the manufacturer's instructions. Energy expenditure was measured by indirect calorimetry for all trials, except for devices that were solely step counters (SK and SL330). Measurements were made using a TrueMax 2400 computerized metabolic system (ParvoMedics, Salt Lake City, UT), which has been validated against the Douglas Bag method in our laboratory (3). Prior to each test, the O_2 and CO_2 analyzers were calibrated using gases of known concentrations, and the flowmeter was calibrated using a 3.00 L syringe.

One electronic pedometer of each brand was worn on the right and left sides of the body, in the midline of the thigh. For the electronic pedometers that had a variable sensitivity switch (OR, OM), it was placed in the middle setting. Each trial consisted of five minutes of walking at the given speed to allow the subject to reach steady state. An average of the last two minutes were used for calculation of actual gross kcals. An investigator tallied actual steps with a hand counter. Between trials the subject stepped off the treadmill for one minute so that values from the electronic pedometers could be recorded.

Resting metabolic rate (RMR) was measured by a TrueMax 2400 metabolic system. The subjects came in early in the morning after an overnight fast, with the exception of water. They were also asked to refrain from the use of stimulants (including caffeine, tobacco, and medication) and intense physical activity. Once the subject arrived they were allowed to relax in a reclining position while the test was explained. Gas exchange measurements were made for 40 minutes. The first 20-minute period allowed the individual to return to resting levels and adapt to the mouthpiece, and the second 20 minute-period was used for the determination of RMR. The measured RMR was then subtracted from the measured gross kcal, during treadmill walking, to obtain net kcal.

Statistical Treatment

Statistical analyses were carried out using SPSS version 11.0.1 for windows (SPSS Inc., Chicago, IL). Initially, 2-way repeated measures ANOVAs (side of body x speed) were carried out on each pedometer brand, but since the results showed no effects of placement site (L vs. R), the two sides were averaged. Intraclass correlation coefficients were used to report comparison between right and left side measures of the same electronic pedometer. Subsequently, 2-way ANOVAs (speed x pedometer brand) were used to compare mean difference scores (pedometer minus actual) for steps taken, distance traveled, and net and gross kcals. An alpha of $P < 0.05$ was used to denote statistical significance. Although mean difference scores were used for statistical analysis, they do not give a good representation of how accurate the pedometer is when presented in a graph, since the total amount of steps are not known. Therefore, all graphs are presented with percent difference scores, which allow for easier illustration of how accurate the pedometers were.

Results

All trials were completed without problems, except that one of the NL pedometers had to be replaced by a new device because of a broken mechanism. Correlation coefficients between the right and left sides exceeded 0.81 for all pedometers except OR (0.76) and SL345 (0.57) (Table 2).

Table 3 shows significant differences from actual steps and figure 1 shows percentage of actual steps at each speed. In general pedometers tended to underestimate actual steps at 54 and 67 $m \cdot min^{-1}$. Several pedometers were accurate at speeds of 80

Table 2. Intraclass correlation coefficients for pedometers worn on the right and left sides of the body.

Pedometer	ICC (95% CI)
SL330	0.91 (0.85, 0.95)
SK	0.83 (0.89, 0.96)
OM	0.83 (0.71, 0.90)
DW	0.98 (0.94, 0.98)
KZ	0.94 (0.90, 0.97)
NL	0.99 (0.98, 0.99)
OR	0.76 (0.61, 0.86)
SL345	0.57 (0.35, 0.73)
FR	0.95 (0.92, 0.97)
WL	0.81 (0.68, 0.89)

Table 3. Pedometer accuracy for measuring steps during horizontal treadmill walking at five different speeds.

Speed ($m \cdot min^{-1}$)	SL330	SK	OM	DW	KZ	NL	OR	SL345	FR	WL
54	-	-					+	-	-	
67		-					+	-		
80						+	+			
94						+	+			+
107		+	+		+	+	+			+

(+) Significant overestimation of actual steps ($P < 0.05$)
(-) Significant underestimation of actual steps ($P < 0.05$)

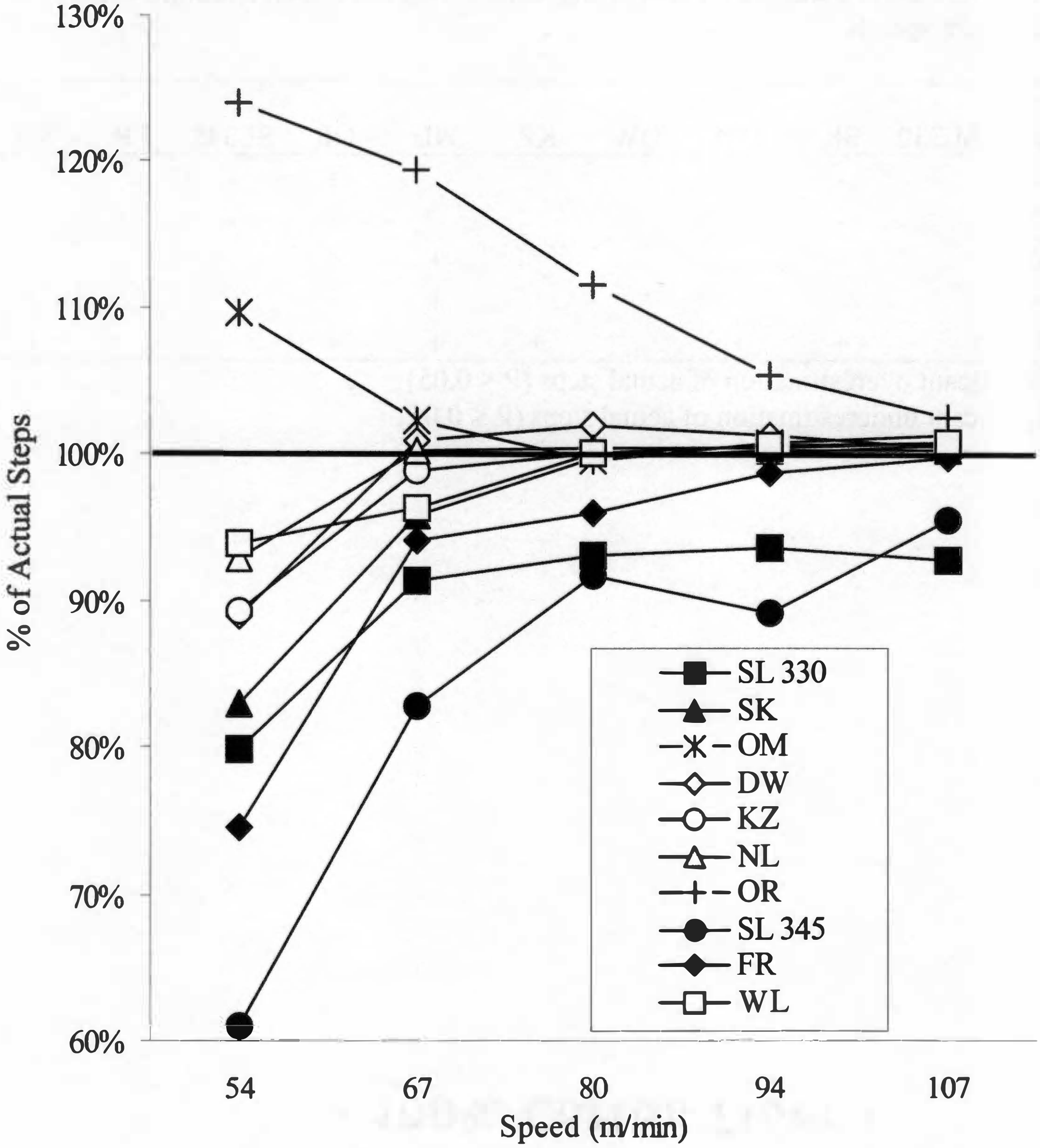

Figure 1. Effect of speed on pedometer accuracy (percentage of actual steps) during treadmill walking.

$m \cdot min^{-1}$ and above, with six models (SK, OM, DW, NL, KZ and WL) providing mean values that were within ± 1% of actual steps. Only one pedometer (DW) did not significantly differ from actual steps at any speed ($P \geq 0.05$), while the OR was significantly different from actual steps at all speeds ($P < 0.05$).

Six pedometers displayed the distance traveled (OM, DW, OR, SL345, FR, WL). Table 4 shows significant differences from actual steps and figure 2 shows percentage of actual distance traveled at each speed. In general, the pedometers tended to overestimate distance traveled at slower speeds and underestimate distance traveled at higher speeds, with 80 $m \cdot min^{-1}$ being the most accurate speed for most pedometers. All electronic pedometers were significantly different ($P < 0.05$) for at least two speeds, except for FR, which was significantly different ($P < 0.05$) at only one speed (107 $m \cdot min^{-1}$).

Eight pedometers displayed estimates of energy expenditure (OM, DW, NL, KZ, OR, SL345, FR, WL). With the exception of NL and KZ it is unclear if they are displaying net or gross kcals. New Lifestyles NL-2000 and KZ estimate gross kcals by taking into account the subject's RMR (based on input of age, gender, weight, and height). Table 5 shows significant differences from actual gross and net kcals. Figure 3 shows the percent difference from actual gross kcals at all speeds and figure 4 shows the percent difference from actual net kcals at all speeds. Only one electronic pedometer (FR) was not significantly different ($P \geq 0.05$) from gross kcals at any speed. For net kcals all electronic pedometers were significantly different ($P < 0.05$) for at least four speeds, except for KZ, which was significantly different ($P < 0.05$) at only one speed (94 $m \cdot min^{-1}$).

Table 4. Pedometer accuracy for measuring distance traveled during horizontal treadmill walking at five different speeds.

Speed ($m \cdot min^{-1}$)	OM	DW	OR	SL345	FR	WL
54	+		+			+
67	+	+	+			+
80	+					
94			-	-		
107		-	-	-	-	-

(+) Significant overestimation of actual distance traveled ($P < 0.05$)
(-) Significant underestimation of actual distance traveled ($P < 0.05$)

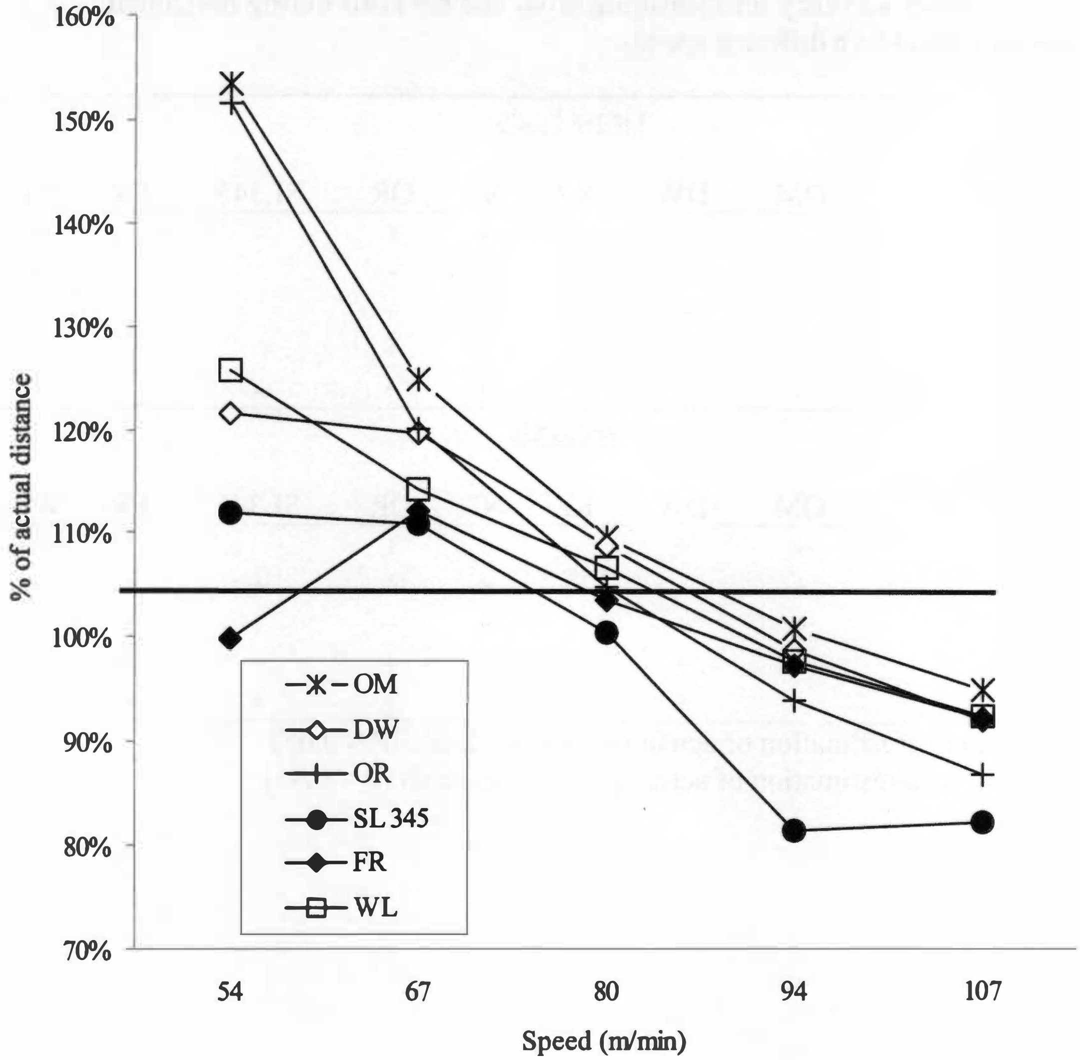

Figure 2. Effect of speed on pedometer estimates of percentage of actual distance traveled during treadmill walking.

Table 5. Pedometer accuracy for measuring gross and net kcals during horizontal treadmill walking at five different speeds.

				Gross kcals				
Speed ($m \cdot min^{-1}$)	OM	DW	KZ	NL	OR	SL345	FR	WL
54				+	+			+
67				+	+			+
80		+	+	+	+			+
94	-		+	+	+			+
107	-			+	+	-		-
				Net kcals				
Speed ($m \cdot min^{-1}$)	OM	DW	KZ	NL	OR	SL345	FR	WL
54	+	+		+	+			+
67	+	+		+	+	+	+	+
80	+	+		+	+	+	+	+
94	+	+	+	+	+	+	+	+
107		+			+	+	+	+

(+) Significant overestimation of actual gross or net kcals ($P < 0.05$)
(-) Significant underestimation of actual gross or net kcals ($P < 0.05$)

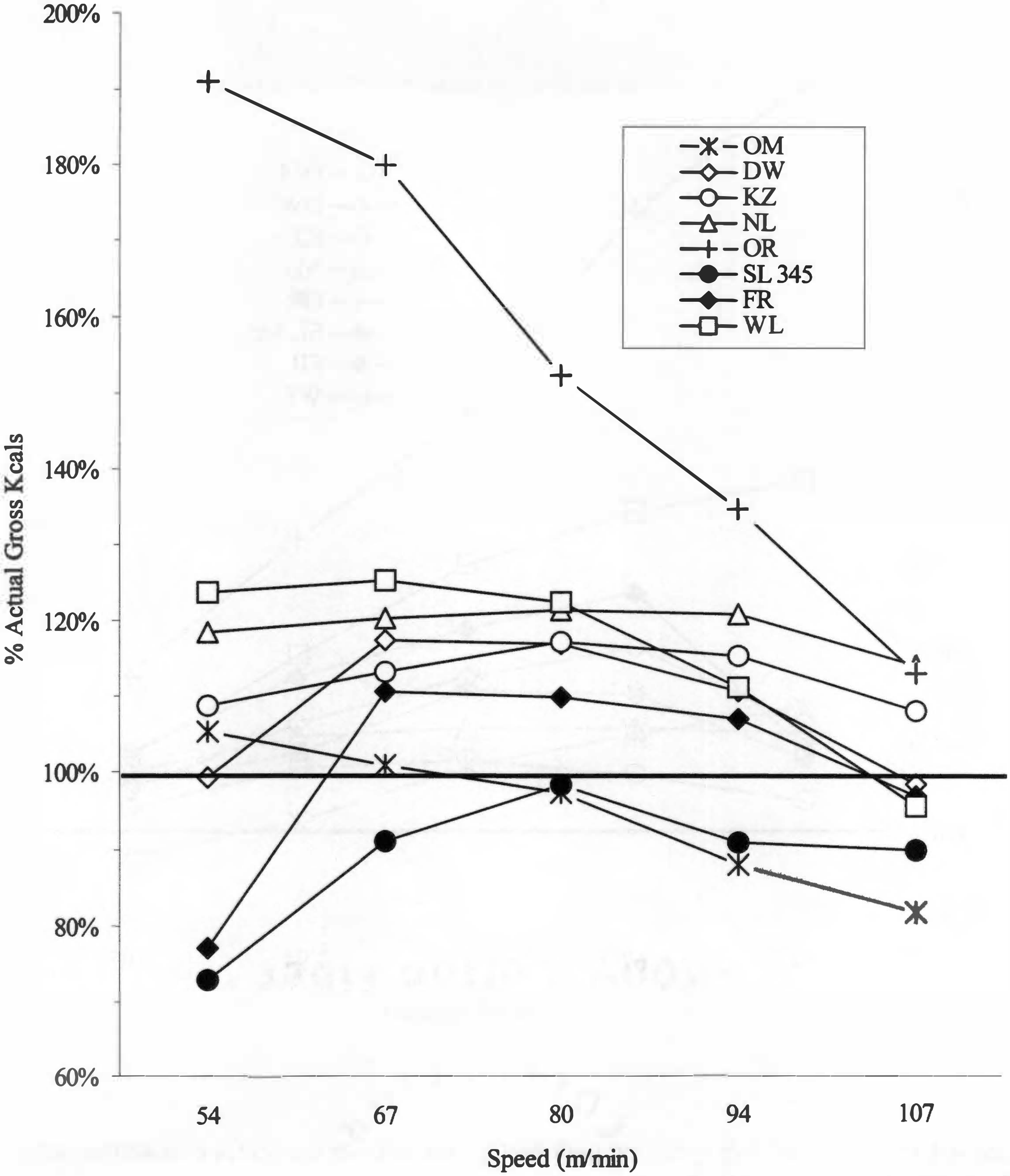

Figure 3. Effects of speed on pedometer estimates of percent of actual gross kcals, during treadmill walking.

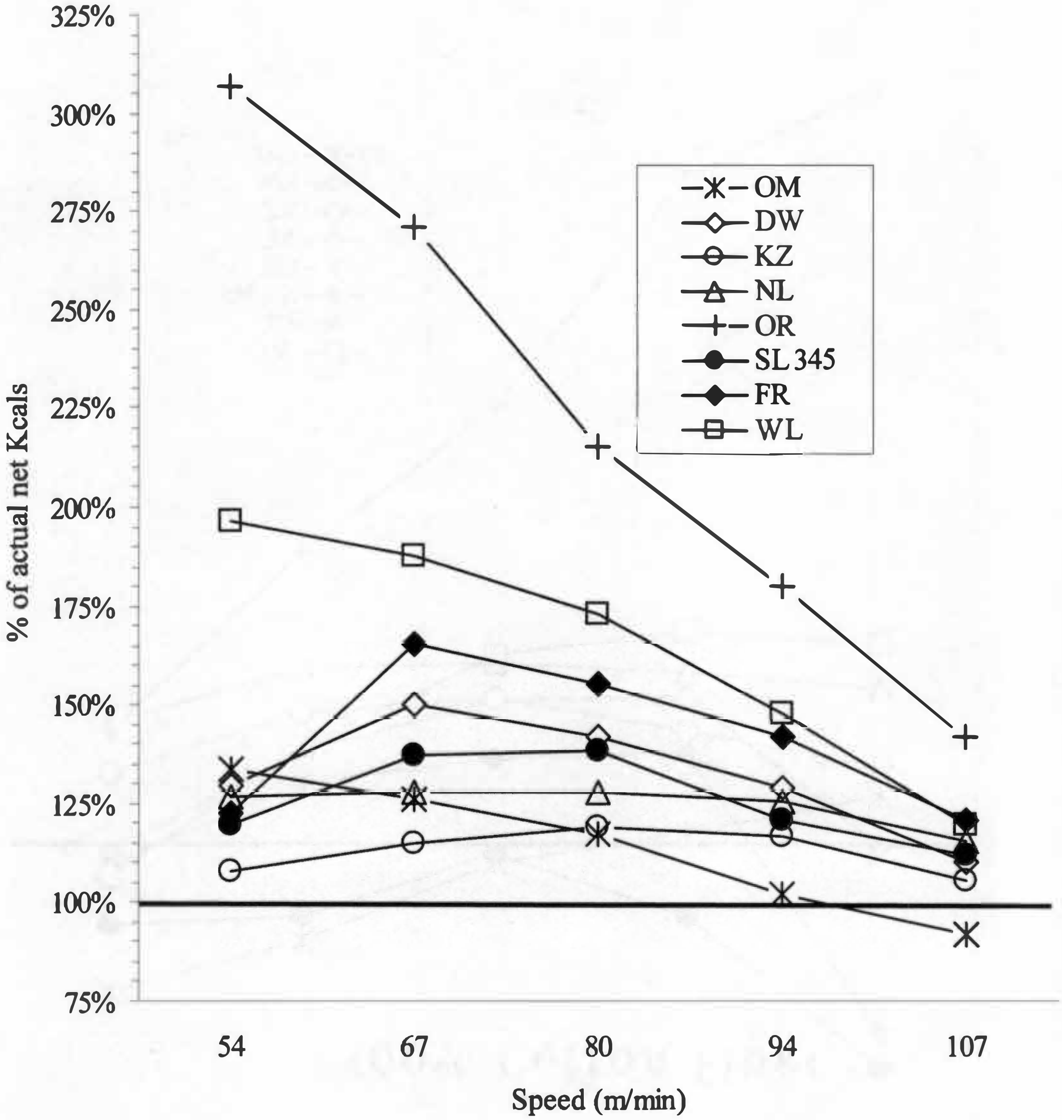

Figure 4. Effects of walking speed on pedometer estimates of percentage of actual net kcals, during treadmill walking.

Discussion

The use of pedometers in both research and practice is rapidly growing, as these devices provide an inexpensive, objective means of assessing physical activity, and they are generally believed to be accurate and reliable. Researchers usually prefer to express pedometer data as "steps", since that is the most direct expression of what the pedometer measures (11, 14, 15). Six pedometers (SK, OM, DW, NL, KZ, WL) out of the ten gave mean values that were within ± 1% of actual values at speeds of 80 $m \cdot min^{-1}$ and above. The Japanese Industrial standards have set the maximum permissible error of miscounting steps at 3%, or 3 steps out of 100 (6). It is interesting that all five of the pedometers made by Japanese companies met this recommendation, while only one of the non-Japanese pedometers (WL, made in Taiwan) was as accurate.

At slower speeds, the pedometers were not as accurate in step counting. This results from the fact that vertical accelerations of the waist are less pronounced at slow walking speeds, so it is less likely that the threshold value to record a step (e.g.- 0.35 G for DW) will be exceeded. Four pedometers (WL, KZ, NL, DW) showed acceptable accuracy at speeds 54 $m \cdot min^{-1}$ (or 2 mph), indicating that these pedometers are a good choice for use in research studies. However, it should be noted that in the frail elderly or others with a slow, shuffling gait, even these brands of pedometers are probably inadequate to obtain a true assessment of walking (4, 13, 18).

Most pedometers were fairly accurate for measuring distance at a speed of 80 $m \cdot min^{-1}$, providing mean estimates that were within ± 10% of the actual values. The stride length that was programmed into the pedometer was determined at self-selected walking speeds, which approximate 84 $m \cdot min^{-1}$ in healthy adults (12). At slower speeds, the actual stride length was shorter than the value programmed into the pedometer, causing an overestimation of distance. At faster speeds, the actual stride length was longer than the programmed value, causing the distance to be underestimated.

The distance traveled was not only affected by stride length, but also by the sensitivity of the pedometers (and accuracy in counting steps). Two of the pedometers FR and SL345 appeared to be the most accurate for measuring distance at slower speeds (< 80 $m \cdot min^{-1}$), but when other factors are taken into consideration it can be seen that they grossly undercounted steps. This is a case of "compensating errors" where overestimation of stride length and underestimation of steps offset each other, and make these two models appear accurate for assessing distance.

In most cases, it is not clear whether pedometers measure gross kcals or net kcals. Previous investigators have reached different conclusions on what the measured kcal value given by the pedometer actually represents. Nelson et al. (9) assumed that the values displayed by the Yamax Digiwalker 500 were gross kcals, and found that at normal walking speeds (80-107 $m \cdot min^{-1}$) it gave a close estimate of gross kcals. Bassett et al. (2), in a study of lifestyle activities (yard work, housework, childcare, occupational tasks, recreation) assumed that they displayed net kcals (above RMR), and found that at walking speeds between 78-100 $m \cdot min^{-1}$ the Yamax SW-701 overestimates net kcals. During most other lifestyle activities however, they saw an underestimation of net kcals. In looking at the kcal data from the present study, it appears that it should be assumed that electronic pedometers are estimating gross kcals if the activity mode is walking. This invariably means that pedometers will underestimate the cost of most other types of "lifestyle" activities, especially those involving arm activity, pushing or carrying objects, walking uphill, or stair climbing. This is a limitation when attempting to use pedometers to quantify daily physical activity energy expenditure (PAEE) (2). Nevertheless, pedometers are useful in that they provide a valid, reliable measure of ambulatory activity, which is one of the most prevalent forms of activity in today's society (5, 14). We believe that expressing pedometer data as "steps$\cdot$day^{-1}" provides an extremely useful index of an individual's overall ambulatory activity level. Expressing the data in this manner eliminates the need to make adjustments for height or body weight when comparing individuals, which is advantageous.

The NL and KZ provide estimates of both net and gross kcal, made possible because they predict the user's RMR based on age, height, weight, and gender. It should be noted that while these devices can be called "pedometers" because they measure steps, they are actually accelerometers in terms of principles of operation. Thus, activity energy expenditure is computed by integrating the acceleration vs. time curve, and activities like jogging (where there is a greater amplitude of the acceleration curve) will be credited with more kcal$\cdot$step^{-1} than activities like walking. These two models are also unique in that they have internal memory chips that allow them to store data. The NL can store up to 7 days of data, while the KZ can store up to 42 days of data in 1-day epochs. This data storage feature may be useful for researchers who do not wish to rely on subjects "logging" their own steps.

Overall, it appears that DW is the most accurate at predicting steps, distance, and gross kcals for walking. The WL is close in terms of accuracy, although the reliability coefficient was only 0.84. The NL and KZ do not have the ability to measure distance, but they were among the most accurate at measuring steps. In addition they have the ability to: (a) store multiple days of data; (b) distinguish between the kcals expended per step in walking and running; and (c) provide rough estimates of net and gross energy expenditure. The KZ can store 42 days of data, which can be downloaded to a computer for subsequent analysis. The drawback to KZ is that it has a higher cost, around $200, plus $250 for the computer interface and software.

In conclusion it is not our intention to endorse any one pedometer for all purposes. Our objective is to make researchers aware of the validity of these devices and allow them to make the judgment of which pedometer to use. Whether the objective outcome is steps, distance, or kcals, consideration should be given as to which variable is the most important when determining which electronic pedometer to use.

Acknowledgements

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PART IV

ACCURACY OF POLAR S410 HEART RATE MONITOR TO ESTIMATE ENERGY COST OF EXERCISE

This part is a paper by the same name published in *Medicine and Science in Sports and Exercise* in 2004 by Scott E. Crouter, Carrie Albright, and David R. Bassett, Jr.

Crouter, S. E., C. Albright, and D. R. Bassett, JR. Accuracy of Polar S410 Heart Rate Monitor to Estimate Energy Cost of Exercise. *Med. Sci. Sports Exerc.*, Vol. 36, No. 8, pp. 1433–1439, 2004.

Abstract

Purpose: The purpose of this study was to examine the accuracy of the Polar S410 for estimating gross energy expenditure (EE) during exercise when using both predicted and measured VO_{2max} and HR_{max} versus indirect calorimetry (IC). **Methods:** Ten males and 10 females initially had their VO_{2max} and HR_{max} predicted by the S410, and then performed a maximal treadmill test to determine their actual values. The participants then performed three submaximal exercise tests at RPE of 3, 5, and 7 on a treadmill, cycle, and rowing ergometer for a total of nine submaximal bouts. For all submaximal testing, the participant had two S410 heart rate monitors simultaneously collecting data: one heart rate monitor (PHRM) utilized their predicted VO_{2max} and HR_{max}, and one heart rate monitor (AHRM) used their actual values. Simultaneously, EE was measured by IC. **Results:** In males, there were no differences in EE among the mean values for the AHRM, PHRM, and IC for any exercise mode ($P \geq 0.05$). In females, the PHRM significantly overestimated mean EE on the treadmill (by 2.4 $kcal \cdot min^{-1}$), cycle (by 2.9 $kcal \cdot min^{-1}$), and rower (by 1.9 $kcal \cdot min^{-1}$) (all $P \leq 0.05$). The AHRM for females significantly improved the estimation of mean EE for all exercise modes, but it still overestimated mean EE on the treadmill (by 0.6 $kcal \cdot min^{-1}$) and cycle (by 1.2 $kcal \cdot min^{-1}$) ($P \leq 0.05$). **Conclusion:** When the predicted values of VO_{2max} and HR_{max} are used, the

Polar S410 HRM provides a rough estimate of EE during running, rowing, and cycling. Using the actual values for VO_{2max} and HR_{max} reduced the individual error scores for both genders, but in females the mean EE was still overestimated by 12%. **Key Words:** MAXIMAL OXYGEN UPTAKE, ENERGY EXPENDITURE, PHYSICAL ACTIVITY, RATING OF PERCEIVED EXERTION

Introduction

Heart rate (HR) monitors are a valuable tool for athletes and those who are interested in improving fitness. HR is often used to estimate exercise intensity or prescribe exercise either based on a percentage of an individual's HR_{max} or HR reserve. Furthermore, because HR is linearly related to oxygen uptake for dynamic activities involving large muscle groups (6, 24), it can provide a reasonable estimate of energy expenditure (EE) during exercise (5, 7). This application could be useful for athletes and for individuals who exercise for weight control.

HR monitoring can also be a valuable tool for researchers seeking to quantify the intensity of exercise bouts. The use of HR does have limitations due to influence of other factors that can affect exercise HR. These include stress, hydration level, environmental factors such as temperature and humidity, mode of exercise (upper vs lower body), gender, and training status. Motion sensors such as electronic pedometers and accelerometers are commonly used to assess PA, but they are mainly limited to ambulatory activities. Motion sensors have been shown to be ineffective at predicting the energy cost of activities such as cycling, upper-body exercise, swimming, rowing, or walking/running up an incline (8, 10, 12, 18, 19, 26). In addition, uniaxial accelerometers and pedometers cannot detect increases in EE that occur at running speeds over 9 $km \cdot hr^{-1}$ (3, 10).

Polar Electro, Inc., is a leading manufacturer of HR monitors. Their instruments have been shown to provide valid measurements of HR when compared with electrocardiograms (14, 15, 27). This company has developed software that allows a user to estimate EE during exercise. To accomplish this, Polar developed the "OwnIndex," which uses nonexercise prediction equations for VO_{2max} and HR_{max}. The estimated EE during exercise is determined from the "OwnCal" software, which is based on user data and exercise HR. The Polar S410 HR monitor is one of the Polar watches that gives users the option to either predict VO_{2max} and HR_{max} or to program the actual, measured values into the watch.

To our knowledge, no published studies have examined the accuracy of Polar HR monitors to predict EE during exercise. Therefore, the purpose of this study was twofold: 1) to examine the accuracy of the Polar S410 for estimating EE during exercise using one's predicted VO_{2max} and HR_{max}, and 2) to determine whether the use of measured VO_{2max} and HR_{max} improves the accuracy of the Polar S410 for estimating EE.

Methods

<u>Subjects</u>

Twenty active participants (10 male, 10 female) from the University of Tennessee volunteered to participate in the study. Inclusion criteria for the study included regular exercise (at least 3 $d \cdot wk^{-1}$) and absence of contraindications to exercise testing. The procedures were reviewed and approved by the University of Tennessee Institutional Review Board before the start of the study. Each participant signed a written informed consent and completed a Physical Activity Readiness Questionnaire (PAR-Q) before participating in the study. Weight and height were measured in light clothing (without shoes) using a calibrated physician's scale and stadiometer, respectively.

Protocol

Each participant performed a maximal exercise test, nine submaximal exercise bouts, and a resting metabolic rate (RMR) test. For all testing, participants were asked to refrain from physical activity 24 h before testing and to refrain from food, alcohol, and tobacco 3 h before the tests.

Predicted VO_{2max} and HR_{max}

The predictions of VO_{2max} and HR_{max} were performed according to the manufacturer's recommendations outlined in the Polar S410 user's manual (22). The Polar S410 devise uses a nonexercise prediction equation based on user information (age, height, weight, gender, physical activity level) and resting heart rate information. The participants defined their physical activity level (low, middle, high, top) based on descriptions given by the Polar S410 user's guide (22). The physical activity level along with the participant's information was then programmed into the S410 HR monitor. The participant was allowed to relax in a reclining position for 15 min before the Polar S410 predicting his/her VO_{2max} and HR_{max}.

Measurement of VO_{2max} and HR_{max}

Participants performed a maximal exercise test on a motor driven treadmill (Quinton model Q55XT, Seattle, WA) for the purpose of measuring VO_{2max} and HR_{max}. The treadmill speed was calibrated by measuring the belt length (3.190 m) and the time required to complete 25 revolutions of the treadmill belt. This was verified using a hand-held digital tachometer (Nidec-Shimpo America Corp. Model DT-107, Itasca, IL) that had been calibrated to an accuracy of within $\pm$ 0.1%. A carpenter's level was used to calibrate the treadmill grade to 0.0%, according to the manufacture's instructions. Metabolic measurements were made by indirect calorimetry (IC) using a TrueMax 2400 computerized metabolic system (ParvoMedics, Salt Lake City, UT), which was validated against the Douglas bag method in our laboratory (1). Before each test, the O_2 and CO_2 analyzers were calibrated using gases of known concentrations, and the flow meter was calibrated using a 3-L syringe.

Before the maximal exercise test the participant warmed up on the treadmill, and a comfortable running speed was determined, which was used as the starting point of the maximal exercise test. A 5-min rest period separated the warm-up and the start of the maximal exercise test. During the first 2 min of the test the participant was brought back to the predetermined running speed and then the grade was increased 1% per minute until volitional fatigue. After 3 min of recovery, a blood sample was taken from a fingertip and analyzed for blood lactate concentration using an automated lactate/glucose analyzer (YSI 2300 STAT Plus, Yellow Springs, OH).

Maximal oxygen uptake (VO_{2max}) was determined from the highest 1-min average of oxygen uptake and was verified by the participant meeting three of the four following criteria; 1) 3-min postexercise lactate $\geq$ 8.0 mmol·L^{-1}, 2) maximal HR within 10 beats per minute of age-predicted maximal HR (220 - age), 3) R value $\geq$ 1.15, and 4) VO_2 plateau ($\leq$ 150 mL·min^{-1} increase between stages) (11).

Submaximal exercise bouts

To examine the accuracy of the Polar S410 to estimate EE during exercise, participants performed three submaximal exercise tests at various intensities on a Quinton Q55XT motor driven treadmill, Lode Excalibur Sport electronically braked cycle ergometer (Groningen, NL), and a Concept II rowing ergometer (Morrisville, VT), for a total of nine submaximal exercise tests. Before the submaximal testing, one watch was programmed with the participant's predicted VO_{2max} and HR_{max}, which hereafter is referred to as the predicted HR monitor (PHRM). A second watch was programmed with the participant's actual VO_{2max} and HR_{max}, which is referred to as the actual HR monitor (AHRM). Each stage consisted of 10 min of exercise at self-selected work rates equivalent to a rating of perceived exertion (RPE) of 3 (moderate), 5 (hard), and 7 (very hard) (0–10 Borg Category-Ratio Scale) (21). The participant was instructed on interpretation of the RPE scale during the warm-up and worked at each RPE during the warm-up (20). The first 5 min of exercise at each work rate allowed for the participant to reach the correct RPE and to achieve a steady state. During the second 5 min, HR and RPE values were recorded from the PHRM and AHRM, while actual EE was measured by IC. Heart rate, RPE, and work rate were recorded at 1-min intervals, and 5-min rest was given between each stage to allow for recovery.

Both the exercise mode and RPE were assigned in random order. For all submaximal tests the participants were blinded as to their HR. For the treadmill submaximal tests the grade was set at 0%, and the participant controlled the speed of the treadmill to reach the desired RPE. To eliminate bias of previous treadmill experience, participants could not see the speed they were walking/running at, and the investigator measured speed with a Nidec-Shimpo DT-107 handheld digital tachometer. On the cycle ergometer, the participant was allowed to pedal at a comfortable cadence that was maintained for all three RPE levels. As on the treadmill, the participant was not able to see the work rate, which was increased by the investigator until the desired RPE was reached. For the rowing ergometer, the participant maintained an average power output (W) that corresponded to the desired RPE.

RMR was measured by IC using a TrueMax 2400 computerized metabolic system. The participants came in early in the morning after an overnight fast, with the exception of water. They were also asked to refrain from stimulants (including caffeine, tobacco, and medication) and intense physical activity for the 12 h before the test. Once the subjects arrived they were allowed to relax in a reclining position while the test was explained. Gas exchange measurements were taken for 40 min. The first 20-min period allowed the individual to return to achieve a stable baseline, and the second 20-min period was used for the determination of RMR.

Statistical Treatment

Statistical analyses were carried out using SPSS version 11.5.0 for windows (SPSS Inc., Chicago, IL). Initially, three-way repeated measures ANOVA (intensity x measurement device x gender) were carried out to compare EE values ($kcal \cdot min^{-1}$) for each exercise device. The initial results showed that there was a gender effect, so all further analyses were done for each gender separately. Subsequently, two-way repeated measures ANOVA (intensity x measurement device) were used to compare EE values ($kcal \cdot min^{-1}$) for PHRM, AHRM, and IC at all three RPE levels for each gender. Where appropriate, post hoc analyses were performed using Bonferroni corrections. An alpha of 0.05 was used to denote statistical significance.

Paired t-tests were performed to examine differences between predicted and actual VO_{2max} and HR_{max}. Pearson product moment correlation coefficients were performed to examine the strength of the relationship between predicted and actual VO_{2max}.

Bland-Altman plots were used to graphically show the variability in individual estimated EE values ($kcal \cdot min^{-1}$) around zero (2). This allows for the mean error score and the 95% prediction interval to be shown. Devices that are accurate will display a tight prediction interval around zero. Data points below zero signify an overestimation, whereas points above zero signify an underestimation.

Results

Descriptive data for males and females are presented in Table 1. In males, the average gross EE values for PHRM, AHRM, and IC on the treadmill, cycle, and rowing

Table 1. Physical characteristics of participants (mean ± SD).

	Men (N = 10)	Women (N = 10)
Age (yr)	26 ± 3.1	23 ± 2.4
Height (cm)	179.6 ± 4.7	167.0 ± 4.0
Weight (kg)	83.6 ± 21.6	58.5 ± 5.7
BMI ($kg \cdot m^{-2}$)	25.9 ± 6.1	21.0 ± 1.8
Measured VO_{2max} ($ml \cdot kg^{-1} \cdot min^{-1}$)	51.0 ± 11.4	42.2 ± 4.0
Predicted VO_{2max} ($ml \cdot kg^{-1} \cdot min^{-1}$)[a]	50.7 ± 15.1	53.0 ± 7.8
Measured HR_{max} (bpm)	190 ± 10.3	191 ± 6.7
Predicted HR_{max} (bpm)[a]	192 ± 3.3	195 ± 2.8
Peak Lactate (mM)[b]	11.7 ± 2.3	9.3 ± 1.7

[a] Predicted using the Polar S410 HR monitor.
[b] Measured 3-min post maximal treadmill exercise test.

ergometer are shown in Figure 1. There were no differences in male EE values among PHRM, AHRM, and IC for any exercise mode ($P \geq 0.05$). Figure 2 shows the individual errors in estimating EE across all exercise modes. For the PHRM the mean error (IC – PHRM) was -0.1 $kcal \cdot min^{-1}$ (-4.6 to +4.3 $kcal \cdot min^{-1}$, 95% CI) and for the AHRM the mean error (IC - AHRM) was -0.5 $kcal \cdot min^{-1}$ (-3.2 to +2.1 $kcal \cdot min^{-1}$, 95% CI).

In females, average gross EE values for PHRM, AHRM, and IC on the treadmill, cycle, and rowing ergometer are shown in Figure 3. The PHRM significantly overestimated mean EE on the treadmill (by 2.4 $kcal \cdot min^{-1}$), cycle (by 2.9 $kcal \cdot min^{-1}$), and rower (by 1.9 $kcal \cdot min^{-1}$) (all $P < 0.05$). The AHRM for females significantly improved the estimation of mean EE for all exercise modes, but it still overestimated mean EE on the treadmill (by 0.6 $kcal \cdot min^{-1}$) and cycle (by 1.2 $kcal \cdot min^{-1}$) ($P < 0.05$). Figure 4 shows the individual errors in estimating EE across all exercise modes. For the PHRM, in females, the mean error (IC - PHRM) was -2.4 $kcal \cdot min^{-1}$ (-5.2 to +0.4 $kcal \cdot min^{-1}$, 95% CI). Although the AHRM still overestimated EE in females, the mean error (IC - AHRM) was improved to -0.7 $kcal \cdot min^{-1}$ (-2.2 to +0.8 $kcal \cdot min^{-1}$, 95% CI).

All participants achieved VO_{2max} based on the criteria used for the present study. For males, the mean predicted and measured VO_{2max} values were not significantly different ($P \geq 0.05$), but they were significantly different for females ($P = 0.001$). For males, there was a significant correlation between predicted and actual VO_{2max} ($r = 0.872$, $P = 0.001$) but not for females ($r = 0.477$, $P \geq 0.05$) (Fig. 5). There were no significant differences between predicted and measured HR_{max} for males or females ($P \geq 0.05$).

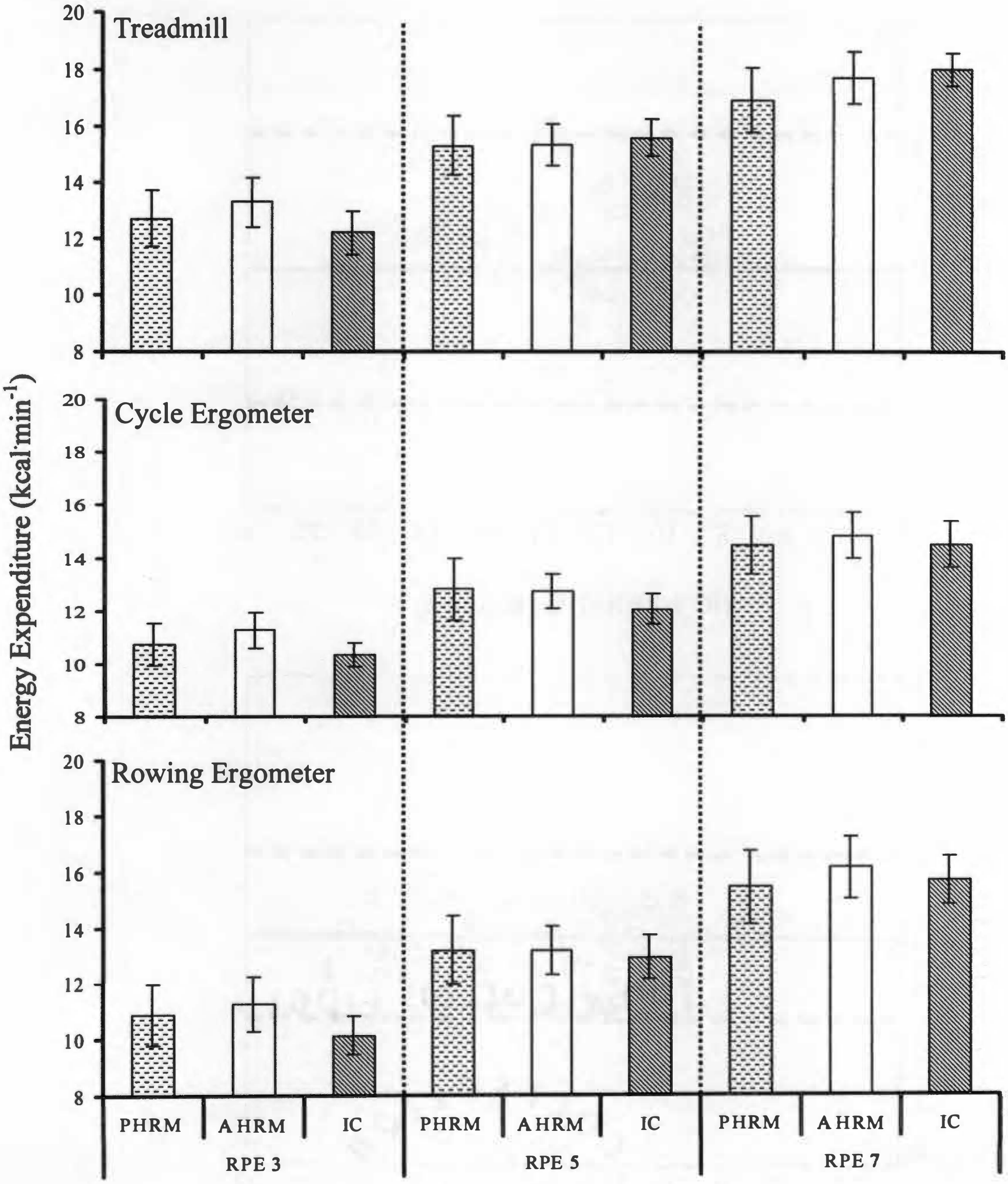

Figure 1. Male energy expenditure values at each RPE level (3,5,7) for the predicted heart rate monitor (PHRM), actual heart rate monitor (AHRM) and indirect calorimetry (IC) on the treadmill, cycle, and rowing ergometer (mean ± standard error).

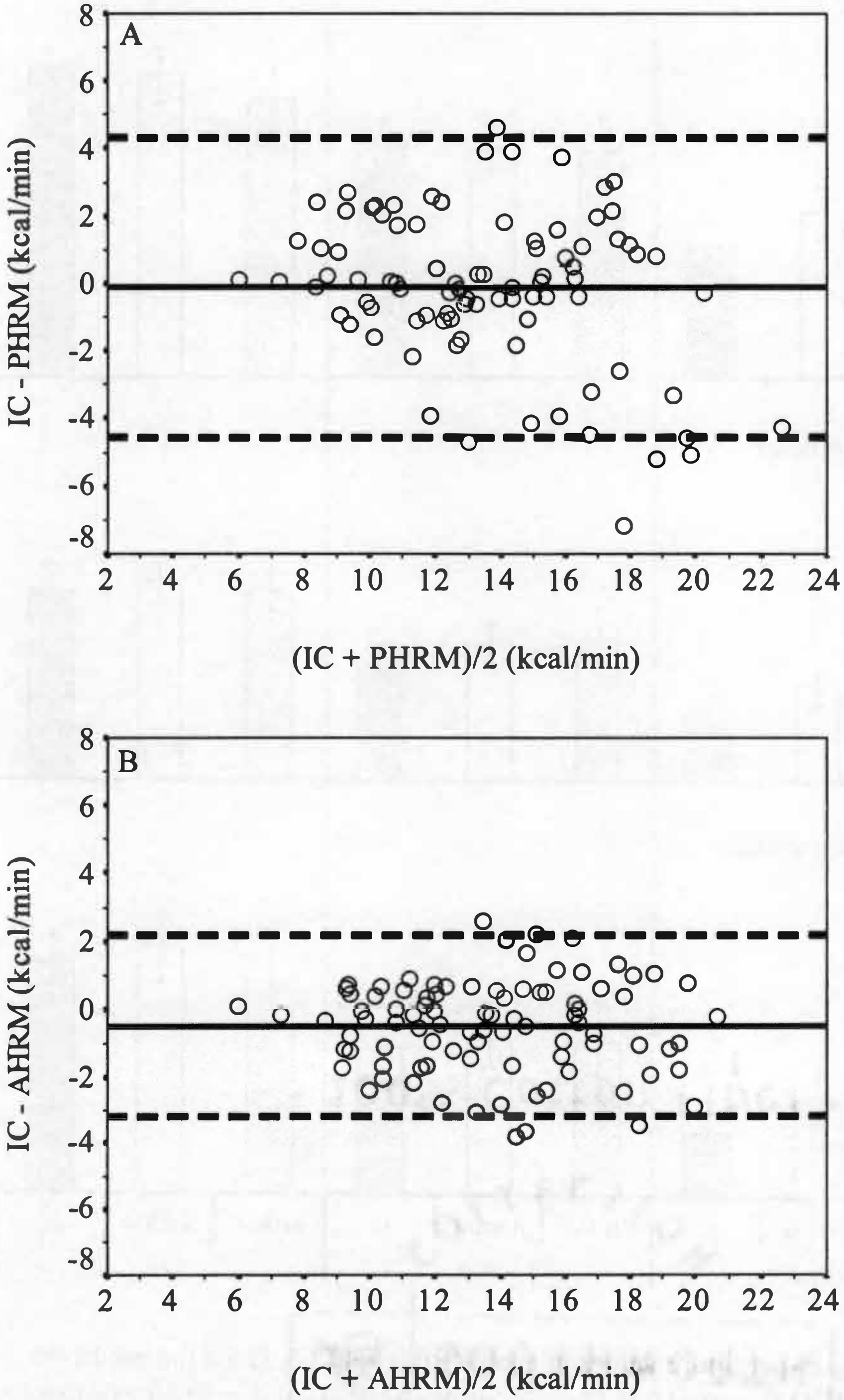

Figure 2. Bland-Altman plots depicting error scores (indirect calorimetry (IC) – device) for each watch in males: (A) Heart rate monitor with the predicted VO_{2max} and HR_{max} (PHRM), and (B) the heart rate monitor with the actual values (AHRM). Solid line represents mean difference; dashed lines represent 95% prediction intervals.

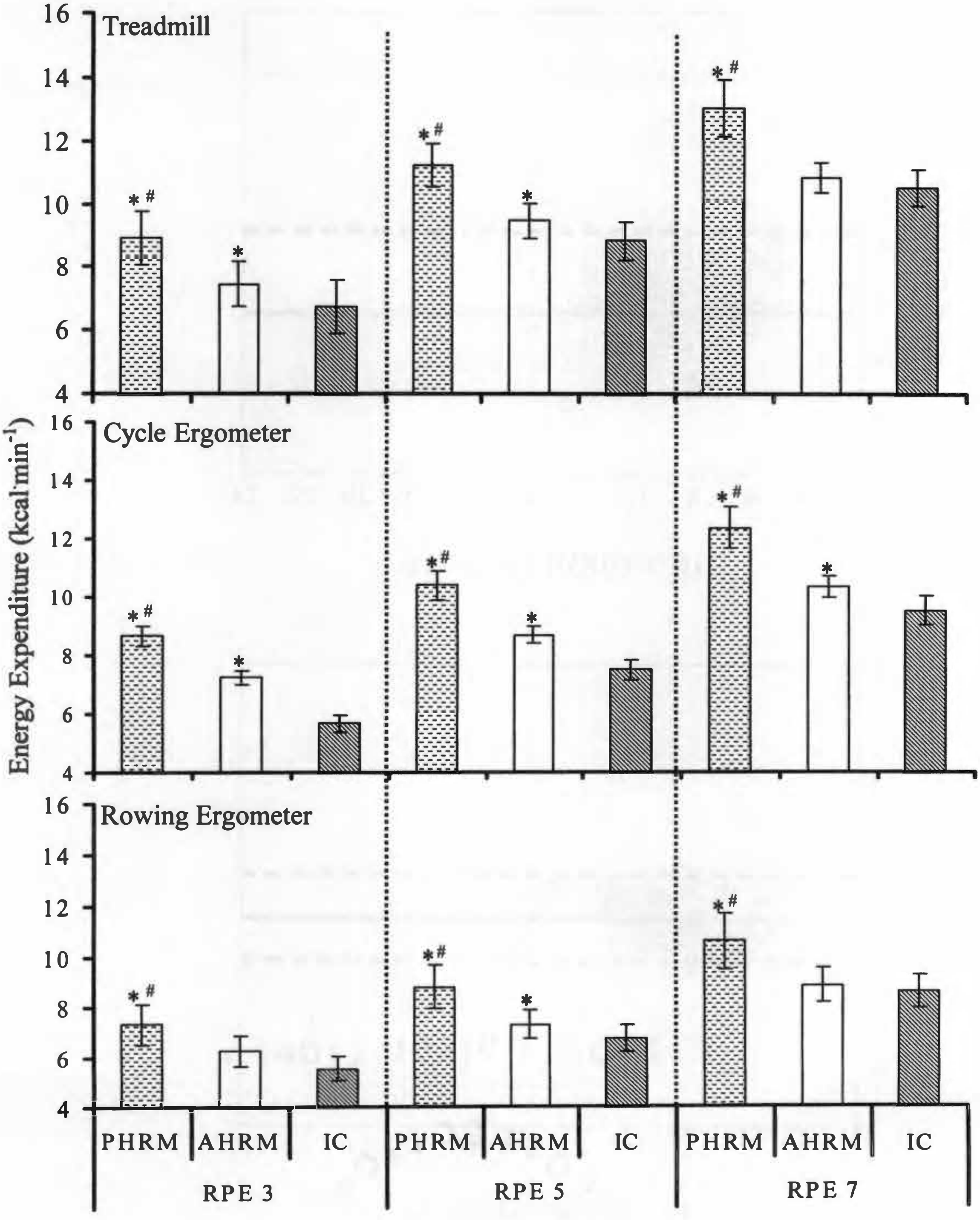

Figure 3. Female energy expenditure values at each RPE level (3,5,7) for the predicted heart rate monitor (PHRM), actual heart monitor (AHRM) and indirect calorimetry (IC) on the treadmill, cycle, and rowing ergometer (mean ± standard error). #Significantly different from AHRM; *significantly different from IC ($P < 0.05$).

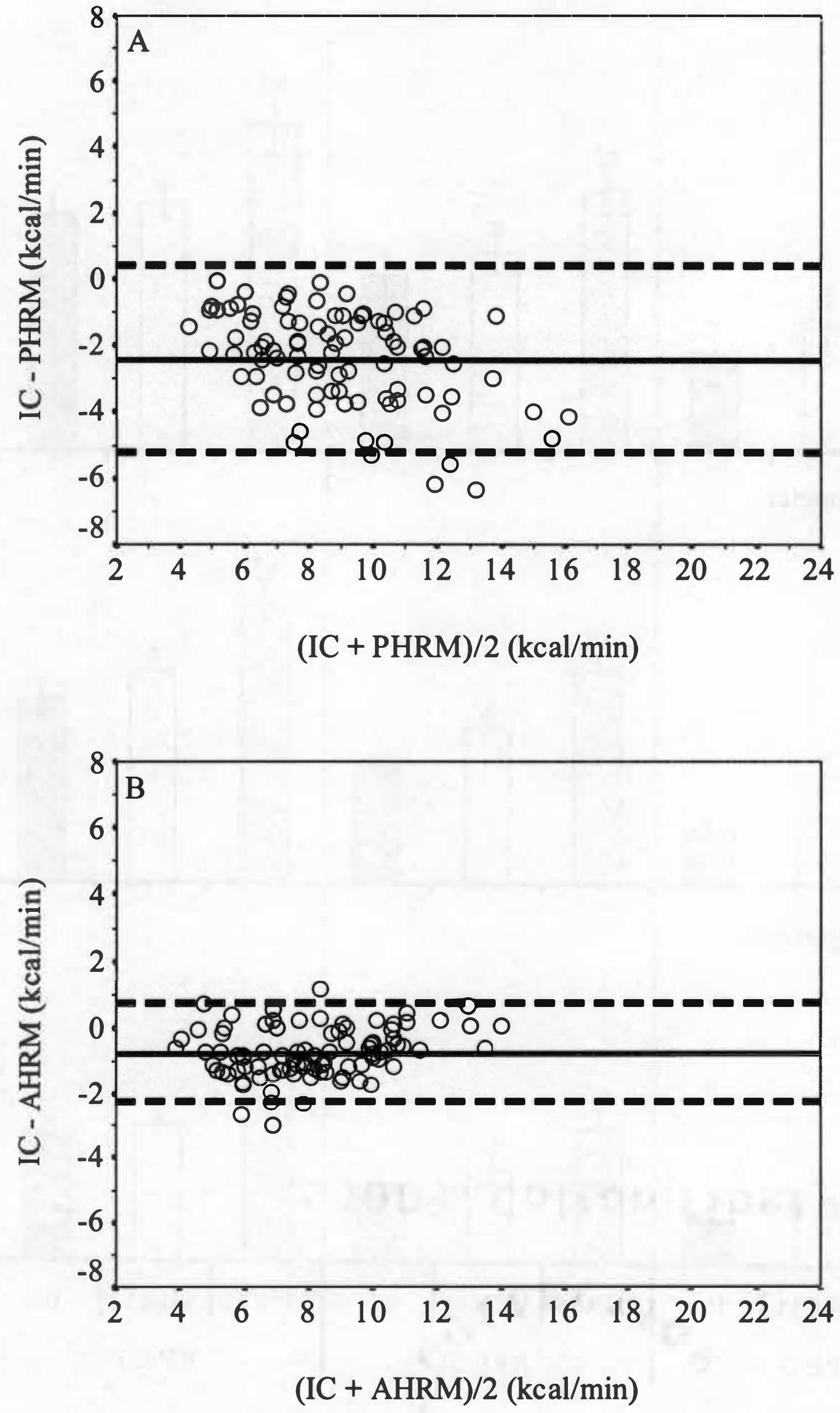

Figure 4. Bland-Altman plots depicting error scores (indirect calorimetry (IC) – device) for each watch in females: (A) heart rate monitor with the predicted VO_{2max} and HR_{max} (PHRM), and (B) the heart rate monitor with the actual values (AHRM). Solid line represents mean difference; dashed lines represent 95% prediction intervals.

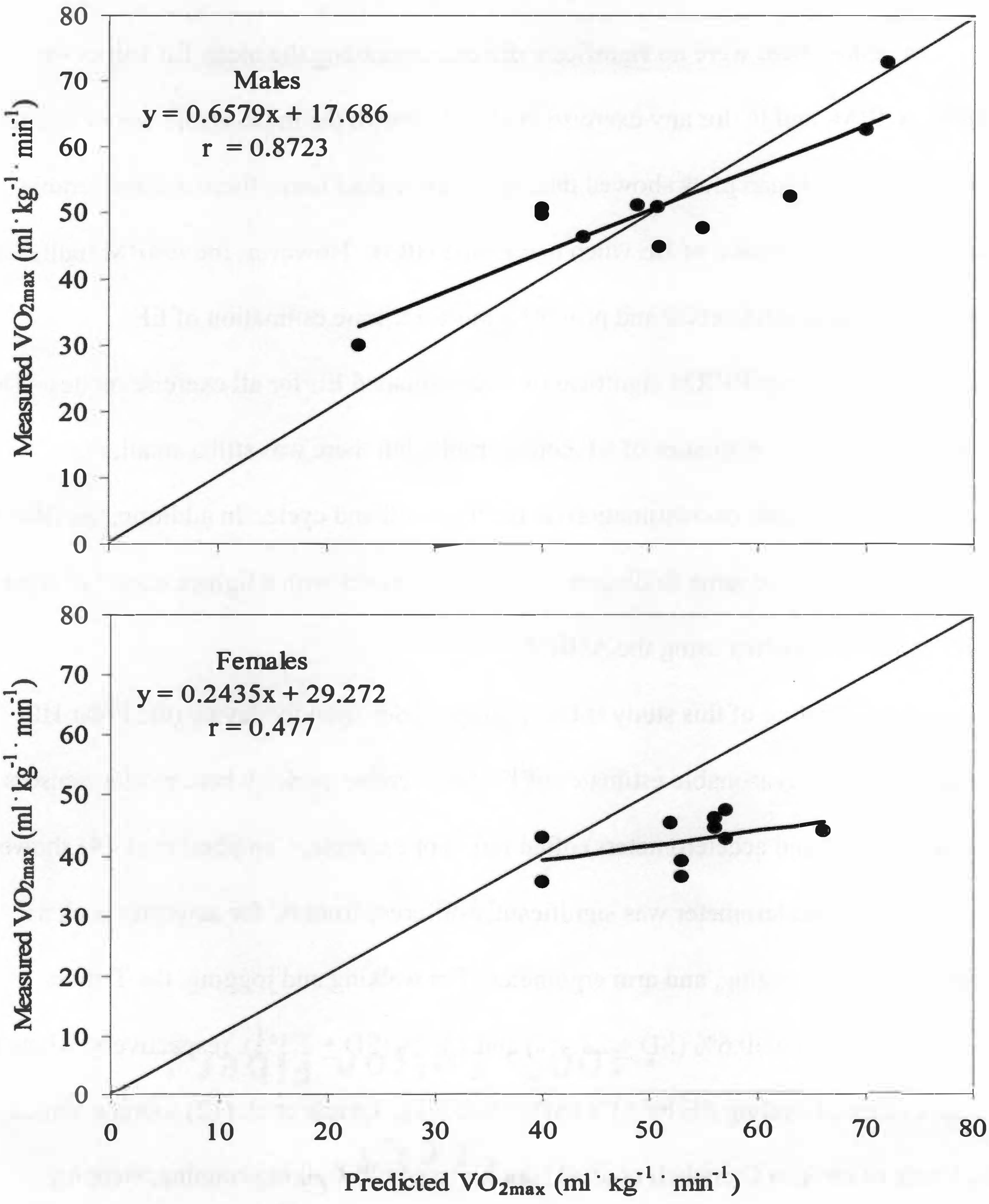

Figure 5. Relationship between measured and predicted VO_{2max} ($ml \cdot kg^{-1} \cdot min^{-1}$) for males and females.

Discussion

In males, there were no significant differences among the mean EE values for PHRM, AHRM, and IC for any exercise mode. Although the mean errors were close to zero, the Bland-Altman plots showed that, on an individual basis, there is considerable variation in the estimation of EE when using the PHRM. However, the AHRM tightened up the 95% prediction interval and provide a more accurate estimation of EE.

In females, the PHRM significantly overestimated EE for all exercise modes. The AHRM improved the estimates of EE considerably, but there was still a small, but statistically significant, overestimation on the treadmill and cycle. In addition, the Bland-Altman plots show the same finding in females as in males with a tighter scatter of error scores around zero when using the AHRM.

A new finding of this study is that a simple, user-friendly device (the Polar HR monitor) can yield reasonable estimates of EE for exercise modes where motion sensors (i.e., pedometers and accelerometers) often fail. For example, Campbell et al. (4) showed that the Tritrac accelerometer was significantly different from IC for activities such as cycling, walking, jogging, and arm ergometer. For walking and jogging, the Tritrac overestimated EE by 30.6% (SD $\pm$ 23.4%) and 15.8% (SD $\pm$ 2.3%), respectively, whereas it underestimated cycling EE by 53% (SD $\pm$ 59.53%). Jakicic et al. (12) found a similar magnitude of error as Campbell et al. (4) during treadmill walking/running, stepping, cycling, and slideboard exercises. In the current study, when the actual VO_{2max} and HR_{max} were used, the Polar S410 had a mean error of 4% (SD $\pm$ 10%) in males, whereas in females the mean error was 12% (SD $\pm$ 13%). The advantage of using HR is that it is a physiological parameter that can detect changes in exercise intensity even when the movement patterns differ greatly. Thus, the HR monitor is able to estimate EE in activities such as rowing and cycling, which do not elicit vertical displacement of the trunk, where pedometers and accelerometers would fail (4, 12).

It is important to note the differences between the Polar method of estimating EE and the Flex HR method. The Flex HR method utilizes HR and VO_2 measured at rest (lying, standing, sitting) and during exercise of various intensities to develop HR-VO_2 calibration curves (9). The Flex HR is defined as the average of the highest HR during rest and the lowest HR during light exercise. In a field setting, the assumed RMR (1MET) is used for any value below the Flex HR, whereas the HR-VO_2 calibration curve is used to estimate EE for any value above the Flex HR. A drawback to this method is that it is time consuming to develop individual calibration curves for individuals (9). The present study examined planned bouts of structured exercise whereas Flex HR studies have used much longer time periods, ranging from 6 h (23, 25) to 3–4 d (17). It should be noted that the Polar watch can only estimate EE during exercise when the HR is $\geq$ 90 bpm or $\geq$ 60% of the individual's HR_{max}. Thus, the Polar watch fails to record EE data at rest and during light-intensity physical activity. For this reason, we considered the possibility that the Polar HR monitor measures net EE, but our analyses showed that it more closely approximates gross EE (data not shown).

A practical application of the Polar S410 is that it provides reasonable estimates of gross EE during exercise when using an individual's measured VO_{2max} and HR_{max}. There is an emerging belief that a combination of devices may yield more accurate estimates of EE than any single method (9, 13). The use of a Polar HR monitor to capture exercise plus motion and position sensors to capture ubiquitous PA (summed together) could be a good way to estimate total EE. Previously, Levine et al. (16) have shown that by using accelerometers and inclinometers to capture body motion and position, they can account for 85% of nonexercise activity thermogenesis (NEAT). NEAT is comprised of several components such as occupational work, walking, sitting, standing, and any other nonexercise movement performed throughout the day. Thus, a person could wear the motion and position sensors throughout the day and remove them and put on the HR monitor when performing structured exercise.

The Polar S410 accurately predicted VO_{2max} in males, but not in females. It is difficult to draw conclusions about this due to the small sample size, but it may be important in explaining some of our results. In addition, Polar uses a proprietary algorithm for estimating VO_{2max}, HR_{max}, and exercise EE. The Polar S410 significantly overestimated the female VO_{2max} by 10.8 $ml \cdot kg^{-1} \cdot min^{-1}$, which led to a greater overestimation of EE than when the actual values were used. In females, but not males, the use of measured VO_{2max} and HR_{max} significantly improved the mean estimate of EE during exercise. Since there was no difference between the predicted and actual VO_{2max} in males, both watches gave similar mean values for EE. However, in both the males and females the use of measured VO_{2max} and HR_{max} provided a tighter prediction interval around zero, which indicates that the actual values must be programmed into the watch for greater accuracy. A limitation of this study is that it examined only healthy college aged students. Thus, the results may not be applicable to individuals who fall outside the age and fitness range of the participants we examined.

In an effort to understand how the Polar S410 estimates EE, we examined the relationship between estimated EE and HR, when the actual VO_{2max} and HR_{max} were programmed into the watch. Figure 6 is a representative graph for two participants (one male and one female), showing that there is a strong linear relationship ($r = 0.99$) between HR and estimated EE, but it is unique to each participant. Therefore, we reasoned that the Polar heart watch must be taking into account the individual's HR_{max} and VO_{2max}. Figure 7 illustrates the positive, linear relationship between the percentage of HR_{max} and the percentage of maximal energy expenditure for the same two participants in Figure 6. This time, the regression line was nearly identical for each participant, and it was similar for all participants, regardless of fitness level, gender, or other variables. Thus, it appears that the Polar S410 is using the percentage of HR_{max} to estimate the percentage of VO_{2max}, which is then converted to caloric expenditure.

An important consideration if using a Polar HR watch is that the "OwnCal" software is only available with certain Polar watches. The S-Series watches (used in the present study) have the capability to program in measured VO_{2max} and HR_{max}. The S-Series watches range in price from $179 to $400, depending on the features of the watch. There are two M-Series watches (M91Ti and M61) that estimate exercise EE, but they utilize gender, body weight, and exercise heart rate. The M-Series watches range in price from $169 to $249, so at the same price the S-Series can provide additional features to improve the accuracy of the estimated exercise EE.

In conclusion, when the predicted values of VO_{2max} and HR_{max} are used, the Polar S410 HRM provides a rough estimate of EE during treadmill, cycling, and rowing. For males, the use of predicted values resulted in a mean error of 2% (SD $\pm$ 18%), whereas in females the mean error was 33% (SD $\pm$ 20.9). To improve on the accuracy, the actual measured values for VO_{2max} and HR_{max} should be used. For males, this resulted in a 4%

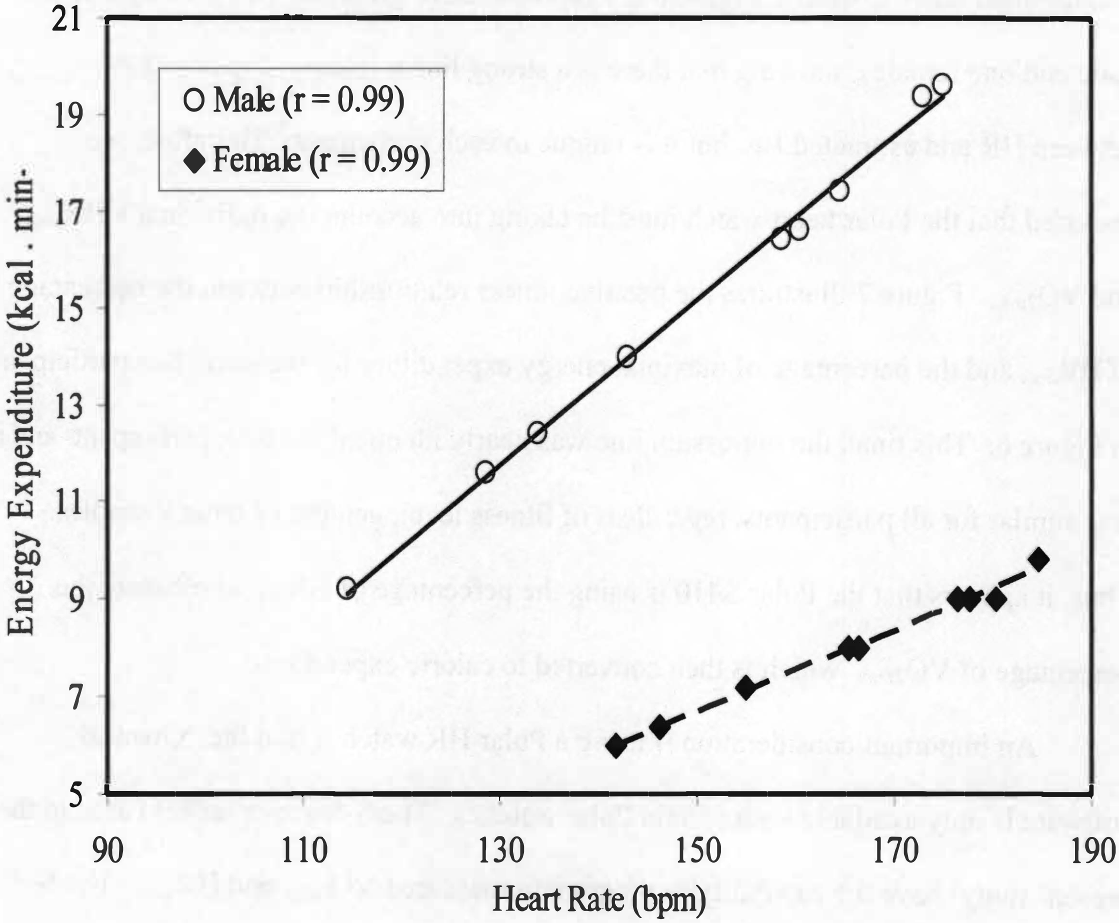

Figure 6. Representative data for two participants (one male and one female), showing the relationship between predicted energy expenditure and heart rate. Male: open circles with solid regression line (VO_{2max} = 52.7 ml·kg^{-1}·min^{-1}, HR_{max} = 186 bpm, Fitness level = top). Female: closed diamonds with dashed regression line (VO_{2max} = 42.8 ml·kg^{-1}·min^{-1}, HR_{max} = 198 bpm, Fitness level = middle).

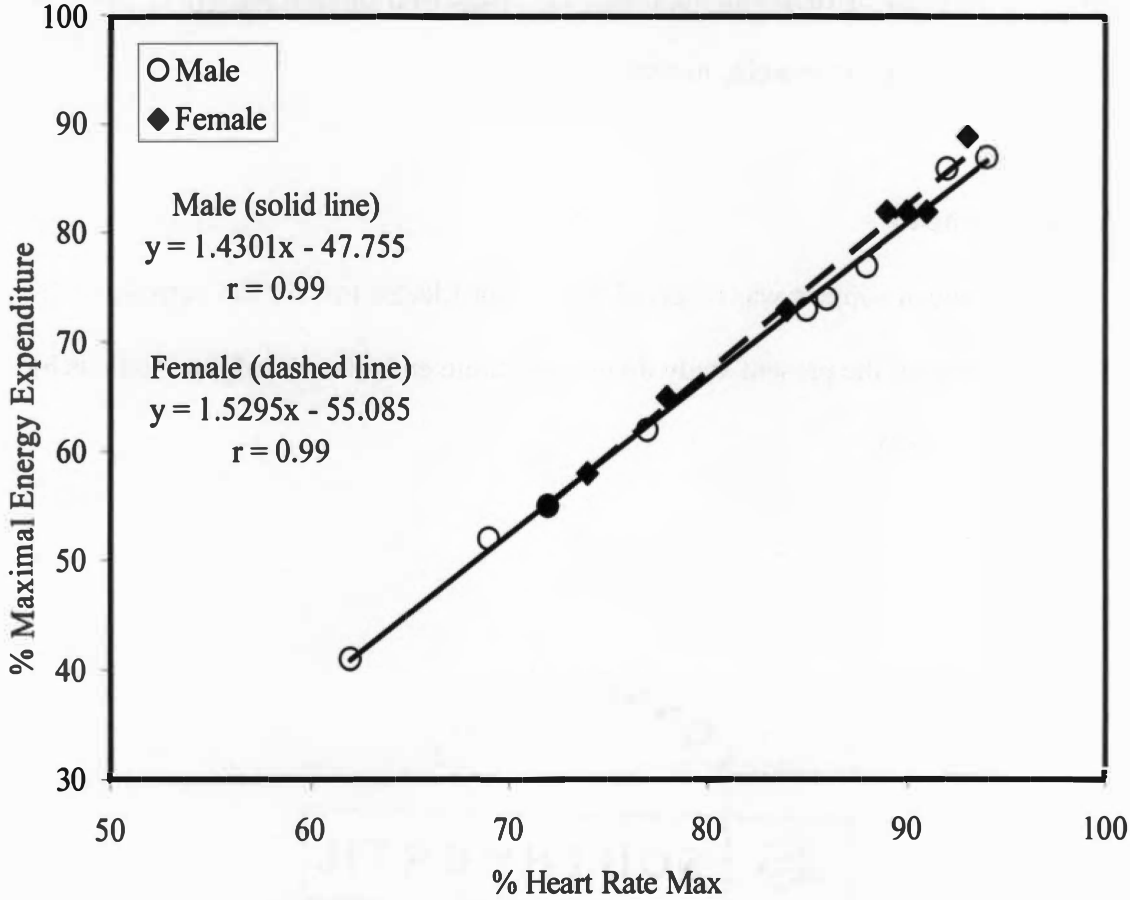

Figure 7. Representative data for two participants showing the relationship between percent of maximal energy expenditure and the percent of maximal heart rate. Male: open circles with solid regression line (VO_{2max} = 52.7 $ml \cdot kg^{-1} \cdot min^{-1}$, HR_{max} = 186 bpm, Fitness level = top). Female: closed diamonds with dashed regression line (VO_{2max} = 42.8 $ml \cdot kg^{-1} \cdot min^{-1}$, HR_{max} = 198 bpm, Fitness level = middle).

error (SD $\pm$ 10%), whereas in females the mean error was improved to 12% (SD $\pm$ 13%). In addition, the Polar S410 has an important advantage over motion sensors in that it is applicable to a variety of exercise modes.

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PART V

VALIDITY OF HEART RATE AND ACCELEROMETRY FOR THE MEASUREMENT OF ENERGY EXPENDITURE

Abstract

In recent years, several new devices have been developed for the purpose of estimating energy expenditure (EE). It is important that the validity of these new devices be examined, and compared to that of existing devices. **Purpose**: The purpose of this study was to examine the validity of three new devices (Actiheart, Actical, and AMP-331) and the Actigraph accelerometer compared to indirect calorimetery, over a wide range of activities. **Methods**: Forty-eight participants (age: 35 ± 11.4 yrs) performed various activities that ranged from sedentary behaviors (lying, sitting) to vigorous exercise. The activities were split into three routines of six activities, and each participant performed one routine. The participants wore four devices (Actigraph accelerometer, Actical, Actiheart, and AMP-331) and simultaneously, EE was measured with a portable metabolic system. For the Actigraph, seven previously published equations were used to estimate EE from the accelerometer counts. For the Actical, two published equations were used to estimate EE from the accelerometer counts. For the Actiheart, EE was estimated using the manufacturer's heart rate (HR) algorithm, activity algorithm, and combined HR and activity algorithm. The AMP-331 estimated EE from the manufacturer's equation. **Results:** The Actiheart HR algorithm was not significantly different from measured EE for any of the 18 activities performed ($P \geq 0.05$), while the Actiheart combined HR and activity algorithm was only significantly different from measured EE for vacuuming and ascending/descending stairs ($P < 0.05$). All remaining prediction equations, for the devices, over- or underestimated EE for at least seven activities. **Conclusion:** The Actiheart HR algorithm was the best predictor of EE over a wide range of activities. The Actigraph and Actical regressions tended to overestimate

walking and sedentary activities and underestimate most other activities. The AMP-331 gave a close estimate of EE during walking, but overestimated sedentary/light activities and underestimated all other activities. **Key Words:** MOTION SENSOR, PHYSICAL ACTIVITY, OXYGEN CONSUMPTION, ACCURACY

Introduction

The ability to accurately track energy expenditure (EE) using objective methods is of increasing interest. Accelerometers provide a means by which researchers can examine the intensity, frequency, and duration of physical activity bouts that individuals are performing. The Actigraph (formerly known as the Manufacturing Technology Incorporated (MTI) Actigraph, and the Computer Science Applications Inc. (CSA)) accelerometer is one of the most widely used devices and is currently being used in the Fourth U.S. National Institute of Health and Nutrition Examination Survey (NHANES IV). In addition, there are some newer devices on the market including the Actical, Actiheart, and AMP-331 that provide information on how much physical activity individuals are obtaining.

Although accelerometers are used extensively in research, they are generally validated in laboratory settings; this limits the generalizability of the results to free-living populations. For example, Leenders et al. (17) found that the Actigraph accelerometer (model 7164) underestimated 24-hour EE by 59% compared to doubly labeled water. They used a regression equation relating counts$\cdot$min^{-1} to METs developed by Freedson et al. (6) during treadmill walking and running. In general, it has been shown that the Freedson equation overestimates the energy cost of walking, while underestimating the energy cost of most moderate-intensity lifestyle activities (1, 26). The underestimation of lifestyle activities is most likely due to a failure to detect the additional EE resulting from arm activity, uphill walking, stair climbing, lifting, and carrying objects (1). Hence Hendelman et al. (12) and Swartz et al. (25) developed regression equations relating counts$\cdot$min^{-1} from the Actigraph to METs using moderate-intensity lifestyle activities. These equations were developed with the intent of obtaining a more accurate estimate of time spent in moderate-intensity activities. However, the Hendelman and Swartz lifestyle regression equations are not likely to be accurate for sedentary and light activities because they have y-intercepts of 2.9 and 2.6 METs, respectively.

Recently, new devices have become available for the measurement of EE. The Actical device (Mini Mitter, Sunriver, OR) uses a small (28 x 27 x 10 mm) omnidirectional accelerometer and weighs 17 grams. To date, only a few studies have examined the validity and reliability of the Actical (11, 15, 21, 27). Generally, it has been found to have a high correlation between counts$\cdot$min^{-1} when worn on the hip and measured METs during treadmill walking, running, and lifestyle activities performed in a laboratory ($r = 0.94$) (15). Another new device is the Actiheart (Mini Mitter, Sunriver, OR) which combines a heart rate (HR) monitor and accelerometer into a single unit that weighs 10 grams and is 188 mm in length. Brage et al. (3) found the device to give valid and reliable HR and accelerometer data under laboratory conditions, but no studies have been published that report on its accuracy in the field.

The AMP-331 (Activity Monitoring Pod, Dynastream Innovations Inc., Cochrane, AB, Canada) is an ankle mounted activity monitor that utilizes accelerometers to estimate steps, distance, speed, and EE. In a recent validation study, the AMP-331 was found to be within ± 4% of actual steps at treadmill walking speeds 54 $m \cdot min^{-1}$ and faster. However, it underestimated distance traveled by approximately 11% at speeds of 40 $m \cdot min^{-1}$ and faster (14). The company's own testing found that the AMP-331 gave mean steps within 1% of actual steps during over-ground walking on a 200 meter track at speeds of 44 to 120 $m \cdot min^{-1}$, while it was within ± 3% of actual distance at the same speeds (7).

With the development of new devices, it is important to validate them in a field setting and compare them against current devices to determine the best method of predicting EE. Therefore, the purpose of this study was to compare the Actical, Actiheart, AMP-331, and Actigraph against indirect calorimetry during sedentary, light, moderate, and vigorous intensity activities in a field setting.

Methods

Subjects

Twenty-four males (Age: 36 ± 12.8 yrs, BMI: 25.7 ± 5.2 $kg \cdot m^{-2}$) and 24 females (Age: 35 ± 10.3 yrs, BMI: 22.7 ± 4.0 $kg \cdot m^{-2}$) from the University of Tennessee, Knoxville and surrounding community volunteered to participate in the study. The procedures were reviewed and approved by the University of Tennessee Institutional Review Board before the start of the study. Each participant signed a written informed consent and completed a Physical Activity Readiness Questionnaire (PAR-Q) before participating in the study. Participants were excluded from the study if they had any contraindications to exercise or were not physically capable of completing the activities. The physical characteristics of the participants are shown in Table 1.

Anthropometric Measurements

Prior to testing participants had their height and weight measured (in light clothing, without shoes) using a stadiometer and a physician's scale, respectively. Body mass index (BMI) was calculated according to the formula: body mass (kg) divided by height squared (m^2). Skinfold measurements were taken using Lange Calipers (Cambridge, MD) at the chest, abdomen and thigh for men and at the tricep, suprailic, and thigh for women (13).

Procedures

Participants performed various lifestyle and sporting activities that were divided into three routines.

Routine 1: Lying, standing, sitting doing computer work, filing articles, walking up and down stairs at a self selected speed, cycling at a self selected work rate.

Routine 2: walking at approximately 3 mph around a track, walking at approximately 4 mph around a track, playing one-on-one basketball, playing singles racquetball, running at approximately 5 mph around a track, running at approximately 7 mph around a track.

Routine 3: vacuuming, sweeping and/or mopping, washing windows, washing dishes, lawn mowing with a push mower, raking grass and/or leaves.

Table 1. Physical characteristics of the participants (mean ± SD (range)).

Variable	Male (N=24)	Female (N=24)	All Participants (N=48)
Age (yr)	36 ± 12.8 (21 – 69)	35 ± 10.3 (22 – 55)	35 ± 11.4 (21 – 69)
Height (in)*	70.9 ± 2.8 (62.8 – 74.2)	65.1 ± 2.3 (60.2 – 68.5)	68.0 ± 3.8 (60.2 – 74.2)
Body Mass (kg)*	83.9 ± 20.2 (59.4 – 141.0)	62.3 ± 12.3 (45.4 – 109.0)	73.1 ± 19.6 (45.4 – 141.0)
BMI ($kg \cdot m^{-2}$)*	25.8 ± 5.2 (19.1 – 40.6)	22.7 ± 4.0 (17.9 – 36.4)	24.2 ± 4.8 (17.9 – 40.6)
Resting VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$)	3.6 ± 0.8 (2.1 – 5.0)	3.4 ± 0.8 (2.0 – 4.9)	3.5 ± 0.9 (2.0 – 5.0)
Sum of 3 skinfold	49.0 ± 27.9 (16.6 – 125.5)	52.0 ± 16.7 (24.5 – 93.7)	50.5 ± 22.5 (16.6 – 125.5)

BMI=Body Mass Index; *Significantly different from females, $P < 0.05$.

Twenty participants performed each routine, and most performed only one routine. Participants performed each activity in the routine for 10 minutes, with a 1 to 2 minute break between each activity. Oxygen consumption (VO_2) was measured continuously by indirect calorimetry (Cosmed $K4b^2$, Rome Italy). Participants also wore four motion sensors for the duration of the routine. For all devices that used body weight, 2 kg was added to account for the added weight of the Cosmed and motion sensors. Routine 1 was performed in the Applied Physiology Laboratory, routine 2 was performed at University facilities, and routine 3 was performed at either the participant's home or the investigator's home. The participants who did not perform routine 1 were asked to sit quietly for 5 minutes before the start of the routine so that a resting VO_2 and HR could be measured.

Indirect Calorimetry

The participants wore a Cosmed $K4b^2$ portable metabolic system for the duration of each routine. The Cosmed $K4b^2$ weighs approximately 1.5 kg, including the battery, and a specially designed harness. The Cosmed $K4b^2$ has been shown to be a valid device when compared against the Douglas Bag method during cycle ergometry (18). Prior to each test, the oxygen and carbon dioxide analyzers were calibrated according to the manufacturer's instructions. This consisted of performing a room air calibration and a reference gas calibration using 15.93% oxygen and 4.92% carbon dioxide. The turbine was then calibrated using a 3.00 L syringe (Hans-Rudolph). Finally, a delay calibration was performed to adjust for the lag time between the expiratory flow measurement and the gas analysis. During each test a gel-seal was used to help prevent air leaks from the face mask.

Motion Sensors

During the routine, participants wore two waist-mounted accelerometers (Actigraph and Actical), an AMP-331 on the right ankle, and an Actiheart attached to the chest using ECG Electrodes. The motion sensors were positioned according to the manufacturer's recommendation. Figure 1 shows the devices used for the study. All devices were synchronized with a digital clock prior to testing. At the conclusion of each test, data from each device were downloaded to a personal computer for subsequent analysis.

The Actigraph (model 7164) is a small (2.0 x 1.6 x 0.6 in) and lightweight (42.5 grams) uniaxial accelerometer that measures accelerations in the range of 0.05 to 2 G's with a band limited frequency of 0.25 to 2.5 Hz. These values correspond to the range at which most human activities are performed. An 8-bit analog-to-digital converter samples at a rate of 10 Hz and these values are then summed over a specified time period (epoch). The Actigraph data can be downloaded to a personal computer via a reader interface unit. The Actigraph was worn at waist level at the right anterior axillary line in a nylon pouch that was attached to a belt. The Actigraph was initialized using one second epochs. The Actigraph accelerometer was calibrated at the beginning and end of the study and each time was found to be within ± 3.5% of the reference value, which is within the manufacturer's standards.

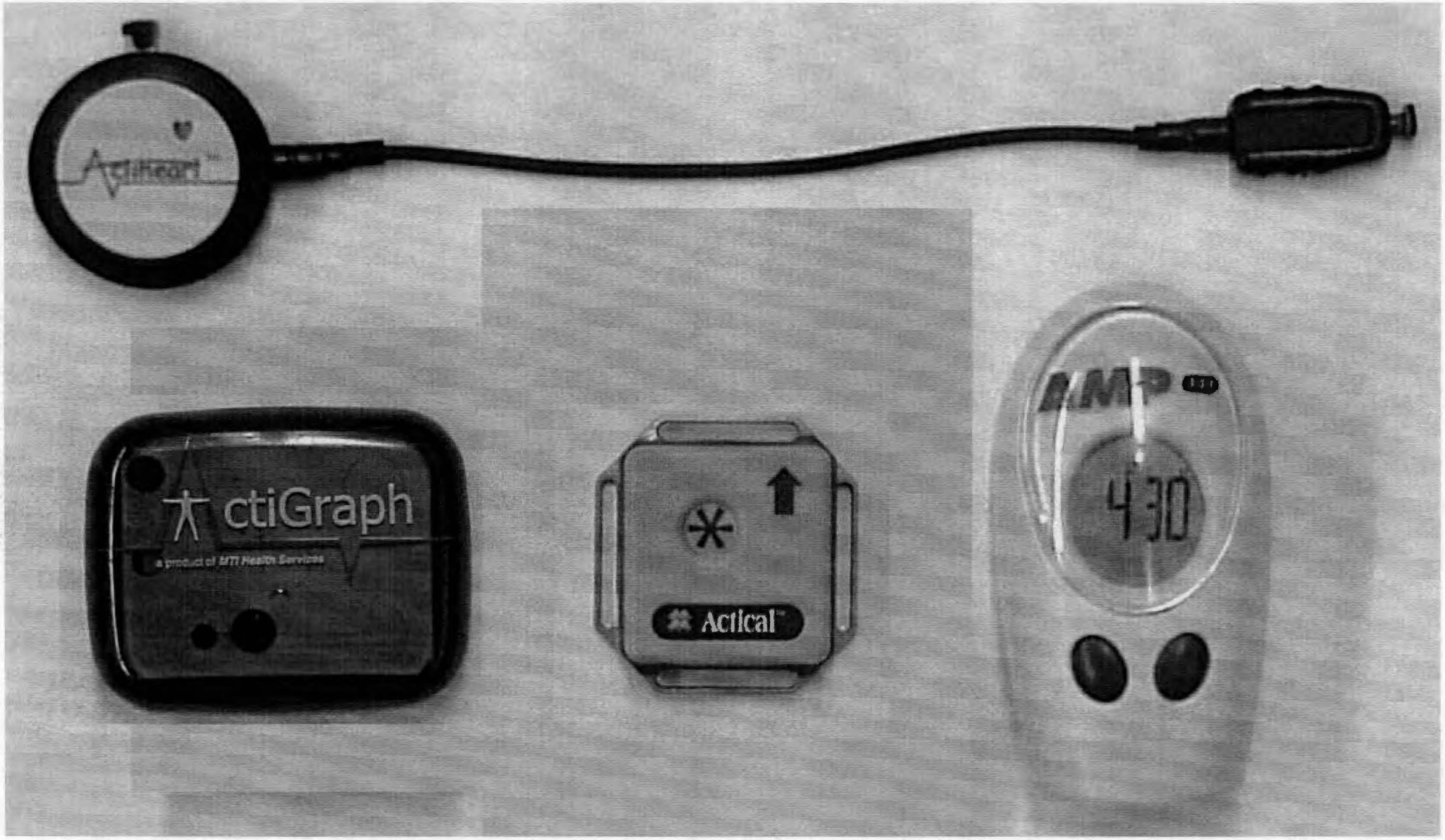


Figure 1. Devices used for prediction of energy expenditure. (Top) Actiheart, (bottom left to right) Actigraph, Actical, AMP-331.

The Actical accelerometer is a small (28 x 27 x 10 mm) device that uses an omnidirectional accelerometer and weighs 17 grams. The Actical is sensitive to movements in the range of 0.5 to 3 Hz. The Actical was worn at waist level in the left anterior axillary line, attached to a belt with velcro straps provided by the manufacturer. The Actical was initialized using 15-second epochs.

The AMP-331 is an ankle mounted activity monitor, which uses two accelerometers that measure acceleration of the shank in the horizontal and vertical directions throughout the gait cycle. This device is able to count steps and measure stride length. The participant's gender, birth date, height, and weight are programmed into the AMP-331 prior to testing. The AMP-331 has a digital display to allow for viewing of activity data during the test, or it can be downloaded to a computer for subsequent analysis. For all activities the AMP-331 was placed in a neoprene case and securely fastened around the right ankle with a velcro strap. The device was positioned directly over the Achilles tendon. The AMP-331 was initialized with 1-minute epochs.

The Actiheart is a relatively new device that combines HR and a movement sensor into a single unit that weighs 10 grams and is 188 mm in length. The device is attached to the chest using ECG electrodes. The main sensor (7 mm thick and has a diameter of 33 mm) attaches over the sternum and contains the movement sensor, rechargeable battery, a memory chip, and other electronics. The smaller sensor (5 x 11 x 22 mm) attaches over the midclavicular line, and is connected to the main sensor by a thin 100 mm long wire. The Actiheart measures acceleration, HR, HR variability, and ECG amplitude. The Actiheart uses a piezo-electric accelerometer with a frequency range of 1-7 Hertz, and a dynamic range of ± 2.5 Gs. The Actiheart ECG measures in a range of 35 to 255 bpm with a sampling frequency of 128 Hz. During all activities the Actiheart was attached to the chest using ECG electrodes (3M Red Dot 2271, London, Ontario). The Actiheart was initialized using 15 second epochs.

Data Analysis

Breath-by-breath data were collected by the Cosmed $K4b^2$, and were averaged over a 30-second period. For each activity, VO_2 ($ml \cdot min^{-1}$) was converted to VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$) and then to METs by dividing by 3.5. For each activity, the MET values from minutes 4 to 9 (for each device) were averaged and used in the subsequent analysis.

The Actiheart provides minute-by-minute values for activity energy expenditure (AEE) ($kcal \cdot kg^{-1} \cdot min^{-1}$) using a HR algorithm, activity algorithm, or a combined HR and activity algorithm. For the HR and combined heart rate and activity algorithms the individual's resting HR is needed; this was determined from the lying activity during routine 1, or the resting measurement before the other routines. In addition, based on the user information (age, height, weight, gender) put into the Actiheart software, resting metabolic rate is calculated using the Harris-Benedict equation (8), and is subsequently used to estimate AEE (i.e. net EE). Therefore, we used the Harris-Benedict equation (8) to estimate the resting metabolic rate per minute ($kcals \cdot min^{-1}$) for each participant, which was then divided by their body mass in kg to obtain $kcal \cdot kg^{-1} \cdot min^{-1}$. This was then added to the AEE of the Actiheart so that gross EE could be obtained. The gross EE was then converted to METs (i.e. 1 $kcal \cdot kg^{-1} \cdot hr^{-1}$ is equal to 1 MET).

The Actigraph accelerometer data were collected in one second epochs and were then converted to one minute averages using a Visual Basic program, written specifically for this study. The counts$\cdot$min^{-1} values were used in the following seven equations for the prediction of METs:

(1) Net EE (kcals$\cdot$min^{-1}) = 0.0000191 x (counts$\cdot$min^{-1}) x body mass in kg, from Actigraph manual (19)

(2) Gross EE (kcals$\cdot$min^{-1}) = (0.00094 x counts$\cdot$min^{-1}) + (0.134 x mass in kg) – 7.37418, from Freedson et al. (6)

(3) Gross EE (METs) = 1.439008 + (0.000795 x counts$\cdot$min^{-1}), from Freedson et al. (6)

(4) Gross EE (METs) = 2.606 + (0.0006863 x counts$\cdot$min^{-1}), from Swartz et al. (25)

(5) Gross EE (METs) = 1.602 + (0.000638 x counts$\cdot$min^{-1}), from Hendelman et al. (12)

(6) Gross EE (METs) = 2.922 + (0.000409 x counts$\cdot$min^{-1}), from Hendelman et al. (12)

(7) Gross EE (METs) = (0.00171 x counts$\cdot$min^{-1}) + (1.957 x height in cm) – (0.000631 x counts$\cdot$min^{-1} x height in cm) – 1.883, from Heil et al. (10)

Equation 1 provides an estimate of net EE (kcals$\cdot$min^{-1}), and thus the Harris-Benedict equation (8) was used to estimate the each participant's resting metabolic rate per minute (kcals$\cdot$min^{-1}), which was divided by body mass in kg to obtain kcal$\cdot$kg$^{-1}\cdot$min^{-1}. The net EE from equation 1 was used to compute gross EE (kcals$\cdot$min^{-1}), which was then converted to METs in the same manner as previously described.

Statistical Treatment

Statistical analyses were carried out using SPSS version 13.0 for Windows (SPSS Inc., Chicago, IL). For all analyses, an alpha level of 0.05 was used to indicate statistical significance. All values are reported as mean ± standard deviation. Independent t-tests were used to examine the difference between genders for anthropometric variables. One-way repeated measures ANOVAs were used to compare actual and predicted METs for each activity and all 18 activities combined. Pairwise comparisons with Bonferroni adjustments were performed to locate significant differences when necessary.

Modified Bland-Altman Plots were used to graphically show the variability in the individual error scores (measured METs minus predicted METs) (2). This allowed for the mean error score and the 95% prediction interval to be shown. Devices that are accurate will display a tight prediction interval around zero. Data points below zero signify an overestimation, while data points above zero signify an underestimation.

Results

Due to errors which occurred during the downloading process, the AMP-331 data were missing for two participants (routine 1 and 3), Actiheart data were missing for one participant (routine 2), and Actigraph data were missing for one participant (routine 3). Table 2 shows the mean (± SD) for the Cosmed K4b^2, Actical, Actiheart, and AMP for each of the 18 activities and for all activities combined. Table 3 shows the mean (± SD) for the Cosmed K4b^2 and the Actigraph prediction equations. The only prediction method that was not significantly different from actual EE (METs) for any activity was the Actiheart HR algorithm ($P \geq 0.05$). The Actiheart combined HR and activity

Table 2. Mean (± SD) MET values for the Cosmed K4b², Actical, Actiheart, and AMP during various activities.

	Measured METs	Actical Single Regression	Actical Double Regression	Actiheart Combined HR and motion algorithm	Actiheart Activity Algorithm	Actiheart HR Algorithm	AMP-331
Lying	0.93 (0.23)	0.97 (0.02)	0.97 (0.02)	0.96 (0.10)	0.95 (0.09)	1.01 (0.14)	1.50 (0.03)*
Standing	1.19 (0.27)	0.90 (0.00)*	0.90 (0.00)*	1.13 (0.34)	0.96 (0.09)	1.61 (0.70)	1.51 (0.03)*
Computer Work	1.03 (0.21)	0.91 (0.23)	0.91 (0.03)	1.05 (0.21)	0.96 (0.09)	1.31 (0.46)	1.50 (0.03)*
Filing papers	1.58 (0.33)	0.99 (0.25)*	0.99 (0.25)*	1.22 (0.33)	1.00 (0.12)*	1.71 (0.68)	1.53 (0.08)
Ascending/Descending Stairs	6.44 (0.79)	4.33 (0.23)*	4.24 (0.22)*	4.55 (1.38)*	2.86 (0.90)*	5.41 (1.31)	2.83 (0.04)*
Stationary Cycling (avg. 99 watts)	6.20 (1.58)	1.89 (0.98)*	1.95 (1.14)*	4.20 (1.86)	1.38 (0.32)*	5.78 (1.76)	2.14 (0.68)*
Slow Walk (avg. 81 $m \cdot min^{-1}$)	3.23 (0.59)	4.34 (0.39)*	4.29 (0.36)*	2.74 (0.57)	2.94 (0.66)	2.53 (0.71)	3.35 (0.50)
Fast Walk (avg. 103 $m \cdot min^{-1}$)	3.93 (0.72)	5.22 (0.54)*	5.11 (0.53)*	3.62 (0.75)	3.61 (0.82)	3.59 (0.95)	4.60 (1.02)
Basketball	7.91 (1.10)	5.11 (0.38)*	5.01 (0.37)*	6.96 (1.44)	3.64 (0.72)*	7.47 (1.38)	3.11 (0.16)*
Racquetball	6.82 (1.46)	4.33 (0.32)*	4.29 (0.28)*	6.30 (1.72)	3.19 (0.58)*	7.02 (1.66)	3.00 (0.03)*
Slow Run (avg. 159 $m \cdot min^{-1}$)	8.10 (0.92)	8.48 (0.80)	8.31 (0.79)	8.15 (0.92)	7.07 (1.78)	8.17 (1.11)	5.17 (1.45)*
Fast Run (avg. 189 $m \cdot min^{-1}$)	8.82 (1.22)	8.93 (0.96)	8.75 (0.94)	8.99 (0.86)	7.58 (2.09)	9.03 (1.11)	5.72 (1.61)*
Vacuum	3.54 (0.56)	2.43 (0.47)*	2.42 (0.48)*	2.25 (0.41)*	1.48 (0.27)*	2.94 (0.64)	2.67 (0.40)*
Sweep/mop	3.57 (0.72)	2.35 (0.52)*	2.39 (0.59)*	2.79 (0.53)	1.79 (0.54)*	3.59 (0.75)	2.37 (0.44)*
Washing windows	2.99 (0.59)	2.02 (0.55)*	2.05 (0.59)*	2.38 (0.56)	1.52 (0.45)*	3.18 (0.89)	1.75 (0.32)*
Washing Dishes	2.07 (0.28)	1.04 (0.20)*	1.04 (0.20)*	2.02 (0.87)	1.05 (0.12)*	3.09 (1.55)	1.51 (0.06)*
Lawn Mowing	6.18 (0.84)	3.91 (0.35)*	4.20 (0.34)*	4.99 (1.55)	2.66 (0.71)*	5.92 (1.52)	2.87 (0.20)*
Raking grass/leaves	4.10 (0.93)	3.02 (0.44)*	3.36 (0.72)*	3.65 (1.12)	2.12 (0.59)*	4.68 (1.31)	2.53 (0.74)*
Total for all activities	4.38 (2.66)	3.41 (2.44)*	3.41 (2.39)*	3.79 (2.60)*	2.61 (2.08)*	4.34 (2.64)	2.77 (1.40)*

* Significantly different from Cosmed K4b² ($P < 0.05$)

Table 3. Mean (± SD) MET values for the Cosmed $K4b^2$ and 7 Actigraph prediction equations during various activities.

	Measured METs	Actigraph Manufacture's Equation	Actigraph Freedson Kcal equation	Actigraph Freedson MET equation	Actigraph Swartz equation	Actigraph Hendelman Walk equation	Actigraph Hendelman Lifestyle equation	Actigraph Heil Equation
Lying	0.93 (0.23)	0.95 (0.09)	1.78 (1.42)	1.44 (0.00)*	2.61 (0.00)*	1.60 (0.00)*	2.92 (0.00)*	1.51 (0.21)*
Standing	1.19 (0.27)	0.96 (0.09)	1.77 (1.42)	1.45 (0.02)	2.61 (0.01)*	1.61 (0.01)*	2.93 (0.01)*	1.52 (0.21)*
Computer Work	1.03 (0.21)	0.95 (0.09)	1.76 (1.42)	1.44 (0.00)*	2.61 (0.00)*	1.60 (0.00)*	2.92 (0.00)*	1.51 (0.21)*
Filing papers	1.58 (0.33)	1.00 (0.14)*	1.79 (1.43)	1.48 (0.09)	2.64 (0.08)*	1.63 (0.07)	2.94 (0.04)*	1.54 (0.24)
Ascending /Descending Stairs	6.44 (0.79)	4.64 (0.79)*	4.35 (0.89)*	4.02 (0.54)*	4.83 (0.47)*	3.67 (0.43)*	4.25 (0.28)*	3.51 (0.42)*
Stationary Cycling (avg. 99 watts)	6.20 (1.58)	1.77 (0.92)*	2.25 (1.63)*	2.02 (0.67)*	3.10 (0.58)*	2.06 (0.54)*	3.22 (0.34)*	1.94 (0.59)*
Slow Walk (avg. 81 $m \cdot min^{-1}$)	3.23 (0.59)	4.85 (0.78)*	4.40 (1.05)*	4.15 (0.56)*	4.95 (0.48)*	3.78 (0.45)*	4.32 (0.29)*	3.60 (0.43)*
Fast Walk (avg. 103 $m \cdot min^{-1}$)	3.93 (0.72)	6.73 (1.18)*	5.76 (0.98)*	5.47 (0.82)*	6.08 (0.71)*	4.83 (0.66)*	4.99 (0.42)*	4.62 (0.64)*
Basketball	7.91 (1.10)	7.42 (1.36)	6.28 (0.97)*	5.95 (0.94)*	6.50 (0.81)*	5.22 (0.76)*	5.24 (0.48)*	5.02 (0.76)*
Racquetball	6.82 (1.46)	5.12 (1.22)*	4.66 (1.09)*	3.34 (0.85)*	5.11 (0.73)*	3.93 (0.68)*	4.42 (0.44)*	3.78 (0.72)*
Slow Run (avg. 159 $m \cdot min^{-1}$)	8.10 (0.92)	10.05 (1.57)*	8.05 (1.10)	7.79 (1.10)	8.09 (0.95)	6.70 (0.88)*	6.19 (0.56)*	6.42 (0.89)*
Fast Run (avg. 189 $m \cdot min^{-1}$)	8.82 (1.22)	10.74 (2.74)	8.68 (2.37)	8.27 (1.91)	8.51 (1.65)	7.09 (1.53)*	6.44 (0.98)*	6.85 (1.80)*
Vacuum	3.54 (0.56)	1.86 (0.41)*	2.36 (1.45)	2.09 (0.30)*	3.16 (0.26)	2.12 (0.24)*	3.26 (0.15)	2.00 (0.27)*
Sweep/mop	3.57 (0.72)	1.73 (0.41)*	2.26 (1.53)	2.00 (0.29)*	3.09 (0.25)	2.05 (0.23)*	3.21 (0.15)	1.93 (0.30)*
Washing windows	2.99 (0.59)	1.38 (0.31)*	2.01 (1.59)	1.75 (0.22)*	2.88 (0.19)	1.85 (0.18)*	3.08 (0.11)	1.74 (0.25)*
Washing Dishes	2.07 (0.28)	1.05 (0.17)*	1.78 (1.59)	1.52 (0.11)*	2.67 (0.10)*	1.67 (0.09)*	2.96 (0.06)*	1.56 (0.21)*
Lawn Mowing	6.18 (0.84)	3.83 (0.85)*	3.67 (1.48)*	3.46 (0.61)*	4.35 (0.53)	3.23 (0.49)*	3.96 (0.31)*	3.06 (0.48)*
Raking grass/leaves	4.10 (0.93)	2.19 (0.53)*	2.59 (1.38)	2.31 (0.37)*	3.36 (0.32)	2.30 (0.30)*	3.37 (0.19)	2.18 (0.34)*
Total for all activities	4.38 (2.66)	3.77 (3.26)*	3.70 (2.57)*	3.41 (2.28)*	4.31 (1.96)	3.18 (1.83)*	3.93 (1.17)*	3.03 (1.79)*

*Significantly different from Cosmed $K4b^2$ ($P < 0.05$)

algorithm only underestimated measured METs for ascending/descending stairs and vacuuming ($P < 0.05$). All the other prediction equations significantly over- or underestimated measured METs for at least seven different activities.

Figures 2a and 2b show the Cosmed $K4b^2$ MET values versus the MET prediction equations for the Actical, AMP, and Actiheart. In general, the Actical gave accurate predictions for sedentary activities and running, overestimated walking, and underestimated all other activities. The AMP-331 accurately estimated walking, overestimated sedentary activities, and underestimated all other activities. The Actiheart HR algorithm predicted all activities to within 1 MET. The Actiheart combined HR and activity algorithm underestimated moderate to vigorous intensity activities except for running. The Actiheart activity algorithm underestimated all activities except for sedentary activities.

Figures 3a shows the Cosmed $K4b^2$ MET values compared to the Actigraph regression equations developed on walking and jogging. In general, these equations overestimated sedentary activities and walking, and underestimated most other activities. Figure 3b shows the Cosmed $K4b^2$ MET values compared to the Actigraph regression equations developed on lifestyle activities. Lifestyle equations overestimated walking and most sedentary and light activities, while underestimating the other activities. The manufacturer's equation responded in a similar manner to the lifestyle equations except it provided a closer estimate of sedentary activities and underestimated light activities.

Figure 4 (a-g) shows the Bland-Altman plots for the Actical single regression, Actiheart HR algorithm, Actiheart HR and activity algorithm, Actigraph Freedson kcal and MET equations, Actigraph Swartz equation, and the Actigraph Hendelman lifestyle

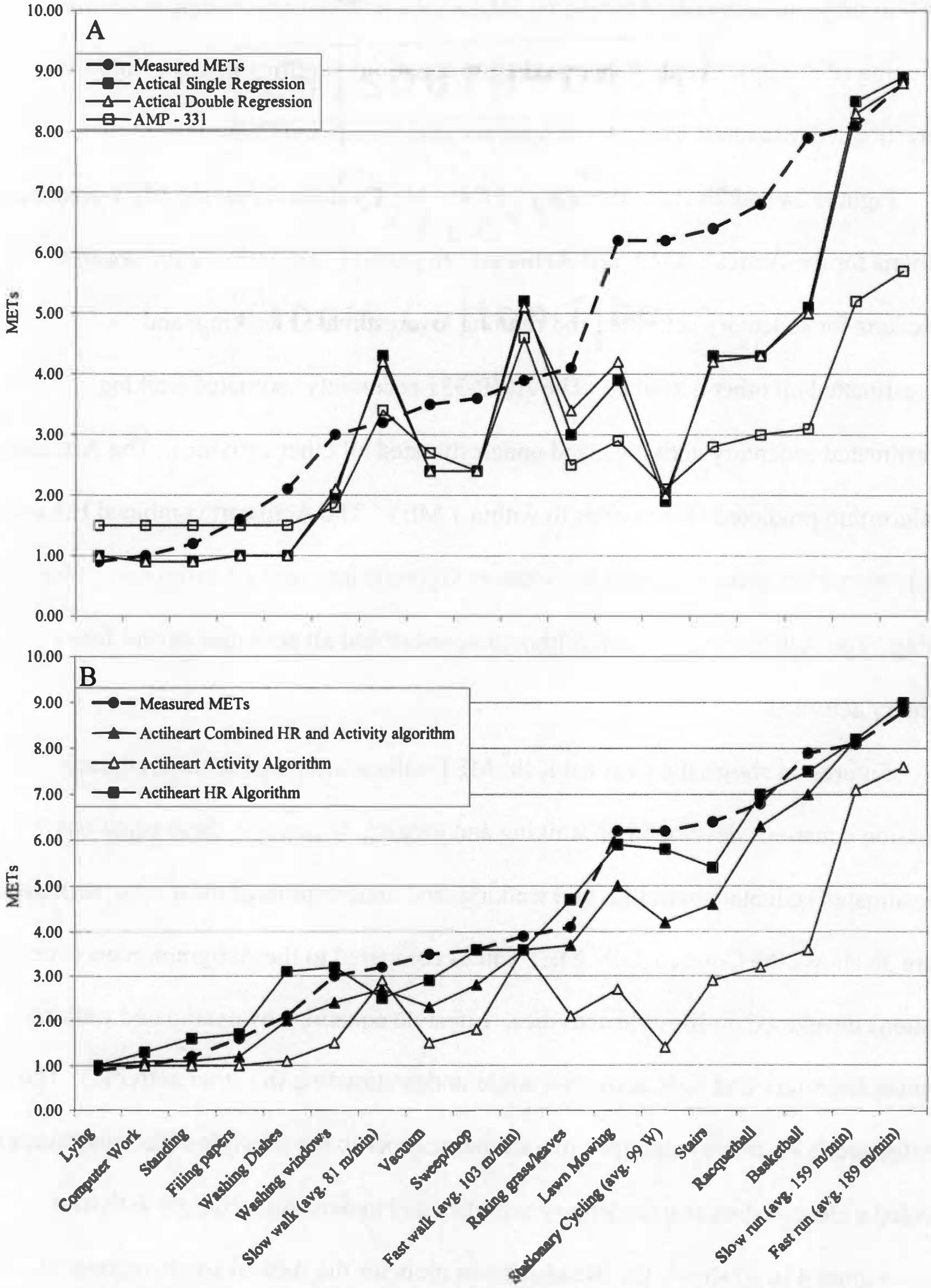


Figure 2. Measured and predicted energy expenditure for 18 different activities. (A) Cosmed K4b^2, Actical (single and double regression models), and AMP-331, (B) Cosmed K4b^2, and Actiheart (HR algorithm, activity algorithm, and combined HR and activity algorithm).

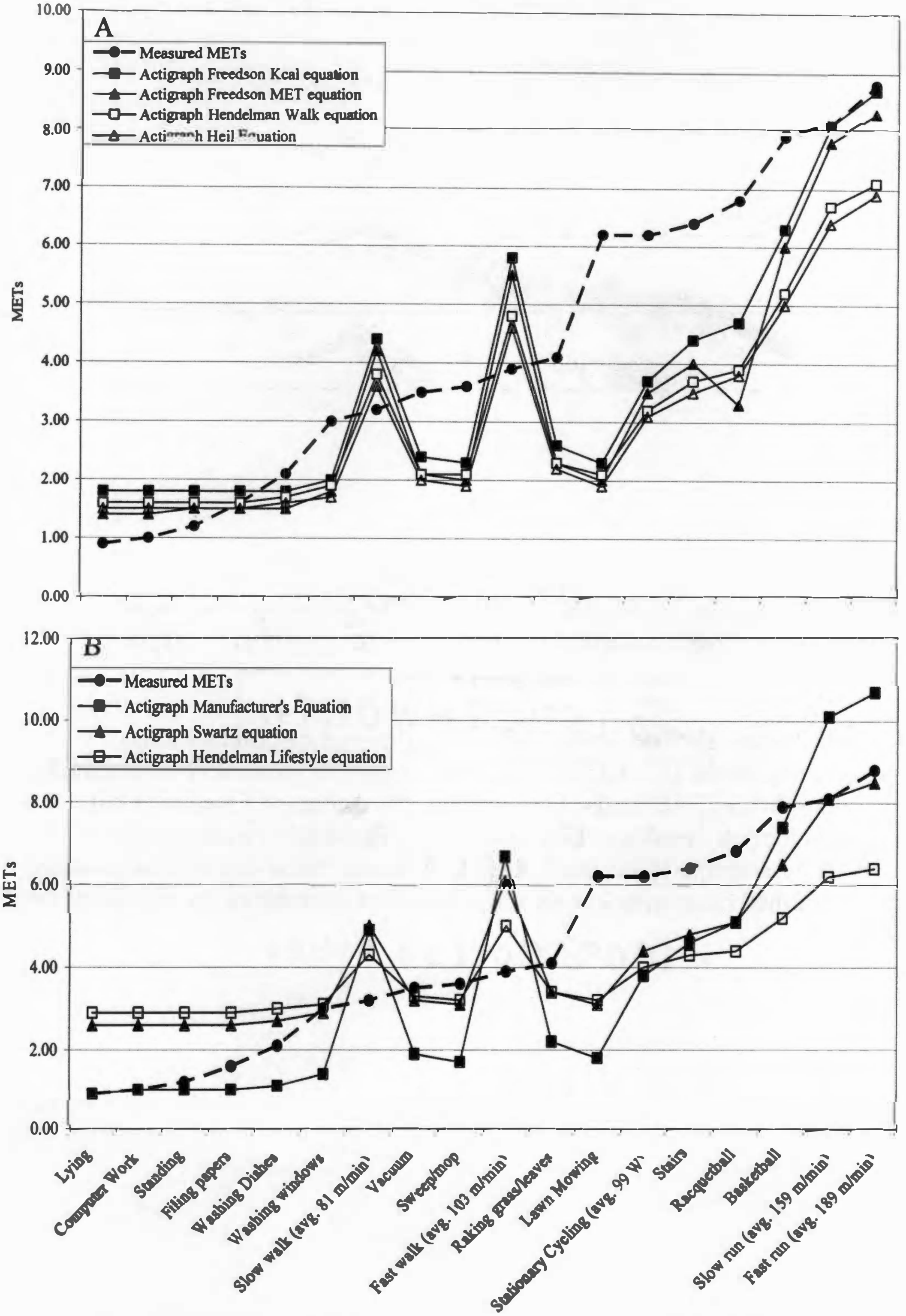


Figure 3. Measured and predicted energy expenditure for 18 different activities. (A) Cosmed K4b^2, Actigraph walk/run regression equations, (B) Cosmed K4b^2, and Actigraph lifestyle and manufacturer's regression equations.

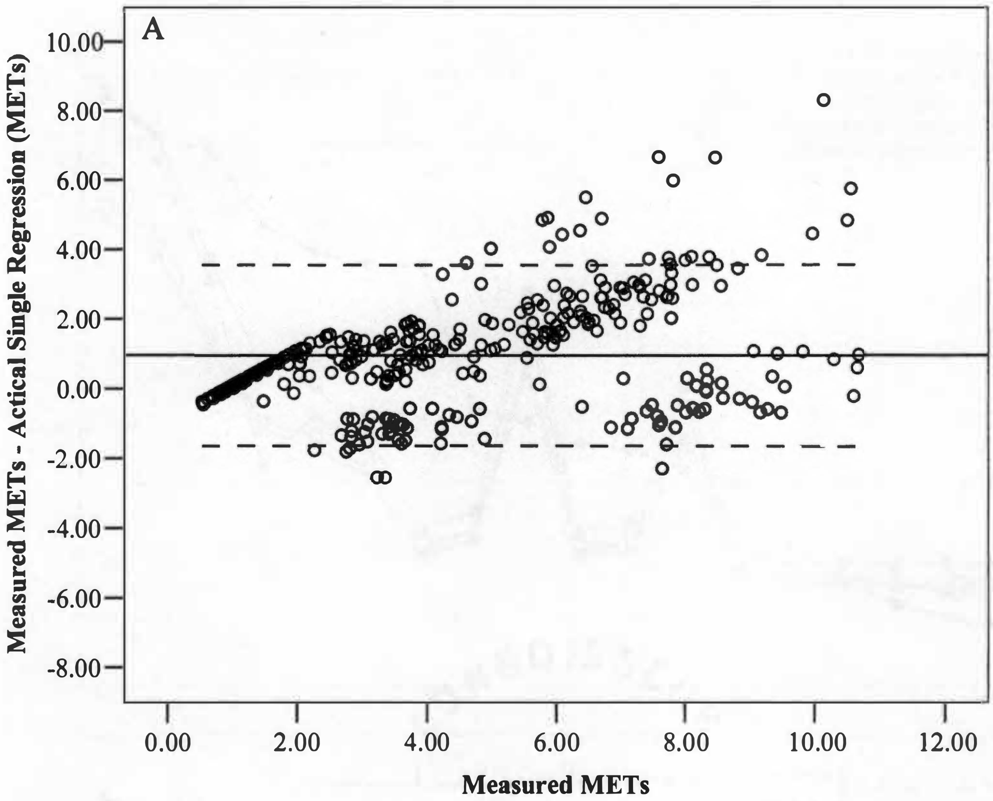
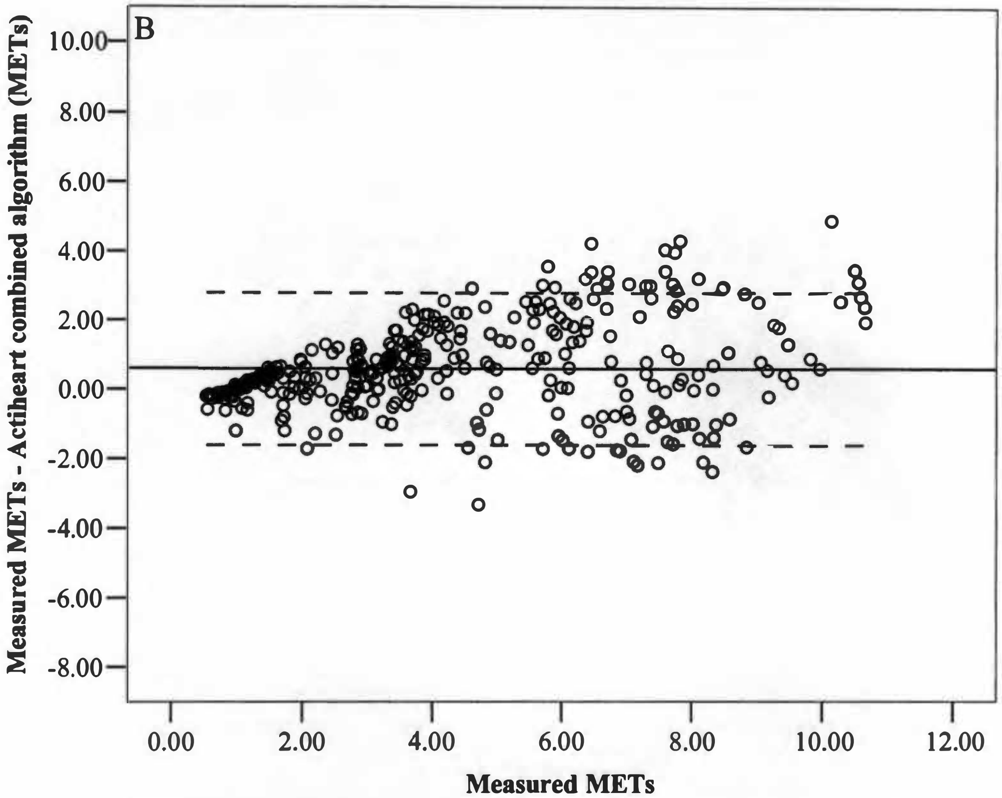


Figure 4. Bland-Altman plots depicting error scores (indirect calorimetry minus prediction equation) for the (A) Actical single regression, (B) Actiheart combined HR and activity algorithm, (C) Actiheart HR algorithm, (D) Actigraph Freedson Kcal equations, (E) Actigraph Freedson MET equation, (F) Actigraph Swartz lifestyle equation, and (G) Actigraph Hendelman lifestyle equation. Solid line represents mean difference, and dashed lines represent the 95% prediction intervals of the individual error scores.



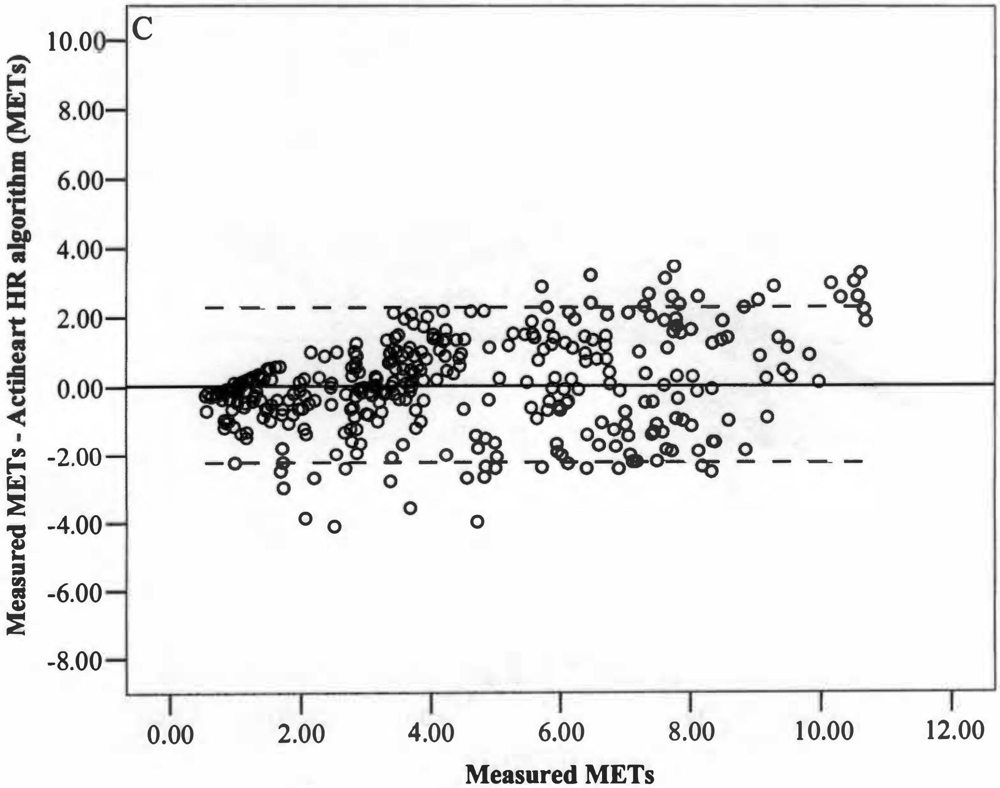


Figure 4. Continued

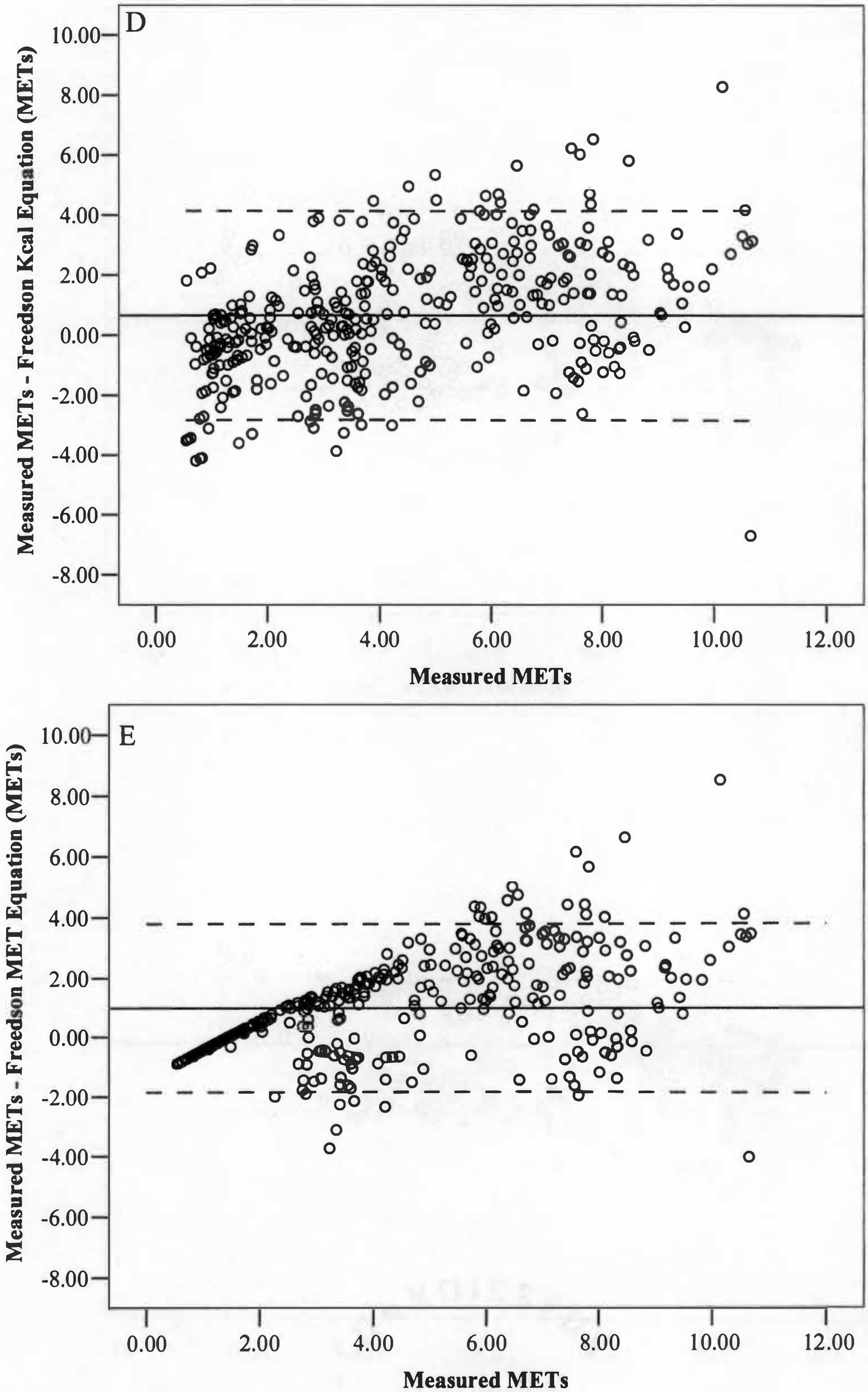
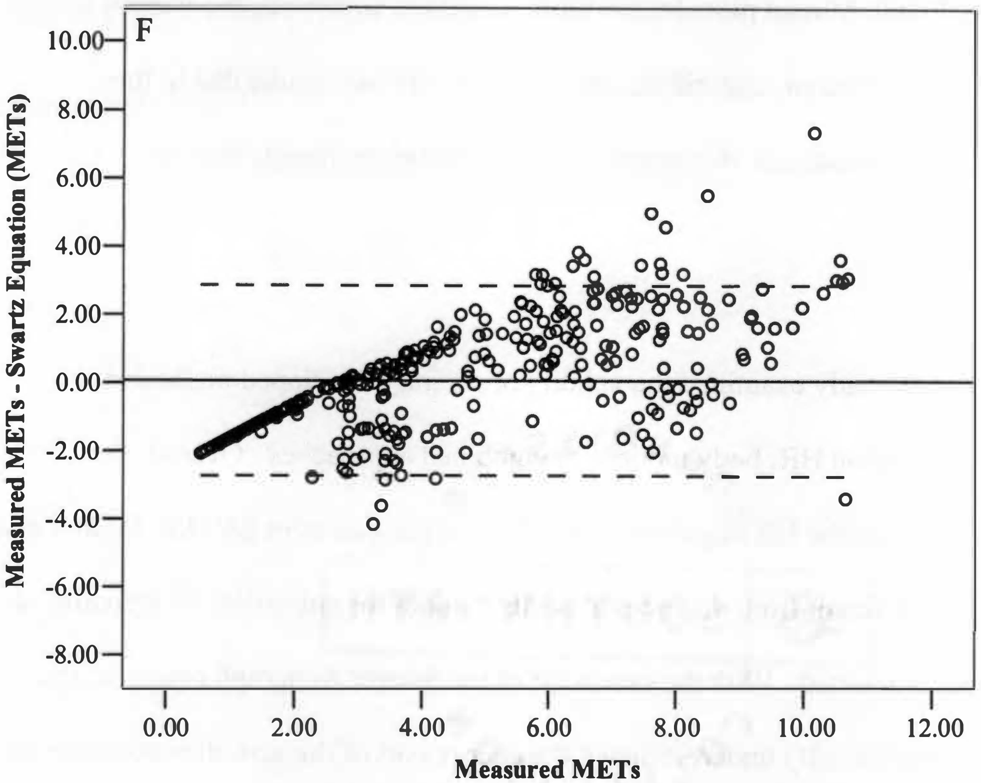


Figure 4. Continued



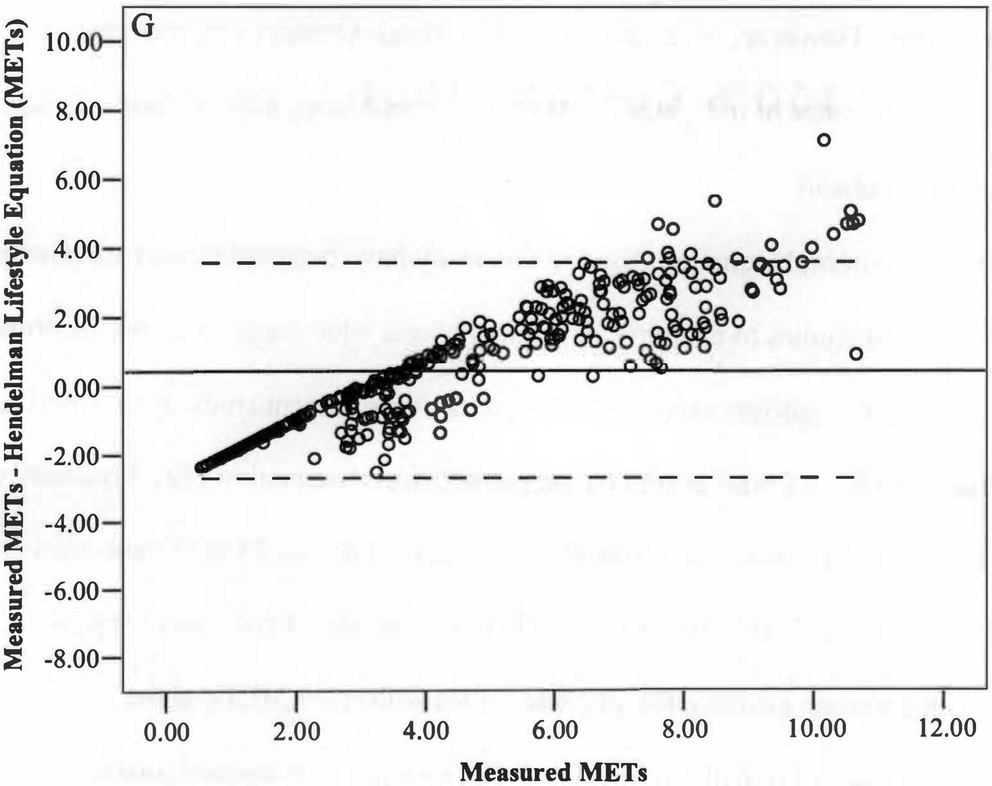


Figure 4. Continued

equation. The Bland-Altman plots for the other Actigraph equations, the Actical double regression, Actiheart activity algorithm, and AMP-331 are not shown due to their similarity with the Actical and Actigraph Bland-Altman plots already shown.

Discussion

The present study examined the validity of recently developed methods for predicting EE, based on HR, body motion, or combined approaches. Overall, the Actiheart, when using the HR algorithm, gave the best prediction of EE (METs) and was not significantly different from the measured MET values for any of the 18 activities or for all activities combined. With the exception of the Swartz Actigraph equation, the other methods significantly underestimated the energy cost of the activities compared to indirect calorimetry. However, as can be seen in the Bland-Altman plots, the various methods had a wide scatter of individual error scores around zero, with the best estimate coming from the Actiheart.

While the Actigraph equations used in this study have been validated extensively, this is one of the first studies to examine all of them over a wide range of activities; from sedentary behaviors to vigorous exercise. The results of the current study agree with the finding of Bassett et al. (1), who examined the manufacturer's equation (19), Freedson's MET equation (6), and Hendelman's lifestyle equation (12) during 28 moderate-intensity lifestyle activities. Specifically, Bassett et al. (1) found that the Hendelman lifestyle equation provided a mean estimate for all 28 activities within 0.5 METs of the criterion measure (Cosmed K4b^2), but had large variability in its over- and underestimation of specific activities. In addition, they found that the Actigraph prediction equations overestimated walking activities, while underestimating virtually all other lifestyle activities. The current study extends these findings by including sedentary activities, over-ground running, basketball, racquetball, etc., in addition to examining more Actigraph equations.

There does not appear to be any single Actigraph equation that is adequate for the prediction of all activities. In general, the use of equations developed on walking and jogging, such as the Freedson MET equation (6) and Hendelman walking equation (12), underestimate most activities except for walking. In contrast, the equations developed on moderate-intensity lifestyle activities such as the Swartz equation (25) and Hendelman lifestyle equation (12) overestimate light activity and walking, while underestimating all other activities. It is important to note that the walking equations predict light activities quite well due to the equation crossing the y-intercept at around 1.4-1.6 METs (i.e. 0 counts$\cdot$min^{-1} = 1.4-1.6 METs), while the lifestyle equations predict moderate-intensity activities quite well, but they over-predict sedentary and light activities due to the equations crossing the y-intercept at around 2.6-2.9 METs (i.e. 0 counts$\cdot$min^{-1} = 2.6-2.9 METs). In addition the walking equations underestimate vigorous activities ($\geq$ 6 METs) by approximately 1 MET more than the lifestyle prediction equations.

The AMP-331 activity monitor is a valid device for estimating the energy cost of walking. However, it provides a poor estimate of EE during most other activities. It overestimates the energy cost of sedentary activities, and it underestimates the energy cost of most light to vigorous activities. A limitation to the AMP-331 is that the activity pod must be positioned directly over the Achilles tendon, but the neoprene case developed to hold it in place often slips to the side of the ankle which hinders the accelerometer's ability to detect motion. This is because the accelerometers are configured to detect movement in the antero-posterior axis, thus when the pod moves to the side it is no longer positioned in the correct axis. In addition, it appears that the AMP-331 it is not able to detect the side to side motion that occurs with many lifestyle activities.

The Actical device, which uses an omnidirectional accelerometer, should in theory provide a better estimate of EE because it has the ability to measure acceleration in more than one movement plane. In addition, two regression equations have been developed for the device; a single regression line and the double regression model of Heil et al. (11) that uses two regression lines of different slopes to predict; (a) light activity and (b) moderate to vigorous activity. In the present study, both Actical regression equations responded in a similar manner to the Actigraph walking equations, in that it overestimated the energy cost of walking, while underestimating most other activities.

The Actiheart was developed with the intent of overcoming some of the limitations of accelerometers worn on the hip. Theoretically, inclusion of a physiological variable (HR) should provide a better estimate of EE, over a wide range of activities, than accelerometry data alone (9, 24). Several investigators have shown that the simultaneous use of HR and motion sensors provides a more accurate estimate of EE than using HR or motion sensors alone, demonstrating that this technique has promise (3, 4, 9, 22-24). However, the Actiheart's algorithm does not utilize individual HR-VO_2 regression lines. Rather it uses resting HR and an algorithm developed on a group of individuals (4). Although it provides a close overall estimate of EE for a group of individuals, there is a large variability for the prediction of EE of specific activities, on an individual basis.

One reason for this is that the Actiheart device does not take into account the individual's fitness level. Thus, it tends to underestimate the EE of fit participants while overestimating the EE of less fit participants. In addition, although the device is intended to use both HR and motion data, the best prediction of EE came from the HR algorithm, possibly due to the poor prediction of EE from the activity algorithm used in the Actiheart. While the Actiheart shows promise for estimating EE, further work needs to be done under field conditions to develop better prediction equations.

The Actiheart does improve slightly on the current methods available to researchers. As can be seen in the Bland-Altman plots, the HR algorithm and combined HR and activity algorithm have less scatter in the individual error scores around zero than the other devices. Specifically the HR algorithm has a mean difference (criterion minus estimate) of 0.03 METs with a 95% prediction interval of -2.68 to 2.76 METs, while the combined algorithm has a mean difference of 0.60 METs with a 95% prediction interval of -2.05 to 3.26 METs. In contrast, the Swartz equation had a mean difference of 0.07 METs, but it had a 95% prediction interval of -3.30 to 3.44 METs, while the Hendelman lifestyle equation had a mean difference of 0.44 METs and a 95%, prediction interval of -3.35 to 4.23 METs. While the Actiheart shows a slight improvement in accuracy over the other devices, the 95% prediction interval is still only within ± 2 METs. The Bland-Altman plots also show that the Actiheart neither over- nor underestimates the energy cost of the 18 activities tested. In contrast, it can be clearly seen that the Hendelman lifestyle equation and Swartz equation overestimate the energy cost of sedentary/light intensity activities and underestimate the energy cost of moderate to vigorous intensity activities.

The proliferation of new Actigraph regression equations to predict EE as well as the introduction of new devices is problematic because it hinders standardization, making it difficult to compare physical activity data between studies. For example, there are currently over 10 different regression equations to predict EE in adults using the Actigraph (5, 6, 12, 16, 20, 25, 28). A major limitation of most devices is that they do not provide an accurate prediction for specific activities. This is of critical importance because each individual performs a unique pattern of activities. However, it is clear that people spend more time sleeping and performing sedentary and light activities and hence accurate estimation of EE at the lower end of the range is critical.

When considering the various devices for use in research, cost is also an issue. Larger studies typically use a device that is less expensive, while smaller studies might spend more money on a measuring device if it enhances accuracy. While the Actiheart gave the best overall estimate of EE, its cost prohibits its use in large studies. The cost of one Actiheart plus the software and docking station is $1500. Similarly, the Actical plus the docking station and software costs $995. The AMP-331 costs $450 per device, plus $750 for the software and docking station. Actigraph recently released (May 2005) the GT1M that will replace the older version (model 7164). Unlike the other devices, the new Actigraph GT1M has a port in the device that a USB cable attaches to, thus eliminating the need for a docking station. The cost of the new Actigraph GT1M is $389 per device. The user can pay $200 for a desktop version of their software, or they now have the option of using the software online for free. In addition, the new GT1M has a rechargeable battery (via the USB port) that does not need to be replaced. To assist in recharging multiple Actigraphs at the same time the company also sells a 7-port USB hub for $75. Currently they are working on additional features such as having the capability of initializing and downloading multiple devices at the same time.

The present study has both strengths and limitations. One strength is that it examined the validity of several devices, using an accepted gold standard for measuring EE in field settings. Another strength, is that it included a wide range of physical activities ranging from sedentary activities (lying, sitting) through vigorous exercise (racquetball, basketball, running). This approach is beneficial because it shows where the devices succeed and fail, and it can help suggest ways to improve upon the prediction of EE in the future. In contrast, most previous validation studies focused solely on locomotor activities and/or moderate-intensity lifestyle activities. Limitations of the current study are that it did not examine the validity of the devices in children, adolescents, or older adults, and the study population was predominantly Caucasian. In addition, the accuracy of these methods in free-living situations was not examined. Future studies should validate these methods over extended periods, using room calorimetery or doubly labeled water.

In conclusion, the Actiheart HR algorithm provides the best estimate of EE on an individual basis, although it still has room for improvement. In general, prediction equations developed using treadmill walking and running overestimate the energy cost of sedentary activities and walking, while underestimating the energy cost of most other activities. Prediction equations developed using moderate-intensity lifestyle activities tend to overestimate the energy cost of walking, sedentary, and light activities, while they underestimate the energy cost of most other activities. The Actical and AMP-331 respond in a similar manner to the Actigraph equations.

The significance of this study is that it provides information on EE estimates for specific activities, and thus could be helpful in suggesting new approaches to quantify and reduce physical activity measurements. Ultimately, if researchers can design a method that will accurately predict the EE over a wide range of physical activities, that method would have the greatest chance of being accurate when validated against doubly labeled water.

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PART VI

A NOVEL METHOD FOR USING ACCELEROMETER DATA TO PREDICT ENERGY EXPENDITURE

Abstract

In recent years there has been an increase in the number of regression equations relating Actigraph accelerometer counts to energy expenditure (EE). A major limitation of these single regression models is that they tend to overestimate the energy cost of walking, and underestimate the cost of most moderate-intensity lifestyle activities. Recently we have found a method to distinguish walking and running from other activities based on the variability in the counts over time. **Purpose:** The purpose of this study was to develop a new 2-regression model relating Actigraph activity counts to EE over a wide range of physical activities, ranging from sedentary pursuits to vigorous exercise. **Methods:** Forty-eight participants (age: 35 ± 11.4 yrs) performed various activities that were split into three routines of six activities. Sedentary, light, moderate, and vigorous intensity activities were chosen to represent the entire range of activities performed by most individuals. Each routine was performed by 20 individuals for a total of 60 tests. Forty-five tests were randomly selected for the development of the new equation and 15 tests were used to cross-validate the new equation and compare it against already existing equations. During each routine, the participant wore an Actigraph accelerometer on the hip and oxygen consumption was simultaneously measured by a portable metabolic system. For each activity the coefficient of variation (CV) for the counts per 10 seconds were calculated to determine if the activity was walking/running, or some other activity. If the CV was $\leq$ 10 then a walk/run regression equation was used, while if the CV was > 10 a lifestyle/leisure time physical activity (LTPA) regression was used. **Results:** With this new method, the Actigraph counts$\cdot$min^{-1} explained 72.3% of the variance in EE for walking/running, and 83.8% of the variance in EE for lifestyle/LTPAs. In the cross-validation group the mean estimates using the new 2-regression model were within 0.84 METs of measured METs for each of the activities performed ($P \geq 0.05$), which was a substantial improvement over the single regression models. The new method had a mean difference (criterion minus prediction) of 0.001 METs and 95% prediction intervals of ± 1.66 METs. **Conclusion:** The new 2-regression model is more accurate for the prediction of EE than currently published regression equations using the Actigraph accelerometer. **Key Words:** MOTION SENSOR, PHYSICAL ACTIVITY, OXYGEN CONSUMPTION, ACTIVITY COUNTS VARIABILITY

Introduction

The association between physical activity and positive health benefits has been well established (3, 4, 11, 15). This has lead to the Centers for Disease Control and Prevention (CDC) and the American College of Sports Medicine (ACSM) recommendation that every US adult should accumulate 30 minutes of moderate-intensity physical activity on most, preferable all days of the week (16). While the benefits of regular moderate physical activity has been clearly shown, the measurement of how much physical activity individuals are performing has proven to be a difficult task.

Accelerometers are objective measurement tools that allow researchers to estimate how much energy individuals are expending, as well as to quantify the amount time spent in light (< 3 METs), moderate (3 – 5.99 METs), and vigorous ($\geq$ 6 METs) physical activity. The Actigraph (formerly the Manufacturing Technology Incorporated (MTI) Actigraph, and the Computer Science Applications Inc. (CSA)) accelerometer is one of the most common devices used for the measurement of physical activity. Several equations have been developed relating the Actigraph activity counts to energy expenditure (EE) (6-8, 12, 14, 17, 18). Theoretically, this allows researchers to estimate total EE over a given period of time. In addition these equations allow researchers to establish cut points (based on counts$\cdot$min^{-1}) for classification of light, moderate, and vigorous physical activity.

In the last five years there has been a dramatic increase in the number of prediction equations relating the Actigraph activity counts to EE. The current regression equations for estimating EE based on the counts$\cdot$min^{-1} from the Actigraph accelerometer were either developed during walking and running (6-8, 12, 14, 18) or during moderate-intensity lifestyle activities (8, 17). However, these different equations pose a problem for researchers because no single regression line is able to accurately predict EE or time spent in different intensity categories, across a wide range of activities. In addition, all of these equations assume a linear relationship between counts$\cdot$min^{-1} and EE, but they all have limitations. Previously, it has been shown that equations developed on walking and jogging slightly overestimate the energy cost of walking and light activities, while they greatly underestimate the energy cost of moderate-intensity lifestyle activities. The lifestyle equations provide a closer estimate of EE for moderate-intensity activities, but greatly overestimate the energy cost of sedentary and light activities and underestimate the energy cost of vigorous activities (2).

It is critical that the predictions equations to estimate EE are accurate across a wide range of activities ranging from rest to vigorous exercise. Using data collected in our laboratory, we observed that walking and running can be distinguished from other activities based on the variability in the activity counts from the Actigraph. Generally, locomotor activities (i.e. walking and running) yield more consistent minute-to-minute counts than other activities (e.g. vacuuming, raking leaves, racquetball, sweeping, etc), which have more erratic movement patterns. Specifically, the coefficient of variation (CV) between the minute-to-minute counts is below 10% for walking activity and greater than 10% for all other activities. In addition, we noted that the slope of the regression line relating $counts \cdot min^{-1}$ (x-axis) to METs (y-axis) is steeper for walking and running activities than it is for moderate-intensity lifestyle activities, meaning that two separate regression lines should be used for the prediction of these activities.

Thus, we hypothesized that by calculating the CV of the counts over six 10-second epochs, we could distinguish walking and running from all other activities. We further hypothesized that by using the appropriate regression line, we should obtain a closer estimate of EE across a wide range of activities. Therefore, the purpose of this study was to develop a new prediction equation for use with the Actigraph accelerometer that would be composed of two regression lines; one for walking and running and one for all other activities. The determination of which line to use was based on the CV of the counts per 10 seconds over a one minute period.

Methods

Subjects

Forty-eight participants (Age: 35 ± 11.4 yrs, BMI: 24.2 ± 4.8 $kg \cdot m^{-2}$) from the University of Tennessee, Knoxville and surrounding community volunteered to participate in the study. The procedures were reviewed and approved by the University of Tennessee Institutional Review Board before the start of the study. Each participant signed a written informed consent and completed a Physical Activity Readiness Questionnaire (PAR-Q) before participating in the study. Participants were excluded from the study if they had any contraindications to exercise, or were physically unable to complete the activities. The physical characteristics of the participants are shown in Table 1.

Anthropometric Measurements

Prior to testing, participants had their height and weight measured (in light clothing, without shoes) using a stadiometer and a physician's scale, respectively. Body mass index (BMI) was calculated according to the formula: body mass (kg) divided by height squared (m^2). Skinfold measurements were taken using Lange Calipers (Cambridge, MD) at the chest, abdomen and thigh for men and at the tricep, suprailic, and thigh for women (9).

Procedures

Participants performed various lifestyle and sporting activities that were broken into three routines.

Routine 1: Lying, standing, sitting doing computer work, filing articles, walking up and down stairs at a self selected speed, cycling at a self selected work rate.

Table 1. Physical characteristics of the participants ((mean ± SD (range)).

Variable	Male (N=24)	Female (N=24)	All Participants (N=48)
Age (yr)	36 ± 12.8 (21 – 69)	35 ± 10.3 (22 – 55)	35 ± 11.4 (21 – 69)
Height (in)*	70.9 ± 2.8 (62.8 – 74.2)	65.1 ± 2.3 (60.2 – 68.5)	68.0 ± 3.8 (60.2 – 74.2)
Body Mass (kg)*	83.9 ± 20.2 (59.4 – 141.0)	62.3 ± 12.3 (45.4 – 109.0)	73.1 ± 19.6 (45.4 – 141.0)
BMI ($kg \cdot m^{-2}$)*	25.8 ± 5.2 (19.1 – 40.6)	22.7 ± 4.0 (17.9 – 36.4)	24.2 ± 4.8 (17.9 – 40.6)
Resting VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$)	3.6 ± 0.8 (2.1 – 5.0)	3.4 ± 0.8 (2.0 – 4.9)	3.5 ± 0.9 (2.0 – 5.0)
Sum of 3 skinfold	49.0 ± 27.9 (16.6 – 125.5)	52.0 ± 16.7 (24.5 – 93.7)	50.5 ± 22.5 (16.6 – 125.5)

BMI=Body Mass Index; *Significantly different from females, $P < 0.05$.

Routine 2: walking at approximately 3 mph around a track, walking at approximately 4 mph around a track, playing one-on-one basketball, playing singles racquetball, running at approximately 5 mph around a track, running at approximately 7 mph around a track.

Routine 3: vacuuming, sweeping and/or mopping, washing windows, washing dishes, lawn mowing with a push mower, raking grass and/or leaves.

Twenty participants performed each routine, with most performing only one routine. Participants performed each activity in a routine for 10 minutes, with a 1 to 2 minute break between each activity. Oxygen consumption (VO_2) was measured continuously throughout the routine by indirect calorimetry (Cosmed $K4b^2$, Rome Italy). Participants wore an Actigraph accelerometer on the right hip for the duration of the routine. For the Cosmed $K4b^2$ and Actigraph, 2 kg was added to account for the added weight of the devices. Routine 1 was performed in the Applied Physiology Laboratory, routine 2 was performed at University facilities, and routine 3 was performed at either the participant's home or the investigator's home. The participants who did not perform routine 1 were asked to sit quietly for 5 minutes before the start of the routine so that a resting VO_2 could be measured.

Indirect Calorimetry

The participants wore a Cosmed $K4b^2$ for the duration of each routine. The Cosmed $K4b^2$ weighs 1.5 kg, including the battery, and a specially designed harness. The Cosmed $K4b^2$ has been shown to be a valid device when compared against the Douglas Bag method during cycle ergometry (13). In addition, during this study there was close agreement between the measured VO_2 from the Cosmed $K4b^2$ during the stationary cycling (avg. 98.7 watts) and the predicted values from the formula of the American College of Sports Medicine's Guidelines for Graded Exercise and Prescription (1) (R^2 = 0.917, SEE = 134.1 $ml \cdot min^{-1}$, $P < 0.05$). Prior to each test the oxygen and carbon dioxide analyzers were calibrated according to the manufacturer's instructions. This consisted of performing a room air calibration and a reference gas calibration using 15.93% oxygen and 4.92% carbon dioxide. The turbine was then calibrated using a 3.00 L syringe (Hans-Rudolph). Finally, a delay calibration was performed to adjust for the lag time that occurs between the expiratory flow measurement and the gas analyzers. During each test a gel-seal was used to help prevent air leaks from the face mask.

Actigraph Accelerometer

The Actigraph accelerometer (model 7164) is a small (2.0 x 1.6 x 0.6 in) and lightweight (42.5 grams) uniaxial accelerometer, and can measure accelerations in the range of 0.05 to 2 G's and a band limited frequency of 0.25 to 2.5 Hz. These values correspond to the range in which most human activities are performed. An 8-bit analog-to-digital converter samples at a rate of 10 Hz and these values are then summed for the specified time period (epoch). If a one minute epoch is used the Actigraph can store 22 days worth of data, which is downloaded to a personal computer via a reader interface unit. The Actigraph was worn at waist level at the right anterior axillary line in a nylon pouch that was attached to a belt. The Actigraph was initialized using 1 second epochs and the time was synchronized with a digital clock so the start time could be synchronized with the Cosmed $K4b^2$. At the conclusion of the test the Actigraph data were downloaded to a laptop computer for subsequent analysis. The Actigraph accelerometer was calibrated at the start and end of the study. On both occasions, the calibration fell within ± 3.5% of the reference value, which is within the manufacturer's standards.

Data Analysis

Breath-by-breath data were collected by the Cosmed K4b^2, which was averaged over a 30 second period. For each activity, VO_2 ($ml \cdot min^{-1}$) was converted to VO_2 ($ml \cdot kg^{-1} \cdot min^{-1}$) and then to METs by dividing by 3.5. For each activity the MET value for minutes 4 to 9 were averaged and used for the subsequent analysis.

The Actigraph accelerometer data were collected in one second epochs and were converted to counts per 10 seconds and counts$\cdot min^{-1}$ using a Visual Basic program, written specifically for this study. The coefficient of variation (CV) of the counts per 10 seconds and the average of the counts$\cdot min^{-1}$ were calculated for minutes 4-9 of each activity.

Statistical Treatment

Statistical analyses were carried out using SPSS version 13.0 for windows (SPSS Inc., Chicago, IL). For all analyses, an alpha level of 0.05 was used to indicate statistical significance. All values are reported as mean ± standard deviation. Independent t-tests were used to examine the difference between genders for anthropometric variables.

Forty-five tests were randomly selected for the development of the new 2-regression model, thus leaving 15 tests for cross-validation of the new equation. Due to waist mounted accelerometers not being able to detect cycling activity, it was excluded from all analyses. Stationary cycling was included to confirm that the Cosmed $K4b^2$ was providing reasonable VO_2 values. For the group used to develop the new prediction algorithms, each activity performed by an individual was classified based on the CV value of the 10 second counts; CV from 0.1 to 10 ($CV \leq 10$) and CV of 0 and >10 ($CV > 10$). During the walking and running the CV was almost always less than 10, while for the other activities the CV was almost always greater than 10 (figure 1). One exception was during activities such as lying, sitting, and standing where the counts per minute could be zero for a full minute, thus giving a CV of zero. In these cases they were placed in the $CV > 10$ group for the purpose of developing the regression equation. Linear regression analyses was then used to predict METs from the counts per minute for the $CV \leq 10$ group and the $CV > 10$ group.

In order to compare the newly developed equation with current regression models, we also estimated METs from the regression equations of Freedson et al. (7), Hendelman et al. (8), and Swartz et al. (17). A one-way repeated measures ANOVA was used to compare actual and predicted METs for each activity using the cross validation group. In addition, a one-way repeated measures ANOVA was used to compare actual and predicted METs for all 18 activities combined. Pairwise comparisons with Bonferroni adjustments were performed to locate significant differences when necessary.

Modified Bland-Altman Plots were used to graphically show the variability in individual error scores (actual METs minus estimated METs) (5). This allowed for the mean error score and the 95% prediction interval to be shown. Devices that are accurate

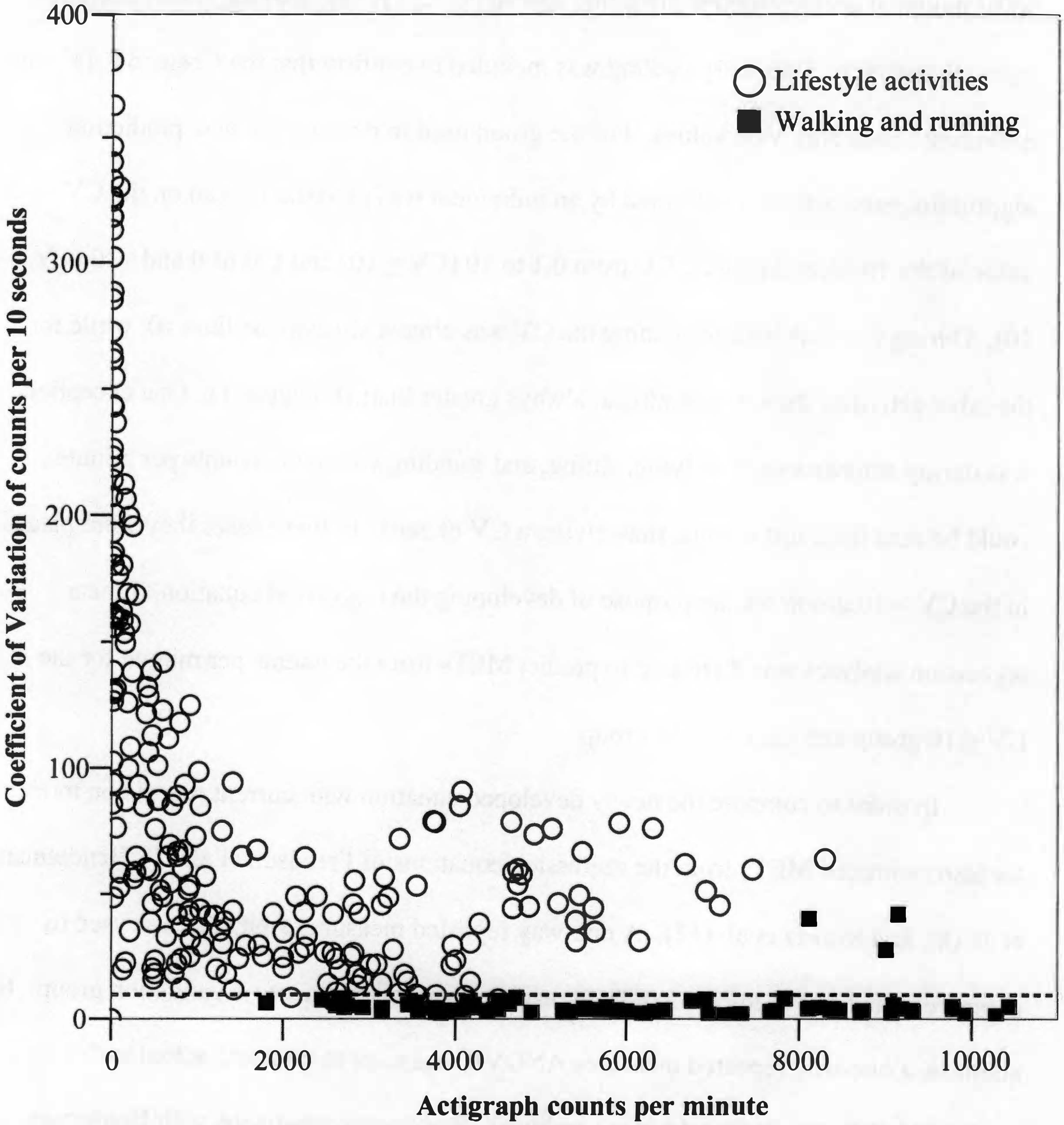


Figure 1. Relationship between counts per minute from an Actigraph accelerometer and the coefficient of variation (CV) of the 10 second counts for various activities. 11 CVs between 400 and 600 were excluded from the graph, all of which were lifestyle activities.

will display a tight prediction interval around zero. Data points below zero signify an overestimation, while points above zero signify an underestimation.

Results

The data for one participant in the developmental group (routine 3) is missing due to an error that occurred during the downloading process. Mean (± SD) counts per minute and CV of the counts per 10 seconds, for each activity from the Actigraph accelerometer are shown in table 2 (developmental group only).

Initially, linear regression lines were used to predict METs from the $counts \cdot min^{-1}$ for activities where the CV was ≤ 10 and activities where the CV was > 10. Further examination of the data revealed that a linear regression might not yield the best fit. For example, the linear regression for activities where the CV is ≤ 10 significantly underestimated walking at 2 mph as well as running speeds greater than 7 mph. Therefore, we chose an exponential curve for activities where the CV was ≤ 10 (figure 2). To verify the use of an exponential curve, we plotted the mean $counts \cdot min^{-1}$ versus METs during treadmill walking and running from the study of King et al. (10) in figure 2.

For activities where the CV was > 10 a cubic curve was found to be the best fit (figure 3). The new equations for the two groups are presented in table 3. Certain activities such as lying and sitting have $counts \cdot min^{-1}$ that are less than 50, but are commonly over-predicted by 0.5 to 2.5 METs depending on the regression equation used. Therefore when the $counts \cdot min^{-1}$ are less than 50, we propose that an individual be credited with 1.0 METs, since this more accurately predicts these sedentary activities.

Table 2. Mean (± SD) counts·min^{-1} and coefficient of variation (CV) for the 10 second counts from the Actigraph accelerometer for all activities (18) using the developmental group.

Activity	N	Actigraph counts·min^{-1}	CV for 10 sec counts
Lying	15	0.2 (0.5)	109.5 (226.8)
Standing	15	13.4 (22.0)	235.3 (145.6)
Computer work	15	3.3 (7.7)	228.1 (234.8)
Filing	15	59.8 (120.1)	186.4 (114.1)
Ascending/descending stairs	15	3211.7 (621.3)	17.4 (9.3)
Slow walk (avg. 81 m·min^{-1})	15	3341.0 (798.3)	5.4 (1.7)
Brisk Walk (avg. 104 m·min^{-1})	15	5050.3 (1078.2)	3.8 (1.6)
Basketball	15	5570.8 (999.8)	52.3 (13.0)
Racquetball	15	3574.6 (1116.3)	57.7 (17.8)
Slow run (avg. 159 m·min^{-1})	15	8101.3 (1377.4)	5.8 (9.6)
Fast run (avg. 192 m·min^{-1})	15	8163.4 (1327.0)	7.4 (10.2)
Vacuum	14	788.7 (304.2)	74.3 (33.5)
Sweep/mop	14	719.0 (340.8)	75.0 (33.7)
Washing Windows	14	420.0 (274.1)	145.3 (45.3)
Washing dishes	14	107.2 (154.1)	193.2 (117.6)
Lawn Mowing	14	2560.7 (804.5)	25.6 (9.7)
Raking grass/leaves	14	1114.0 (481.6)	49.9 (21.5)

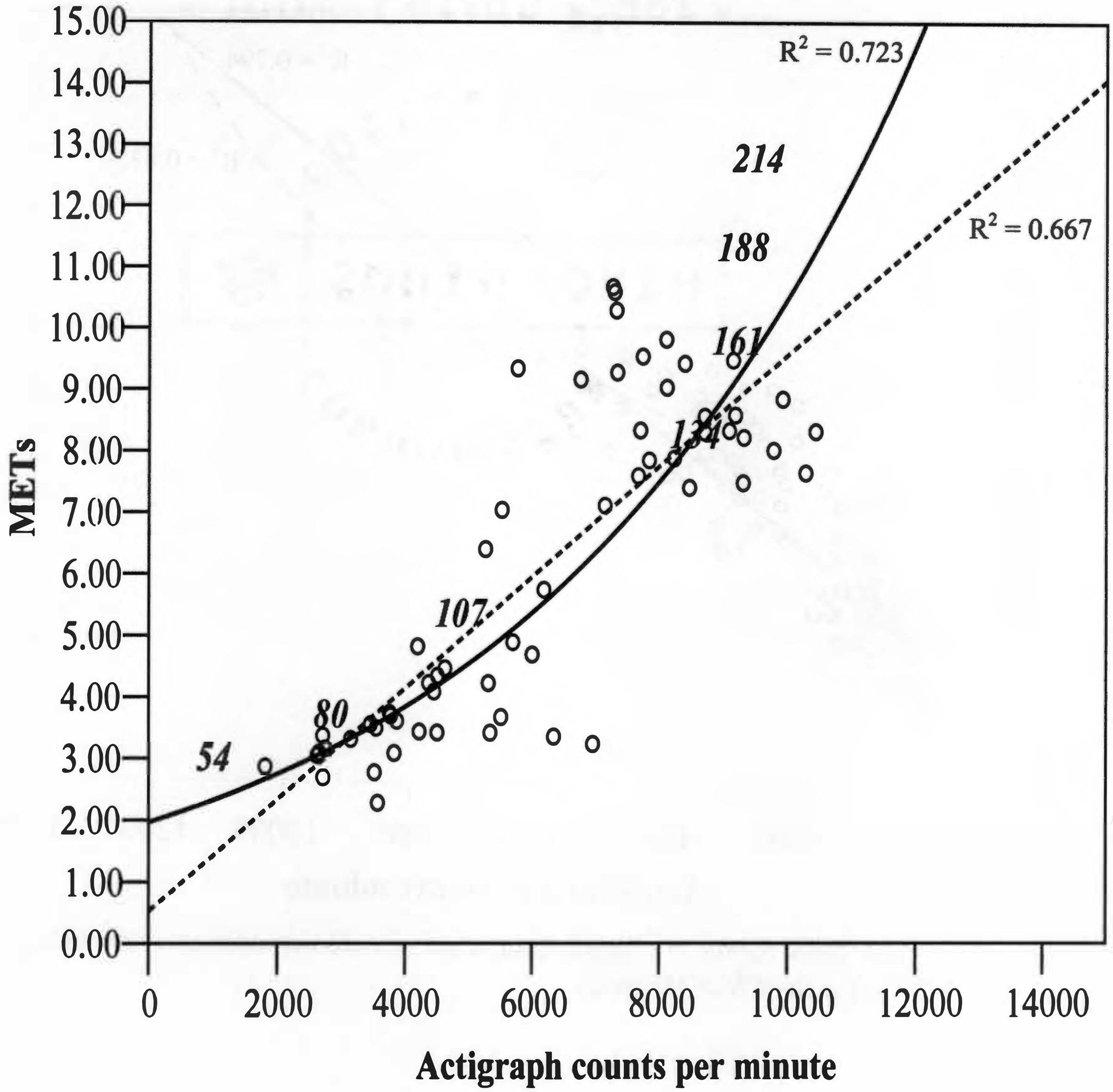


Figure 2. Regression lines for the Actigraph counts·min^{-1} versus measured energy expenditure (METs) for the CV $\leq$ 10 group. Numbers on graph represent mean data (N = 10) from King et al. (10).

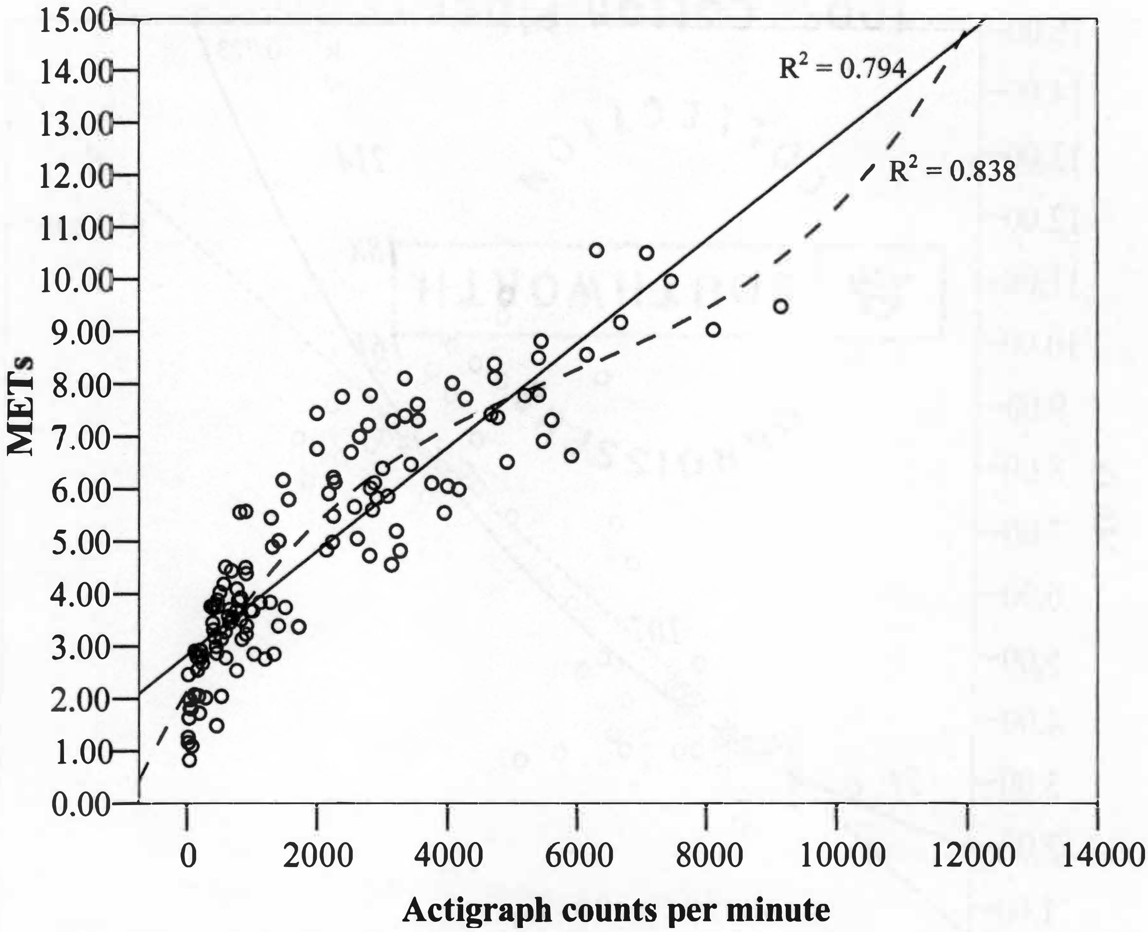


Figure 3. Regression lines for the Actigraph counts per minute versus measured energy expenditure (METs) for the CV > 10 group.

Table 3. Regression equations to predict resting metabolic equivalents (METs) from the Actigraph accelerometer.

Prediction Model	Equation	R^2	SEE
CV < 10 group	Energy Expenditure (METs) = 1.966446 * (exp(0.00016737 * Actigraph counts·min^{-1}))	0.723	0.248
CV ≥ 10 group	Energy Expenditure (METs) = 2.12771 + (0.002087 * Actigraph counts·min^{-1}) – (2.6862 x 10^{-7} * (Actigraph counts·min^{-1})^2) + (1.5246 x 10^{-11} * (Actigraph counts·min^{-1-1})^3)	0.838	0.918

Thus the newly developed equation to predict gross energy expenditure (METs) from the Actigraph counts would consist of a three part algorithm;

(1) if the counts·min^{-1} are ≤ 50, energy expenditure = 1.0 MET,

(2) if the counts·min^{-1} are > 50

a. and the CV of the counts per 10 sec are 0.1 to 10, then energy expenditure (METs) = 1.966446 * (exp(0.00016737 * Actigraph counts·min^{-1})),

b. or the CV of the counts per 10 sec are 0 or > 10, then energy expenditure (METs) = 2.12771 + (0.002087 * Actigraph counts·min^{-1}) – $(2.6862 \times 10^{-7}$ * (Actigraph counts·$min^{-1})^2$) + $(1.5246 \times 10^{-11}$ * (Actigraph counts·$min^{-1})^3$)

Table 4 shows the measured METs and estimated METs for the cross-validation group using the new prediction equation and three other commonly used Actigraph equations, for each activity. Figure 4 shows the measured and predicted MET values for each of the activities using the current Actigraph regression equations in the cross-validation group. Figure 5 shows the measured and predicted MET values for the cross-validation group using the new 2-regression model. The new 2-regression model was within 0.84 METs compared to measured METs for each of the 17 activities and was not significantly different from actual METs for any activity, or for all activities combined. In addition, the correlation between the predicted METs from the new 2-regression model and measured METs was $r = 0.94$ ($P < 0.05$). The other equations overestimated at least

Table 4. Mean (± SD) MET values of the cross-validation group for the Cosmed $K4b^2$ (measured METs), the new Actigraph 2-regression model and 3 other Actigraph prediction equations during various activities.

	Measured METs	Actigraph New 2-regression model	Actigraph Freedson MET equation	Actigraph Swartz equation	Actigraph Hendelman Lifestyle equation
Lying	0.91 (0.20)	1.00 (0.00)	1.44 (0.00)*	2.61 (0.00)*	2.92 (0.00)*
Standing	1.19 (0.18)	1.00 (0.00)	1.44 (0.03)	2.61 (0.03)*	2.93 (0.02)*
Computer Work	1.03 (0.13)	1.00 (0.00)	1.44 (0.00)*	2.61 (0.00)*	2.92 (0.00)*
Filing papers	1.56 (0.16)	1.27 (0.60)	1.46 (0.03)	2.62 (0.03)*	2.93 (0.02)*
Ascending/ Descending Stairs	6.83 (0.65)	6.06 (1.34)	4.21 (0.65)*	5.00 (0.56)	4.35 (0.34)*
Slow walk (avg. 83 $m \cdot min^{-1}$)	2.94 (0.27)	3.44 (0.40)	4.08 (0.56)	4.88 (0.48)*	4.28 (0.29)*
Fast walk (avg. 98 $m \cdot min^{-1}$)	3.60 (0.44)	4.44 (0.81)	5.25 (0.82)*	5.89 (0.71)*	4.88 (0.42)*
Basketball	7.33 (0.52)	7.75 (0.76)	6.11 (0.95)	6.64 (0.82)	5.33 (0.49)*
Racquetball	6.63 (0.46)	7.21 (0.51)	4.73 (0.62)*	5.45 (0.53)	4.62 (0.32)*
Slow run (avg. 160 $m \cdot min^{-1}$)	7.69 (0.56)	7.53 (1.78)	7.72 (1.10)	8.02 (0.95)	6.15 (0.57)
Fast run (avg. 183 $m \cdot min^{-1}$)	8.05 (0.70)	7.64 (1.44)	7.81 (1.00)	8.10 (0.86)	6.20 (0.51)
Vacuum	3.37 (0.51)	3.62 (0.86)	2.09 (0.43)	3.17 (0.37)	3.26 (0.22)
Sweep/mop	3.32 (0.56)	3.26 (0.73)	1.92 (0.32)*	3.02 (0.28)	3.17 (0.16)
Washing windows	2.86 (0.93)	2.79 (0.48)	1.71 (0.21)	2.84 (0.18)	3.06 (0.11)
Washing Dishes	1.98 (0.33)	1.55 (0.75)	1.49 (0.05)	2.65 (0.04)	2.95 (0.03)*
Lawn Mowing	6.06 (0.59)	5.65 (0.68)	3.27 (0.53)*	4.19 (0.46)*	3.87 (0.27)*
Raking grass/leaves	3.69 (0.89)	3.79 (0.78)	2.17 (0.35)*	3.24 (0.30)	3.30 (0.18)
Total for all activities	4.06 (2.49)	4.06 (2.56)	3.43 (2.23)*	4.32 (1.92)	3.95 (1.15)

*Significantly different from Cosmed $K4b^2$ ($P < 0.05$)

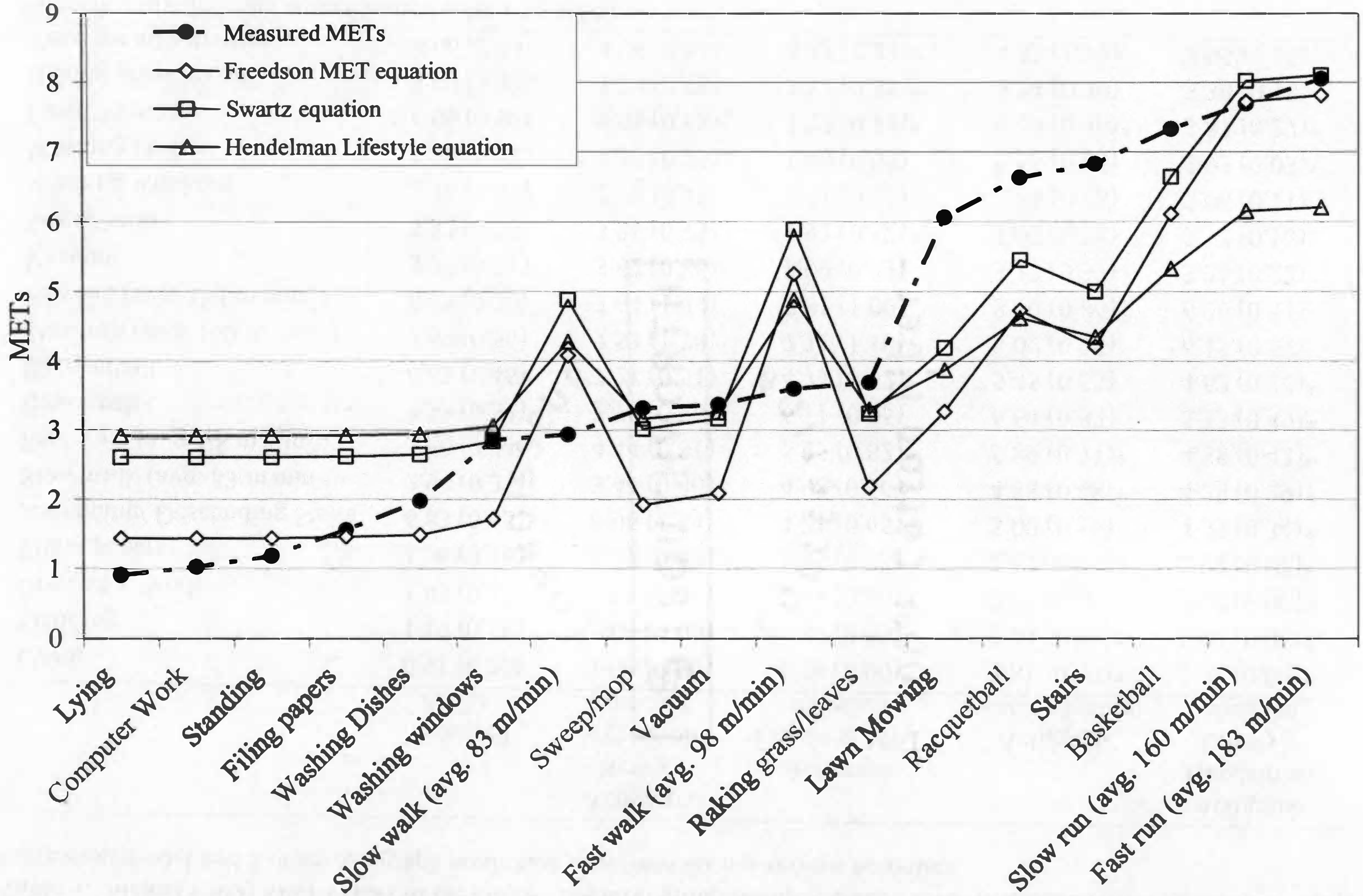


Figure 4. Measured and estimated METs for the cross-validation group, using 3 different regression equations for various activities.

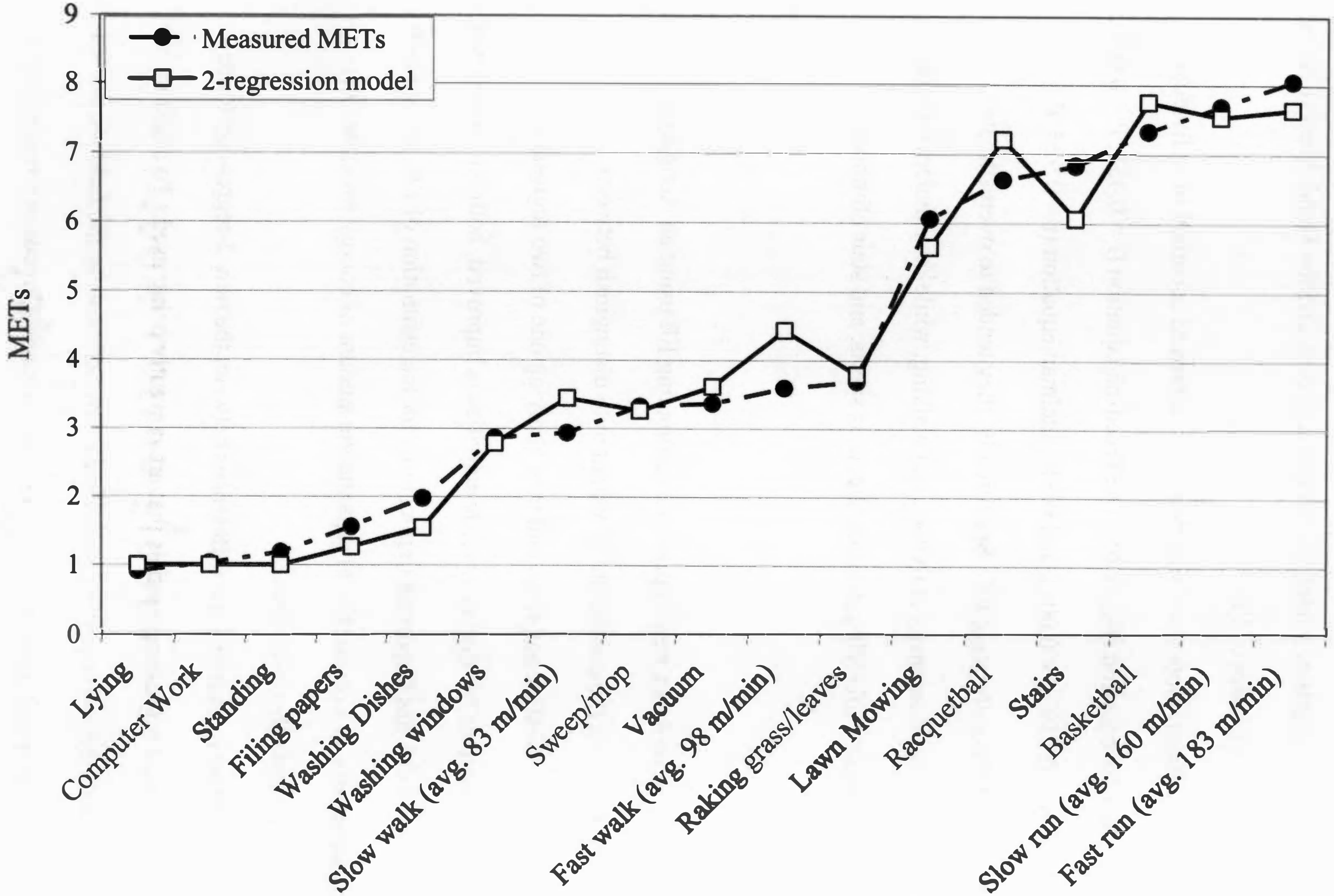


Figure 5. Measured and estimated METs for the cross-validation group using the new 2-regression model for various activities.

one walking speed and most activities below 2 METs. The Freedson equation was the only one that was significantly different from actual EE for all 17 activities combined ($P < 0.001$). The new 2-regression model, the Swartz equation, and the Hendelman equation all gave close overall estimates of EE.

The Bland-Altman plots show that there was improved accuracy of individual activities with the new equation (figure 6). The Freedson equation ($r = 0.455$, $P < 0.001$), Swartz equation ($r = 0.639$, $P < 0.001$), and the Hendelman equation ($r = 0.924$, $P < 0.001$) all had problems estimating EE. Specifically, they tended to overestimate sedentary behaviors, light-intensity activities, and walking, while they underestimated many moderate-intensity lifestyle activities, vigorous sports, and stair climbing.

Discussion

This study describes a new approach to estimating EE using an Actigraph accelerometer. By using the coefficient of variation to distinguish between walking/running and lifestyle activities and then applying one of two regression equations, the estimate of EE during specific activities is improved, both on a group and individual basis, which has important implications for the estimation of EE. In addition, the new equation allows a researcher to separate the amount of energy expended in walking, running, and other activities.

It is important to examine the differences between the new 2-regression model and other single linear regression models that are currently being used. To assist in explaining how the new two equation model is an advancement for the field we pooled all of our data together and drew in our two regression model, Freedson's regression line,

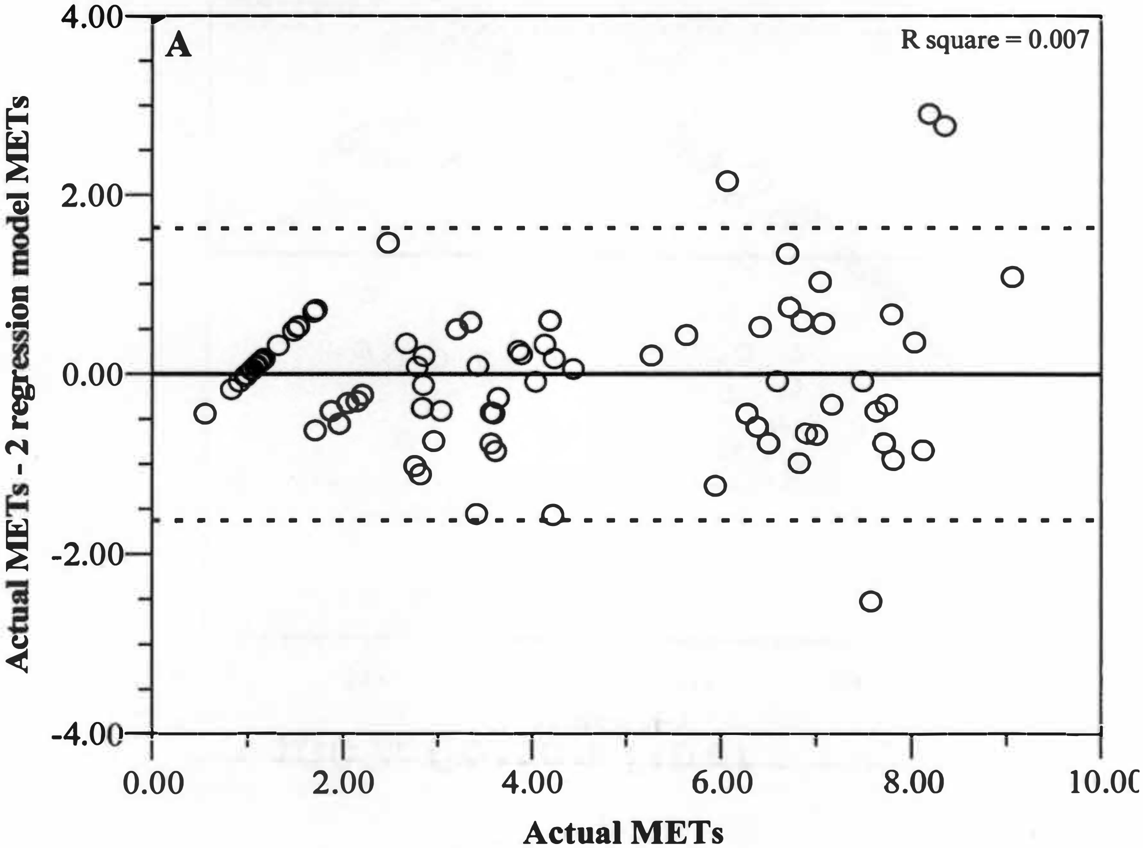
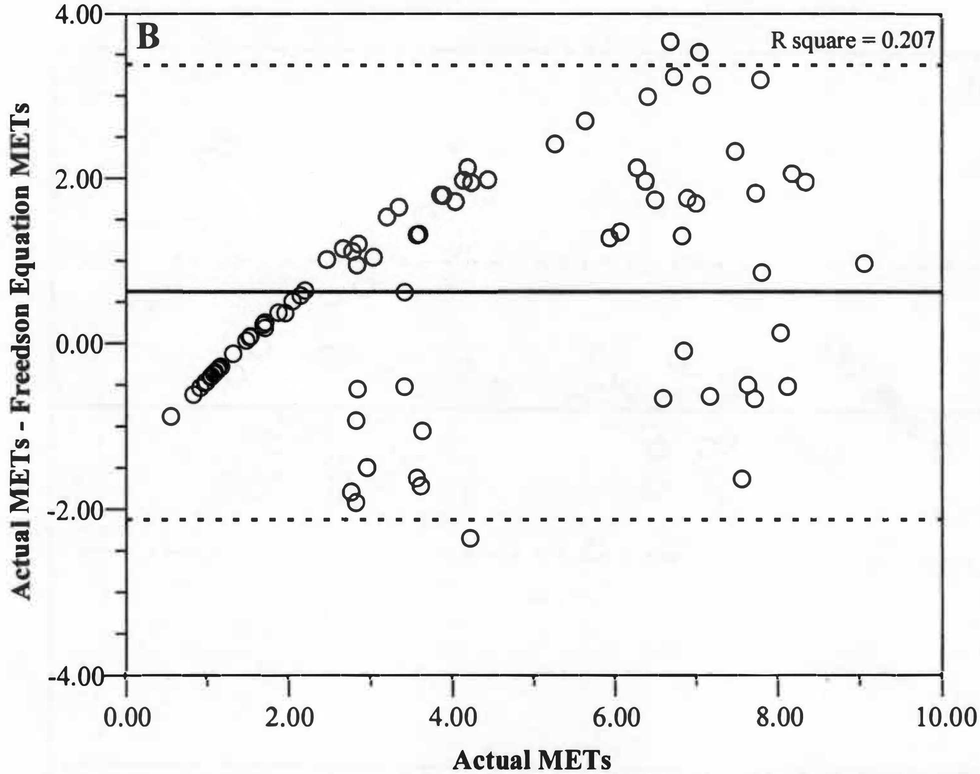


Figure 6. Bland-Altman plots depicting error scores (Actual minus estimation) for (A) the new 2-regression model, (B) Freedson MET equation, (C) Swartz equation, and (D) Hendelman equation. The solid line represents the mean, and dashed lines represent the 95% confidence interval of the observations.



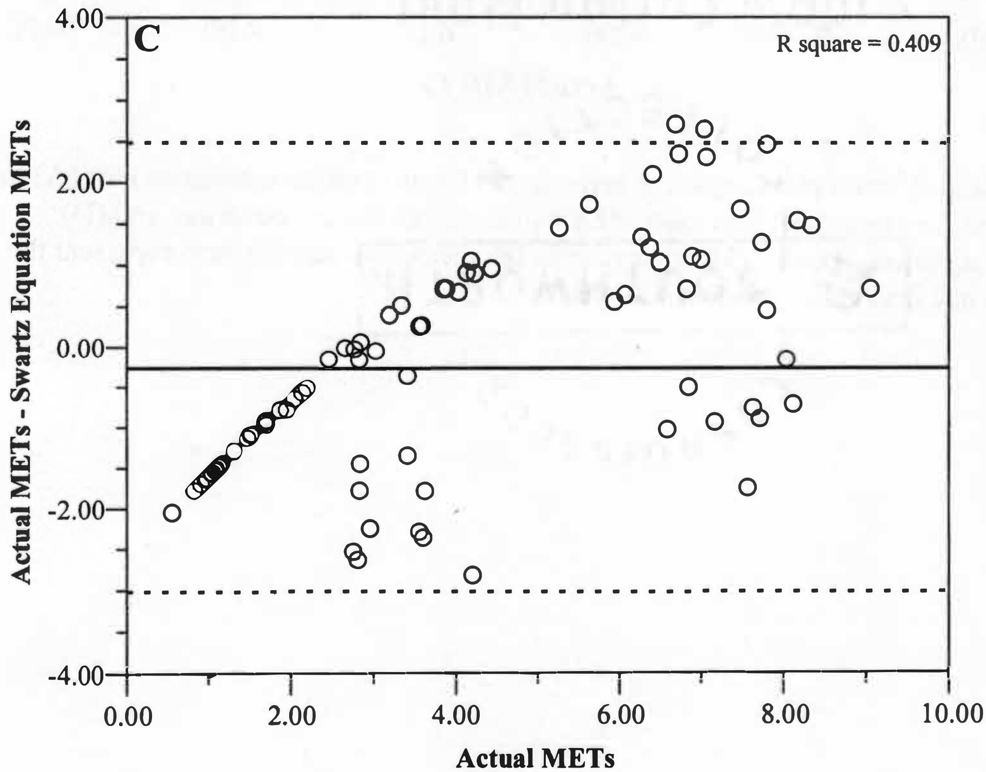


Figure 6. Continued

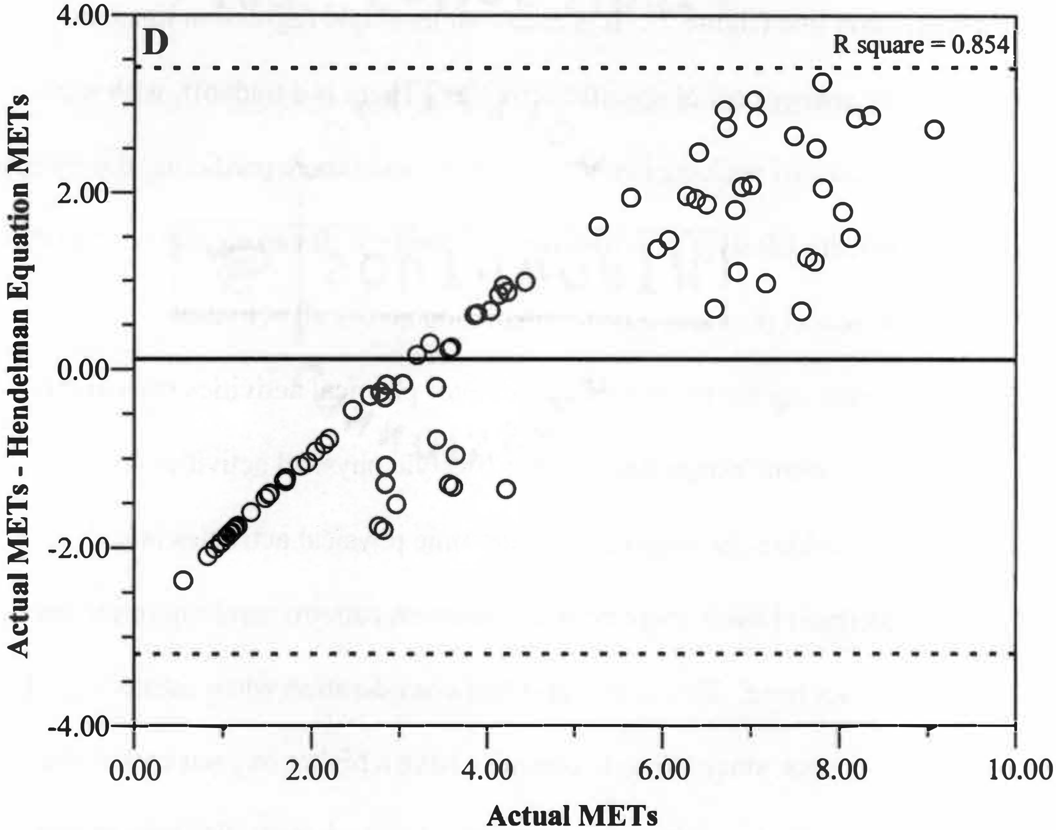


Figure 6. Continued

and Swartz's regression line (figure 7). It is clear that no single regression line can accurately predict the energy cost of specific activities. There is a tradeoff, with some predicting the energy cost of walking better than others, and others predicting the energy cost of moderate-intensity lifestyle activities more accurately. It can clearly be seen that the new 2-regression model provides a better prediction across all activities.

Walking and running are rhythmical, locomotor physical activities with highly consistent acceleration counts across time. Other lifestyle physical activities (e.g. vacuuming, sweeping, raking, mowing) and leisure time physical activities (e.g. basketball and racquetball) have a more erratic movement pattern, resulting in greater variability in counts over time. This is an important consideration when estimating EE using accelerometer counts, since lifestyle activities have a higher oxygen cost at the same $counts \cdot min^{-1}$, compared to walking and running. Lifestyle activities may include components in them that increase EE, but are not measured by the Actigraph. This includes arm activities, lifting and carrying objects, hill climbing, stairs, and changing directions in the horizontal plane. The advantage of the new method is that we can account for this increased EE that occurs during lifestyle activities by using 2-regression lines to estimate EE.

Given that ambulatory physical activity is an important component of overall EE, the new approach has the added benefit of being able to distinguish between walking, running and other activities, which could be useful to researchers. For the discrimination between walking and running we propose that a threshold of 6500 $counts \cdot min^{-1}$ be used. This is similar to the threshold of 6683 $counts \cdot min^{-1}$ chosen by Brage et al. (6) in a study which used treadmill walking and running. Epidemiologists can now examine how much

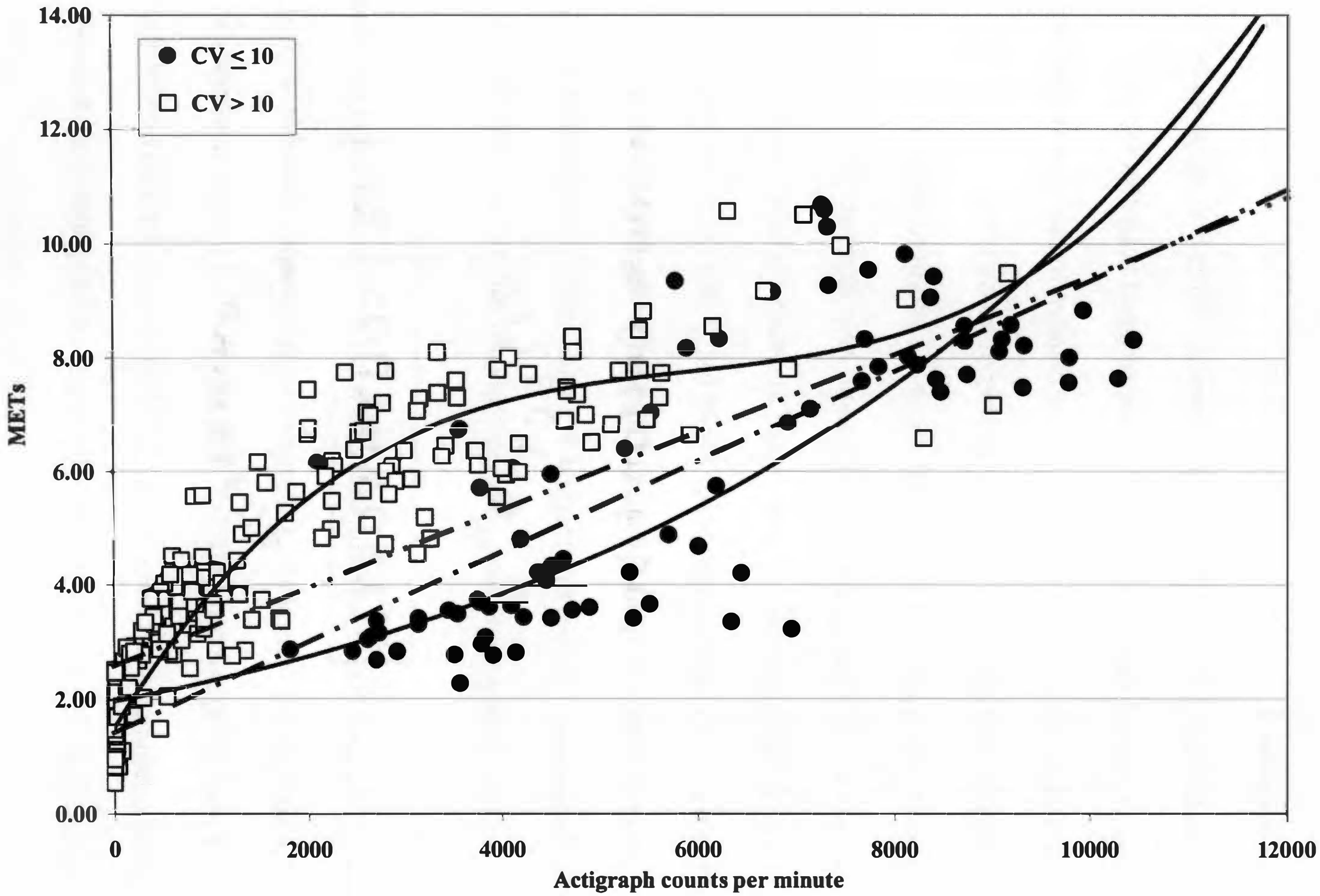


Figure 7. Relationship between Actigraph counts per minute and measured energy expenditure (METS) for various activities. The closed circles are activities with a CV 0.1 to 10 and the open squares are the activities with a CV 0 or > 10. The solid lines represent the new 2 regression model; the dashed line with 2 dots represents the Swartz equation; the dashed line with 1 dot represents the Freedson MET equation.

walking individuals perform and distinguish it from running and other moderate-intensity lifestyle activities for the purpose of validating "walking" items on questionnaires. In addition, those interested in weight loss interventions can track individuals in walking programs with better accuracy and determine how much walking individuals are doing during unsupervised sessions.

The current study does have strengths and weaknesses. Strengths of the study are that the new 2-regression model was developed on a wide range of activities ranging from sedentary behaviors to vigorous exercise. This is in contrast to previous studies that developed single regression equations on a limited number of activities (i.e. walking/running or moderate-intensity lifestyle activities). In addition, this study examined activities outside of the laboratory, which should help improve the generalizability to free-living situations. Limitations of the study include a small cross validation group, but there was still enough power (> 0.9 for 15 of the 17 activities) to find significant differences between the EE values of the various methods used. Future research should be designed to validate this method in a wide range of individuals for 24-hour EE (i.e. with doubly labeled water) and with indirect calorimetry using other types of physical activities.

In conclusion, the new 2-regression model, which is based on the counts$\cdot$min^{-1} and variability in counts between 10 second epochs, improves on currently available methods for the prediction of energy expenditure (METs). The new method is more accurate on both a group and individual basis and has a bias of 0.001 METs (95% prediction interval of ± 1.66). In addition, this new method has the advantages of being able to distinguish between walking, running, and other activities and it predicts the energy cost of specific activities with improved accuracy, which should ultimately result in a closer estimate of 24-hour EE.

Acknowledgements

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APPENDICES

APPENDIX A

PART III

Informed Consent Form

INFORMED CONSENT FORM
The Validation of Electronic Pedometers

Investigator: Patrick L. Schneider

Address:
The University of Tennessee
Department of Health, Safety, and Exercise Science
1914 Andy Holt Ave.
Knoxville, TN 37919

Telephone: 865-974-5091

Purpose
You are invited to participate in a research study. The purpose of this study is to examine the use of electronic pedometers to measure steps taken, distance walked, and caloric expenditure. If you give your consent, you will be asked to participate in one part of the study. The section checked below is the part of the study you are volunteering for. Before exercising, you will be given a brief questionnaire to determine your health status and you will be measured for height and weight in the laboratory.

Procedures
_____ Part 1. Course validation – You will take 20 strides and the total distance covered will be divided by 20 to determine stride length. You will then be asked to walk around a 400 meter outdoor track a total of 2 times for each pedometer of the same brand. A total of 12 different brands of pedometers will be tested. Therefore, you will be asked to walk around the 400 meter track a total of 24 times which is equivalent to 6 miles. A researcher will accompany you on each walk, manually counting each step. The testing will take place over the course of 1-5 days and will require a total of about 2-4 hours of your time.

____ Part 2. Effects of walking speed – You will be asked to walk on the treadmill at 2.0, 2.5, 3.0, 3.5, and 4.0 mph (5 minutes per stage). The effects of walking speed on the accuracy of each of the 10 brands of pedometers being tested will be examined. The testing will take place over the course of 3-5 days and will require about 4-5 hours of your time. You will be asked to wear a nose-clip and mouthpiece, and breathe into a device to measure oxygen uptake for each of the five 25 minute trials you will be asked to complete. The liters of oxygen actually consumed will be compared against the estimated value from the pedometer. You will also have your resting metabolic rate measured using the nose-clip and mouthpiece for 40 minutes on a separate day from the walking trials.

____ Part 3. 24-hour comparison – You will be asked to wear a Yamax SW-200 pedometer on one hip and another model on the other for 24 hours and record the number of steps registered on both pedometers at the end of each day. A comparison will then be made between the Yamax SW-200 and the comparative model. A total of 12 pedometers will be compared to the Yamax SW-200, which will require a total of 12 days of testing. You will not be asked to do any activities beyond which you would normally do on any other day. You will be given instructions on how to use each pedometer and will not be asked to return to the laboratory until all 12 pedometers have been compared.

Risks and Benefits

There are very few risks associated with moderate exercise. The risks include abnormal blood pressure responses and heart rhythm disturbances. These risks of participating in this study are equivalent to the risks of activities requiring moderate exertion (yard work, light sport activities, etc.) that you engage in during everyday activities. The benefits to participation include knowledge of your stride length, and exposure to a device that may provide accurate information about "steps taken" and "distance walked." You will also be given information on your resting metabolic rate.

Confidentiality

The information obtained from these tests will be treated as privileged and confidential and will consequently not be released to any person without your consent. However, the information will be used in research reports or presentations, but your name and other identity will not be disclosed.

Right to Ask Questions and to Withdraw

You are free to decide whether or not to participate in this study and are free to withdraw from the study at any time.
Before you sign this form, please ask questions about any aspects of the study which are unclear to you.

Consent

By signing this paper, I am indicating that I understand and agree to take part in this research study.

____________________________ ________________

Your signature Date

____________________________ ________________

Researcher's signature Date

APPENDIX A1

PART III, IV, V, VI

Physical Activity Readiness Questionnaire (PAR-Q)

Physical Activity Readiness Questionnaire (PAR-Q)

Regular physical activity is fun and healthy, and increasingly more people are starting to become more active every day. Being more active is very safe for most people. However, people should check with their doctor before they start becoming much more physically active.

If you are planning to become much more physically active than you are now, start by answering the seven questions in the box below. If you are between the ages of 15 and 69, the PAR-Q will tell you if you should check with your doctor before you start. If you are over 69 years of age, and you are not used to being very active, check with your doctor.

Common sense is your best guide when you answer these questions. Please read the questions carefully and answer each one honestly: check YES or NO.

YES NO 1. Has your doctor ever said that you have a heart condition <u>and</u> that you should only do physical activity recommended by a doctor?

YES NO 2. Do you feel pain in your chest when you do physical activity?

YES NO 3. In the past month, have you had chest pain when you were not doing physical activity?

YES NO 4. Do you lose your balance because of dizziness or do you ever lose consciousness?

YES NO 5. Do you have a bone or joint problem that could be made worse by a change in your physical activity?

YES NO 6. Do you know of <u>any other reason</u> why you should not be doing physical activity?

I have read, understood and completed this questionnaire. Any questions I had were answered to my full satisfaction.

Name ________________________________

Signature ______________________________ Date _________________

APPENDIX B

PART IV

Informed Consent Form

INFORMED CONSENT FORM

Accuracy of the Polar S410 heart rate monitor for measuring energy cost of exercise

Investigator: Scott E. Crouter
Address:
The University of Tennessee
Department of Health, Safety, and Exercise Science
1914 Andy Holt Ave.
Knoxville, TN 37996
Telephone: 865-974-5091

Purpose

You are invited to participate in a research study. The purpose of this study is to examine the use of the Polar S410 heart rate monitor to estimate energy expenditure during exercise. If you give your consent, you will be asked to perform the testing listed below. Before exercising, you will be given a brief questionnaire to determine your health status and you will be measured for height and weight in the laboratory.

Procedures

1. Resting metabolic rate (RMR) will be measured by indirect calorimetry using a Parvo-Medics metabolic cart. The test will be performed early in the morning after an overnight fast, with the exception of water. In addition, you need to refrain from the use of stimulants (including caffeine, tobacco, and medication) and intense physical activity for 12-hours prior to the test. Upon arrival you will be allowed to relax in a reclining position for the duration of the test. You will be fitted with a nose clip and mouthpiece, which will be supported by a head device. For the test you will be breathing only through your mouth into a hose that is connected to a metabolic cart for the measurement of oxygen uptake, which will allow us to determine your RMR. The total time that you will be breathing though the mouthpiece will be 40 minutes.

2. You will perform a maximal exercise test on a motor-driven treadmill for the determination of your VO_{2max}. The test will begin with a three minute walking warm-up. For the test the speed will be at a fast walk or comfortable running pace, based on your current physical activity and the grade will be increased 1% every minute until volitional fatigue. Three minutes after the completion of the test a sterile lancet will be used to puncture the skin on your fingertip so that 100-

microliters may be drawn out for blood lactate analysis. Including the warm-up the test will last 10-15 minutes. It is important for you to realize that you may stop when you wish because of feelings of fatigue or any other discomfort. We may stop the test at any time because of signs of fatigue, symptoms you may experience, or equipment malfunction. During the test you will also be asked to wear a nose-clip and mouthpiece as described above. You will also be asked to wear a heart rate monitor that will be strapped to your chest.

3. On each of the following motorized treadmill, cycle ergometer, and a rowing ergometer, you will performing three exercise tests at a moderate, hard and very hard exercise intensity, for a total of nine exercise tests. Each test will last for 12 minutes and the exercise intensity of moderate, hard, or very hard are based on your rating of perceived exertion. You will be given five minutes rest between exercise tests and may complete a maximum of six in one day. It will take a total of 138 minutes, including rest time, to complete the nine exercise tests. For each test you will be equipped with a nose clip, mouthpiece, and heart rate monitor.

For both the $VO_{2\max}$ test and the exercise tests you will need to refrain from strenuous exercise 24-hours before the test and to refrain from food, alcohol, and tobacco within two hours of the test. The expected time commitment to complete the tests will be approximately 4-5 hours and will be spread over 3-5 days. You cannot perform the $VO_{2\max}$ testing and exercise testing on the same days but you may perform one of these tests after the RMR test. In addition 48 hours will be given between days in which you exercise to allow for recovery.

Risks and Benefits

There are very few risks associated with moderate exercise for healthy individuals. The risks include abnormal blood pressure responses, musculo-skeletal injuries, dizziness, difficulty in breathing, and in rare instances heart attack or death. The risks of maximal stress testing are somewhat greater, but are still reasonable in light of the anticipated benefits. There is also an added risk of infection from the finger puncture which will be reduced by using sterile equipment. The benefits to participation include knowledge of your RMR, $VO_{2\max}$, and exposure to a device that may provide accurate information about how many calories you burn during exercise.

Confidentiality

The information obtained from these tests will be treated as privileged and confidential and will consequently not be released to any person without your consent. However, the information will be used in research reports or presentations, but your name and other identity will not be disclosed.

Contact Information

If you have questions at any time about the study or the procedures, (or you experience adverse effects as a result of participating in this study,) you may contact the Investigator, Scott Crouter. If you have questions about your rights as a participant, contact Research Compliance Services of the Office of Research at (865) 974-3466.

Right to Ask Questions and to Withdraw

You are free to decide whether or not to participate in this study and are free to withdraw from the study at any time.

Before you sign this form, please ask questions about any aspects of the study, which are unclear to you.

- -

Consent

By signing this paper, I am indicating that I understand and agree to take part in this research study.

______________________________ ______________

Your signature Date

______________________________ ______________

Researcher's signature Date

APPENDIX B1

PART IV

Rating of Perceived Exertion (RPE) Scale

Description	*RPE*	*Feelings*
Nothing at all	0	Nothing at all
	0.5	
Very little effort	1	
	1.5	
Very Comfortable	2	Easy Exercise
	2.5	
Easy to talk; no problem to continue	3	Moderate Exercise
	3.5	
Could keep this up for a long time	4	Somewhat Hard
	4.5	
More challenging; not as comfortable	5	Hard Exercise
	5.5	
Feels hard and I am getting tired	6	
	6.5	
Tough; now I must push myself	7	Very Hard Exercise
	7.5	
Challenging; breathing is rapid and deep; difficult to talk	8	
	8.5	
Uncomfortable; can't last much longer	9	Very, Very Hard Exercise
	9.5	
Can not talk; need to stop	10	Exhausting Maximal Exercise

APPENDIX C

PART V, VI

Informed Consent

INFORMED CONSENT FORM

Measurement of Physical Activity Energy Expenditure during Lifestyle Activities

Investigator: Scott E. Crouter
Address:
The University of Tennessee
Department of Exercise, Sport, and Leisure Studies
1914 Andy Holt Ave.
Knoxville, TN 37996
Telephone: 865-974-5091

Purpose

You are invited to participate in a research study. The purpose of this study is to examine the use of motion sensors, positioned at various body locations (e.g., hip, ankle, and wrist), to estimate energy expenditure. If you give your consent, you will be asked to perform the testing listed below. Before exercising, you will be given a brief questionnaire to determine your health status and you will be measured for height, weight, and percent body fat in the laboratory.

Procedures

4. You will be asked to perform 1 of the 3 following routines:

Routine #1	Routine #2	Routine #3
1) Lying	1) Walking around a track at approximately 3 mph	1) Vacuuming
2) Standing	2) Walking around a track at approximately 4 mph	2) Sweeping/mopping floors
3) Sitting working on a computer	3) Playing basketball	3) Washing windows
4) Standing doing office work	4) Playing Singles Racquetball	4) Washing dishes
5) Walking up and down stairs	5) Running around a track at approximately 5 mph	5) Raking leaves/grass
6) Stationary cycling at approximately 75 watts	6) Running around a track at approximately 7 mph	6) Lawn Mowing

If you choose, you may perform more than one routine, but you are not required to do so. Routines 1 and 2 will be performed on the campus at the University of Tennessee. Routine 3 will be performed at your place of residence or if needed at the home of the investigator. Each activity listed will be performed for 8-10 minutes and a 2 minute recovery will be given between each activity.

5. To measure energy expenditure during the routine you will be asked to wear a face mask that will be attached to a portable unit that will be worn on your upper body using a harness. The entire unit weighs approximately 4 pounds.
6. During the routine you will also be asked to wear 7 motion sensors. 1 will be worn on the wrist, 3 on the waist, 2 on the ankle, and 1 on the chest.
7. It is important for you to realize that you may stop when you wish because of feelings of fatigue or any other discomfort. We may stop the test at any time because of signs of fatigue, symptoms you may experience, or equipment malfunction.

The expected time commitment to complete the tests will be approximately 1.5 hours. If you choose to perform more than one routine then it will add an additional 1.25 hours per routine.

Risks and Benefits

There are few risks associated with moderate exercise. The risks include abnormal blood pressure responses and heart rhythm disturbances. The risks of participating in this study are equivalent to the risks of activities requiring moderate exertion (yard work, light sport activities, etc.) that you engage in during everyday life. The benefits to participation include exposure to a device(s) that may provide information on energy expenditure. You will also obtain your body mass index, which, is used to assess your risk of obesity-related diseases. In the unlikely event that physical injury occurs as a result of participating in this study, financial compensation is not automatically available and medical treatment will not be provided free of charge. If a physical injury should occur over the course of the study, immediately notify the primary investigator, Scott Crouter.

Confidentiality

The information obtained from these tests will be treated as privileged and confidential. Some of the data (i.e.- your age, height, weight, gender, energy expenditure data, and the data from one of the waist-mounted motion sensors) will be shared with David Pober, an investigator at the University of Massachusetts-Amherst. However, your name will not be disclosed. This researcher is investigating a new technique that can detect different activities based on your movement pattern. None of the remaining data will be released to any person without your consent. The information will be used in research reports or presentations, but your name and other identity will not be disclosed.

Contact Information

If you have questions at any time about the study or the procedures, (or you experience adverse effects as a result of participating in this study,) you may contact the investigator, Scott Crouter. If you have questions about your rights as a participant, contact Research Compliance Services of the Office of Research at (865) 974-3466.

Right to Ask Questions and to Withdraw

You are free to decide whether or not to participate in this study and are free to withdraw from the study at any time.

Before you sign this form, please ask questions about any aspects of the study, which are unclear to you.

- -

Consent

By signing this paper, I am indicating that I understand and agree to take part in this research study.

______________________________ ______________

Your signature Date

______________________________ ______________

Researcher's signature Date

VITA

Scott Edward Crouter was born in Walla Walla, Washington on June 17, 1976. He was raised in Seaside, Oregon where he attended school and graduated from Seaside High School in June 1994. He completed a Bachelors of Science in Exercise Physiology from Linfield College in December 1998. He then attended the University of Wisconsin – La Crosse where he obtained a Masters of Science in Adult Fitness and Cardiac Rehabilitation in August 2000. After working for two years in Los Angeles, California, at El Camino Community College, he accepted a teaching assistantship at The University of Tennessee, Knoxville, in the Department of Exercise, Sport and Leisure Studies. He graduated with a Doctor of Philosophy degree in Education in August 2005. He accepted a position as a post-doctoral research fellow in the Division of Nutritional Sciences at Cornell University in Ithaca, New York.