Predicting energy expenditure from physical activity, heart rate and anthropometry in female Indian tea pluckers

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ABSTRACT

Predicting energy expenditure from physical activity, heart rate and anthropometry in female Indian tea pluckers

The objective of this study was to test a methodological procedure for estimating energy expenditure for a population of Indian female tea pluckers. Subjects (N=40; age 20-50y) working on a tea estate in West Bengal, India participated in the study. Each subject wore an Actigraph accelerometer, Polar heart rate monitor and Cosmed K4b^2 indirect calorimeter during a 90-minute period to assess minute-by-minute physical activity (PA), heart rate (HR) and energy expenditure (EE), respectively. The testing period was meant to replicate a normal tea plucker's workday which included 2 periods of rest, 3 periods of plucking while carrying weight (0, 5, and 10 kg) and 3 periods of walking while carrying weight (15,20, 25 kg). An EE prediction equation was generated using a branched method that first distinguishes time during normal workday activities (resting, plucking, walking) using accelerometer counts. Resting EE was estimated from age and weight, while minute-by-minute non-resting EE was estimated from HR and BMI. Rather than creating individually calibrated curves for each subject, individuals can be grouped based on BMI categories (<18.5, 18.5≤BMI≤24.5, >24.5) to predict EE during the work day. Predicted EE will be used to evaluate the efficiency of performing work (weight of tea plucked/kcal EE) relative to iron status in an independent sample of 248 tea pluckers. We conclude that energy expenditure can be accurately predicted with a branched equation based on PA, HR, age, weight, and height for a specific population participating in a known set of activities.

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INTRODUCTION

Nutrition intervention trials are commonly conducted to assess the functional outcomes of studies that introduce novel foods or supplements into communities with prevalent micronutrient deficiencies. Intervention trials often examine outcomes in the workplace to show the effect of the intervention. Where work output can be quantified, productivity is an easy outcome variable to assess. Edgerton et al. (1979) examined quantity of tea plucked following an iron-based intervention. Similar methods were employed by Rajagopalan & Vinodkumar (2000) to look at changes in worker output. However a better approach is to examine the ratio between productivity and energy expended during workplace activity (productivity efficiency). This statistic controls for motivation and effort and may reveal the impact of a nutrient intervention on a community.

Quantifying productivity efficiency requires the estimation of energy expenditure for subjects over long periods of time. Currently, methods for the direct measurement of energy expenditure for many subjects over a long period of time are extremely limited. Recent studies including one from Assah et al. (2010) have shown that energy expenditure can be predicted using heart rate, physical activity and anthropometric characteristics. These methods are limited however, in that prediction equations are population-specific. Our previous unpublished work has shown that energy expenditure prediction equations developed for one population performing a particular set of tasks cannot be applied to a different population performing different activities.

In order to implement nutrient interventions that seek to quantify worker productivity efficiency, population-specific energy expenditure prediction equations must first be developed and validated. The objective of the present study is to develop a group prediction equation of energy expenditure for female tea pluckers in West Bengal, India based on height, weight, age, heart rate and physical activity for use during normal activity of the workday. The single group-level equation will allow for estimation of energy expenditure for any subject in this population performing workday tasks. The equation will need to be validated against individual energy expenditure prediction equations which have been asserted to be the only option for predicting energy expenditure.

LITERATURE REVIEW

Productivity and Energy Expenditure

If a job has quantifiable output, worker productivity can be an obtainable functional outcome measured in nutrition intervention trials, often in terms of units produced or net weight of production. Two previous iron-based intervention trials in tea pluckers (Edgerton et al., 1979; Rajagopalan & Vinodkumar, 2000) measured productivity in kilograms of tea plucked to quantify the effect of iron supplementation (200 mg ferrous sulfate/day; double fortified salt, respectively) on workplace activity. Edgerton et al. (1979) examined the effect of an iron supplementation on quantity of tea plucked per day on a tea plantation in Sri Lanka. A group of 199 tea pickers were randomly assigned to receive either 200 mg of iron as ferrous sulphate or placebo for one month. After treatment, the iron supplemented group picked significantly more tea (in kg/day) than the placebo group. Several additional studies have shown the effect of iron insufficiency on raw productivity in various other workers including rubber-tappers in Indonesia and Mexican factory workers (Basta et al., 1979; Rahn et al., 2004). Productivity in the workplace is a simple and effective way to measure the effect of an iron intervention, but can be influenced by individual motivation, quotas and the amount of physical effort put forth.

A more useful measure of productivity that accounts for individual variations in motivation and physical effort is Productivity Efficiency (PE) which is equal to the ratio of units produced divided by Energy Expenditure (EE). Li et al. (1994) looked at the effect of iron supplementation (60 mg ferrous sulfate/day) on productivity efficiency of 80 iron deficient female cotton mill workers in Beijing, China. Productivity efficiency was calculated as the ratio of productivity (yuan/day) to energy expenditure (MJ/day) to account for the constant running pace of the machines in the cotton mill. After treatment, the iron supplemented group significantly increased PE from baseline, while the placebo group remained unchanged.

Measuring Energy Expenditure

Accurate assessment of productivity efficiency in the workplace depends upon an accurate measurement of energy expenditure. Energy expenditure has frequently been measured in the research literature to assess metabolic needs, fuel utilization, and the thermic effect of food through indirect calorimetric methods, direct calorimetric methods and non-calorimetric methods (Levine, 2005). Each mode of assessment has different applications and limitations on accuracy, duration, environment of use and type of activity.

Recent literature argues in favor of doubly labeled water (non-calorimetric method) as the ‘gold standard’ method of measuring EE in humans (Ainslie et al., 2003). It was first reported by Schoeller & van Santen (1982) as a technique to evaluate EE in free-living humans. The use of doubly labeled water involves the consumption of naturally occurring non-radioactive isotopes (^{18}O and ^{2}H) in the form of water ($^{2}H_2{}^{18}O$) followed by estimation of carbon dioxide production (from which EE can be estimated) based on elimination of stable isotopes from the body in the form of carbon dioxide and water (Ainslie et al., 2003). Westerterp (1999) has shown that measurement of EE by doubly labeled water is accurate and can be used on almost any subject population including premature infants, hospitalized patients, obese people and pregnant women. However, the process is also expensive, requires specific expertise, is not useful for brief periods of activity (less than 5 days) and is difficult to use in field settings due to inaccurate estimation of the respiratory quotient (Westerterp, 1999). Measuring productivity often occurs in field settings and rarely needs to be done over the course of multiple days, making doubly labeled water an impractical method for measuring energy expenditure.

Direct calorimetry involves placing a test subject in a thermally-isolated chamber and measuring the total heat loss from the body. This technique was historically popular, but has since been recognized as limited in practical interest of estimating EE in free-living populations. Metabolic chambers used for direct calorimetry will never be able to reproduce complex activities and are not practical for use over extended periods of time (Ainslie, 2003). Developments in open-circuit indirect calorimetry have lead to techniques to measure EE in a wider range of applications. This technique requires subjects to breathe air through a contained hood such that volume of airflow and percentage of oxygen and carbon dioxide can be measured. The volume of oxygen inspired and carbon dioxide expired can be used to estimate EE using an equation developed by Weir (1949) to relate oxygen and carbon dioxide measurements to respiration rate. However, subjects are still limited in their range of activities and the application to free-living populations is still unclear. Portable calorimeters, relying on this indirect technique, were developed to expand the measurement of energy expenditure into field settings without compromising accuracy (Kofranyi and Michaelis, 1940). More recently, small, portable, light-weight battery-operated devices such as Metamax (Borsdorf, Germany), Cosmed $K4b^2$ (Rome, Italy) and MedGraphics VO2000 have been developed to measure breath-by-breath gas exchange. The development of portable technologies such as MedGraphics VO2000 initially came with the cost of decreased reliability (Crouter et al., 2006a). These technologies rely on the previously established indirect calorimetry methods, but in a system that does not limit subject mobility and can be taken into the field. The Cosmed $K4b^2$ system is able to provide accurate measures of respiratory gas exchange during a variety of activities (Meyer et al., 2001). This system provides the advantages of being comfortable and light-weight as well as portable, without compromising accuracy to allow for estimation of EE in nearly any field or laboratory environment. However, these portable systems are also expensive and may be impractical for a study with a large number of subjects or in a study where subjects are working for long periods of time. Simplified estimations for EE need to be developed based on convenient and reliable EE measurements.

Estimation of Energy Expenditure

The relationship between heart rate (HR) and EE has been analyzed extensively in the scientific literature. It is possible to accurately predict EE from HR alone for individual subjects or a homogenous group of subjects due to the close relationship between HR and EE during periods of activity (Spurr et al., 1988). The relationship is not linear, but is segmented with two linear functions separated by a single "flex point." The flex point represents a HR above and below which there are two separate linear equations for predicting EE. While HR and physical activity (PA) can predict EE in individual subjects, the slopes and intercepts of subject specific prediction equations vary depending on age, height, weight and fitness of the subjects (Crouter et al., 2006b).

Equations predicting EE are specific to the type of activities and the population of subjects used to generate the equations. Utilizing equations generated during high intensity activity are not as accurate in predicting EE during low intensity activity. Our previous work has shown that equations generated in a population of Cornell students over-estimated EE in a population of Mexican subjects who differ in body size, age and general fitness levels. Preliminary work has also shown that using an equation based on Mexican women who were assessed at various levels of effort on a cycle ergometer and applied to Indian tea pickers systematically overestimates EE by approximately 20 percent with a large variation in individual predicted values.

A recent study by Assah et al. (2010) examined the validity of predicting EE based on gender, HR, and PA in adults in Cameroon. Physical activity energy expenditure (PAEE) was measured in 33 adults using doubly labeled water over a consecutive seven day period. HR and PA were concurrently measured using a heart rate monitor and uni-axial accelerometer. There was found to be no significant difference between the PAEE estimated from equations based on gender, HR and PA compared to measurement of PAEE by doubly labeled water. Combined HR and PA sensing in a branched equation (first distinguishing the type of activity being performed and subsequently using HR to calculate EE based on the activity type) was found to be a valid method for estimating PAEE for individuals as well as groups of adults in Cameroon.

The current study will assess EE by portable indirect calorimetry along with HR and PA during typical activities of Indian tea pluckers during their 8 hour workday. These measures will be used to create EE prediction equations that can more accurately estimate EE for future nutritional interventions that assess changes in worker PE of this population.

RATIONALE AND AIMS OF THE PRESENT STUDY

Nutrition interventions trials are commonly performed to assess the impact of novel foods or supplements in specific communities with widespread deficiencies in the particular nutrient of interest. Trials assess the ability of the intervention to improve health of those affected and the ability of the intervention to have functional outcomes such as worker productivity, time spent with family and growth in pediatric populations. The evaluation of nutrient interventions (with iron or other micronutrients) in adults should include functional measures such as work productivity to understand the effect of the intervention. In previous studies, productivity has been measured as the amount of rubber tapped, cotton spun and tea picked. It would be useful to know the productivity efficiency, or the amount produced per unit of energy expended. This requires measuring not only productivity, but also the amount of effort (energy expended) while working.

The objective of the present study is to develop an equation to predict energy expenditure specific to female tea pluckers in West Bengal, India. We will measure a set of predictors of energy expenditure such as heart rate, physical activity, height, weight and age during normal work day activities in order to more accurately predict energy expenditure in this specific population. With these equations established, future nutrient intervention studies will be able to predict energy expenditure in order to estimate productivity efficiency [Productivity Efficiency =

weight of tea picked (kg/hr) / Energy Expenditure (kcal/hr)] (Zhu and Haas, 1998). Productivity efficiency will then be used to evaluate the effectiveness of a nutritional intervention designed to improve the iron status of the tea pluckers.

METHODS

Subjects

In a cross-sectional study, a sample of pre-menopausal women aged 20 to 50 years who work on a tea estate in West Bengal, India (Panighatta Tea Garden) were invited to participate in the validation study to develop a group prediction equation for energy expenditure. We were interested in only healthy, non-pregnant, non-lactating, temporary pluckers at the tea estate with at least 5 years of experience (to control for a training effect). Each subject signed a written informed consent and procedures were reviewed and approved by the Cornell University Committee on Human Subjects. Consent forms were translated into both native languages (Nepali and Adivasi) and in the case of subjects who were unable to read the informed consent form, the form was read to them by a research assistant and participants gave consent with a thumb print.

Subjects had their hemoglobin (Hb) measured with a Hemacue (HemoCue AB. Angelholm, Sweden) via left ring finger stick with disposable blood lancets. Subjects with Hb <8.0 g/dL were not included in the study. Each woman also had her age, height (with stadiometer) and weight measured (with digital scale). Clothing weight of each woman was also measured using the digital scale to determine net weight of each subject. After the screening process, 40 women (20 Nepali and 20 Adivasi) were selected and agreed to participate in the energy expenditure assessment portion of the study.

Procedures

Each subject was monitored individually for a single 90-minute testing period. Participants were asked to wear an Actigraph triaxial physical activity monitor, a Polar heart rate monitor and a Cosmed indirect calorimeter during the 90-minute period of measurement. A female research assistant attached the accelerometer to a belt around the waist and strapped the heart rate monitor around the chest. The Cosmed was connected to straps around the subject's torso with an attached battery pack held against the subject's back. The subject was fitted for a mask to contain inspired and expired air. In the case of improperly fitting masks, silicon seals were placed around the edge of the mask to prevent air from escaping. Before initiating the measurement period, the ambient air temperature, barometric pressure and relative humidity of the air were recorded entered into the CosMed.

The test period sought to summarize the normal range of activities for a tea plucker workday. The average day combines rest periods, plucking with varying loads of tea and carrying loads of tea across the gardens. Subjects began the test period with a five minute period of rest, sitting upright either on the ground or on a bag of tea leaves. This rest interval was followed by three continuous periods of plucking tea leaves in the garden with increasing loads. During the first plucking interval, the subject carried no load, while the second and third intervals of plucking incurred increasing loads (5 and 10 kg, respectively) of tea that were hung down the back and supported at the head. Following the three plucking intervals were three periods of walking with increasing loads (15, 20, and 25 kg), each for 5 minutes. After the final walking interval, the subject rested for 10 minutes before the Cosmed was turned off and all equipment was removed. For the duration of the monitoring period, a research monitor followed the subject taking notes on the timing and nature of the subject's activity as well as abnormalities (coughing, laughing, mask removal, disconnection of cords or monitors).

Throughout the procedure, the subjects were given the opportunity to pause and break to take water. They were also given time warnings to alert them of when the current interval was going to end and when the next one would begin. Subjects had the opportunity to rest or quit during the testing period if the activity was becoming too stressful or the heat overbearing.

Measurement

<u>Physical Activity</u>

Subjects each wore an ActiGraph GT3X physical activity monitor attached to an elastic belt around the waist. The accelerometer was placed on the anterior axillary line on the right hip (Crouter et al. 2006b). The ActiGraph GT3X is a triaxial solid state accelerometer which measures acceleration of the subject in all three dimensions of space. The GT3X is 3.8cm x 3.7cm x 1.8cm and weighs 27g and provides lightweight, non-obstructive assessment of physical activity. The device has a battery life of 20 days when fully charged, but data was downloaded from the device daily onto a portable laptop computer. The device was re-initialized daily after each downloading session. Output was obtained in 1-second epochs, 10-second epochs and 1-minute epochs in order to assess a range of resolutions.

<u>Heart Rate</u>

Subjects each wore a Polar heart rate monitor during monitoring periods. The Polar monitor consists of a Polar T31C Coded Transmitter and Polar A3 receiver. The Polar T31C Coded Transmitter Set is fixed on an elastic band and strapped around the subject's chest, making contact with the skin. Before testing, the T31C transmitter was moistened where it contacts the skin to insure conductivity. The transmitter is lightweight (100g), small (25") and does not interfere with normal physical activity. The A3 receiver is in the form of a watch which was kept in a pouch and hung around the neck. The CosMed K4b^2 also had a built in receiver which was able to provide an additional monitoring source. Heart rate data was downloaded daily from both the CosMed and the Polar watch receiver. The Polar A3 receiver was initialized at the start of each test. Memory was cleared daily from the A3 receiver after downloading. Heart rate data output was obtained at breath-by-breath frequency and 1-minute averages from the CosMed receiver; the A3 receiver provided output in 15-second intervals.

Energy Expenditure

Subjects were each fitted with the CosMed K4b^2 (Rome, Italy) portable indirect calorimeter. The device consists of a transmitter (with gas analyzer), battery pack (rechargeable Ni-MH battery with average life of about 6 hours), flowmeter, mask and sampling tube. The transmitter unit is tethered to the ventral torso with adjustable straps in order to insure comfort and stability, while the battery pack attaches with the straps to the dorsal side. The transmitter is lightweight (475g) and non-invasive (170mm x 55mm x 100 mm). Before each testing period, the CosMed K4b^2 requires input of current temperature and relative humidity. The L.L. Bean First Watch Weather Station was kept with the CosMed and provided ambient temperature (degrees Centigrade) and relative humidity (%).

The CosMed K4b^2 required four calibration steps for proper function. The ambient air calibration was performed prior to each test to assess the composition of ambient air. The known gas concentration calibration was performed daily. This test calibrated the gas analyzer relative to a known gas sample (16.30% O_2, 4.01% CO_2). The flowmeter calibration was performed before each test session. This calibrated the flowmeter relative to a known volume (3 L) of air passing through the detector. The sampling tube calibration was performed daily and calibrated the amount of time it takes for gas to pass from the entrance of the sampling tube to the gas analyzer.

Data Analysis

Output from the Actigraph accelerometer was compiled for each subject and condensed to 1-minute epochs. Each subject needed a complete monitoring period with accompanying accelerometry data to be included. Each minute epoch was designated as "rest," "plucking," or "walking" based on the researcher's notes of physical activity type and matched to the corresponding count value obtained by the Actigraph. Each minute epoch for each subject was designated as a period of either "rest," "walking" or "plucking." Count values per minute were collected from all subjects into these three physical activity categories. Unexplainable repeated 0 count values were labeled as missing. If >50% of the monitoring period was missing, the subject was dropped from analysis.

The Polar A3 receiver generated heart rate output in beats per minute (bpm) at 15-second intervals for each subject's period of monitoring. These outputs were summarized into 1-minute averages by taking the average of four continuous 15-second intervals for each minute for every subject. While the Polar A3 receiver provided heart rate output, data was preferentially taken from the CosMed due to its reliability. Heart rate values of >180 bpm were counted as missing and Polar output was not utilized if >50% of the monitoring time was missing. The Polar A3 receiver experienced frequent interference and as a result, 22 subjects had their Polar A3 heart rate data dropped.

The CosMed K4b^2 provided breath-by-breath output of heart rate (bpm), volume of oxygen consumption (VO_2) in L/min, energy expenditure (kJ/min), time (hh:mm:ss). Output was condensed to minute-by-minute values to better summarize the data. Each subject had their output data matched with the researcher notes by aligning the time of day. Alignment allowed designation of intervals of resting, plucking and walking to the output. For each subject, energy expenditure vs. time curves were made for entire length monitoring period and for each of the eight activity intervals (2 resting, 3 picking with increasing loads, 3 walking with increasing loads). The curves made during specific activity intervals were examined for steady state conditions (when energy expenditure becomes constant for the interval). Steady state energy expenditure values (with corresponding heart rate and VO_2) were then consistently selected for each activity interval of each subject (for 5 minute intervals, minutes 3 and 4; for 10 minute intervals, minutes 7, 8, and 9). Steady state values were compiled for each subject and were separated based on activity type.

Subjects were categorized into three groups based on BMI (<18.5, $18.5 \leq \text{BMI} \leq 24.5$, >24.5). One subject had to be excluded from data analysis based on insufficient heart rate data. However, no subjects were had to be excluded based on low Hb values or missing physical activity data. A final sample of 39 female tea pluckers was used in the statistical analysis.

Statistical Analysis

Statistical analyses for the purpose of this research was performed using SPSS Version 15.0 (SPSS inc. Chicago, Illinois). Mixed model regression analysis was performed to develop prediction equations for energy expenditure utilizing subject ID as a random effect and fixed effects including height (cm), weight (kg), logHR, BMI (categorically), age (years). Mixed models were made to predict logEE for all activity types (rest, walking, plucking) grouped together and separately. Additionally, energy expenditure prediction equations were generated for the activities of walking and plucking grouped together. Frequency histograms were generated to compare activity counts between activity types. Descriptive statistics were generated for activity counts and subject characteristics and are expressed in terms of mean +- one standard deviation. Independent t-tests were used to compare groups including energy expenditure predicted by a group equation compared to individually calibrated heart rate vs. energy expenditure curves. Statistical significance, where indicated uses an alpha level of 0.05.

RESULTS

Table 1 shows the descriptive statistics of the subjects whose data were used to generate the group energy expenditure prediction equation. Subjects were categorized based on BMI group with the mean values of BMI, age, height and weight shown.

The frequency of activity counts by activity type are shown in Figure 1. They generally show independent distributions with minimal overlap between activity types. As rigor of activity increases, the spread of activity counts per minute increases.

The descriptive statistics of the activity counts are shown in Table 2 for each activity type. The cutoff to distinguish rest from non-rest activity is set at 157.1 counts per min. This value represents the mean plus one standard deviation of counts per minute for rest activity, though it accounts for more than 84% of the data since the distribution of counts during rest is right skewed. If counts were normally distributed for rest, this would account for 84% of the data. Increasing rigor of activity correlates with a greater spread in the activity counts (larger standard deviation).

The final group branched equation is presented in Figure 2. While heart rate, weight and age are continuous variables, BMI is a categorical variable (1: <18.5; 2: $18.5 \leq$ BMI ≤ 24.5; 3: >24.5). This equation was generated using a mixed model regression analysis with loge as a continuous variable predicted from the random effect of subject and fixed effects of logHR and BMI (for non-rest activity) or weight and age (for resting activity).

An individual subject's energy expenditure vs. heart rate curve is shown in Figure 3. Linear regression above and below a flex point determines the individually calibrated curve (Spurr et al., 1988). The portion below the flex point probably does not have a linear relationship, but instead clusters at a constant low energy expenditure value based on weight and age, independent of heart rate change. Above the flex point, the relationship between energy expenditure and heart rate is linear.

Table 3 shows a comparison of the estimation of energy expenditure via the branched group equation developed here compared to an individually calibrated energy expenditure prediction equation using the methodology developed by Spurr et al. (1988) for 5 days of work. The figure shows no significant difference between the energy expenditure during a day of work for a single subject when predicted with the group equation for female tea pluckers in West Bengal, India compared to the energy expenditure prediction equation calibrated specifically for this individual subject. The energy expenditure predictions for the two approaches were not significantly different for 5-day energy expenditure while at work ($p<0.05$).

Figure 4 shows a Bland-Altman plot comparing the difference in predicted energy expenditure between the group and individual equations across the range of energy expenditures estimated by the individually calibrated curve. The plot reveals a systematic over-estimation of energy expenditure by the branched group equation developed here for times when the subject is in high-intensity physical activity (>4.5 kcal/min) and at very low levels of exertion near rest (<2 kcal/min). The group equation systematically underestimates energy expenditure at medium levels of exertion (2 kcal/min > EE < 4.5 kcal/min).

Figure 5 shows a comparison of the group and individual energy expenditure prediction equations across the range of energy expenditures estimated by the individually calibrated curve for four subjects over the course of one week of monitoring during working periods. The group equation shows the greatest deviation from the individual equations at high levels of exertion (>4 kcal/min). The 95% limits of agreement for group and individual equations (-0.37,0.33) contain 95% (8130/8579) of the difference scores. The mean difference of the measurements between the two methods is -0.0203 kcal/min with a standard deviation of 0.17267 kcal/min.

DISCUSSION

The objective of the current study was to develop an equation to predict energy expenditure for a group of 40 female tea pluckers in West Bengal, India for normal workday activities. The hypothesis tested was that an energy expenditure prediction equation could be developed for a specific population of people performing similar tasks by measuring predictors of energy expenditure including height, weight, age, heart rate and physical activity. The goal was to develop a single equation that could predict energy expenditure for individuals within a specific group as well as individually calibrated curves from heart rate vs. energy expenditure.

The results of the current study show that the group prediction equation developed for the entire sample predicts energy expenditure no differently than individually calibrated energy expenditure curves. The group equation over-estimates energy expenditure during high levels of exertion and very low levels of exertion, and under-estimates energy expenditure at medium levels of exertion. The under-estimation is not severe as the over-estimation. However, when validated by comparing the ability of the group equation to predict energy expenditure relative to individually calibrated curves, there is no difference between predicted energy expenditure over the course of the same 5-day work period. These results are in agreement with those found by Assah et al. in Cameroon (2010).

The resulting group equation uses a previously described branched approach whereby the first branch determines the type of activity and depending on the result, selects an activity-specific equation to predict energy expenditure. The equation developed discriminates between resting and non-resting activity based on physical activity patterns. One path is taken based on whether the activity is determined to be rest or non-rest. The prediction equation for resting energy expenditure utilizes weight and age as predictors, similar to previously published REE equations (Mifflin et al., 1990). The prediction equation for active energy expenditure (AEE) utilizes BMI, heart rate and the interaction of the two in order to predict energy expenditure in an active state.

The equation for predicting REE is:

$$\log REE = 0.501564 + 0.011546 * weight - 0.007846 * age$$

The equation for predicting AEE is:

$$\log AEE = -20.948266 + 11.179237 * \log HR - 3.61537 * BMI + 1.91938 * \log HR * BMI$$

(BMI is categorical: 1, <18.5; 2, $18.5 \leq BMI \leq 24.5$; 3, >24.5)

Another finding of the study is the usefulness of the Actigraph in distinguishing periods of activity from periods of inactivity. Though, distinguishing types of non-rest activity is more difficult to obtain. There was a distinct separation in Actigraph activity counts between resting periods and non-resting periods. Looking within periods of non-rest activity, there was less separation between different tasks such as plucking and walking. These activity types had large standard deviations in their count values, which lead to overlap between distributions and therefore difficulty discerning walking from plucking based on Actigraph counts. This finding led to the unification of non-resting activities when predicting energy expenditure. Since different types of non-rest activity were difficult to distinguish from each other, a branched equation would often incorrectly classify activity type thereby causing energy expenditure to be predicted by the incorrect equation and thus increase error.

Though the group equation and the individually calibrated equations predict energy expenditure without significant difference for 5-day working periods, their agreement shows greater variability for shorter periods of time. A total of 5 days of monitoring provides a large sample of data. Over-predictions and under-predictions by the group equation balance out over these extended periods. When using the group equation for short periods of time like a single day, there is an increase in the difference between the energy expenditure predicted by the group equations and the individually calibrated equations.

Additionally, these methods showed success in condensing much of the data into more workable files while still generating a usable energy expenditure prediction equation. The Actigraph physical activity counts were condensed into 1-minute epochs and the heart rate data were summarized into 1-minute averages of beats per minute. Additionally, much of the data output was dropped because it fell in between activity intervals or was within the interval but did not represent steady state values. Using only steady state values meant that only 30-40% of the condensed data within each interval was extracted for analysis in the mixed model. The 1-minute intervals for Actigraph counts and heart rate were not too long and managed to capture variability.

This also suggests that the use of steady state energy expenditure values can be used to create a model for predicting energy expenditure. However, whether or not non-steady state values would be just as useful is not addressed in this analysis. One limitation of the study is that it does not compare similar methods of making a prediction equation for energy expenditure. For example, this methodology does not address the issue of whether more frequent data collection (recording physical activity counts and heart rate every 10 seconds) would result in a more accurate model. The study also does not address the use of steady state values compared to all values without discrimination. Inclusion of non-steady state values may have added more variability to create a model that is more accurate at extremes, or it could have added noise such that the prediction equation has greater error.

Another limitation of the study is that it was cross sectional. The approach did not include day-to-day variability in energy expenditure or efficiency of energy production. Women were only measured once for a short (90 minute) period of time. Time of day and weather conditions (excluding temperature) were not controlled for, which could have altered some subjects' energy expenditure. There was high variability in the weather throughout the time the study was taking place. Some women had to pluck outside in the sun while others worked in rainy conditions. The effect of these weather conditions on the equipment was also not explored. Another limitation of the study was that hemoglobin was the only indicator of iron status measured. It would have been useful to look at other indicators of iron status such as ferritin and sTfR.

In the future, it will be useful to look at the effects of an iron intervention on productivity efficiency (using the equation developed in the study) for this population. It will also be useful to develop similar equations for energy expenditure it other populations performing different activities in their respective workplace. It will be interesting to compare these equations and the predictors of energy expenditure between populations and workplace activities. It will also be useful to quantify training (or experience) and include this variable in the prediction for energy expenditure to understand the role it plays in affecting energy expenditure in the workplace.

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TABLES AND FIGURES

Subject Anthropometry

BMI group	N	BMI	age	height	weight
1 (<18.5)	10	17.41	33.5	152.77	40.72
2 (18.5≥BMI≤24.5)	22	21.18	33.77	152.2	49.15
3 (>24.5)	7	26.91	33.86	151.83	62.09

Table 1: A comparison of the anthropometry for the three groups of subjects based on BMI category. Subjects were significantly different between each groups for BMI and weight ($p<0.05$). Height and age showed no significant difference between groups.

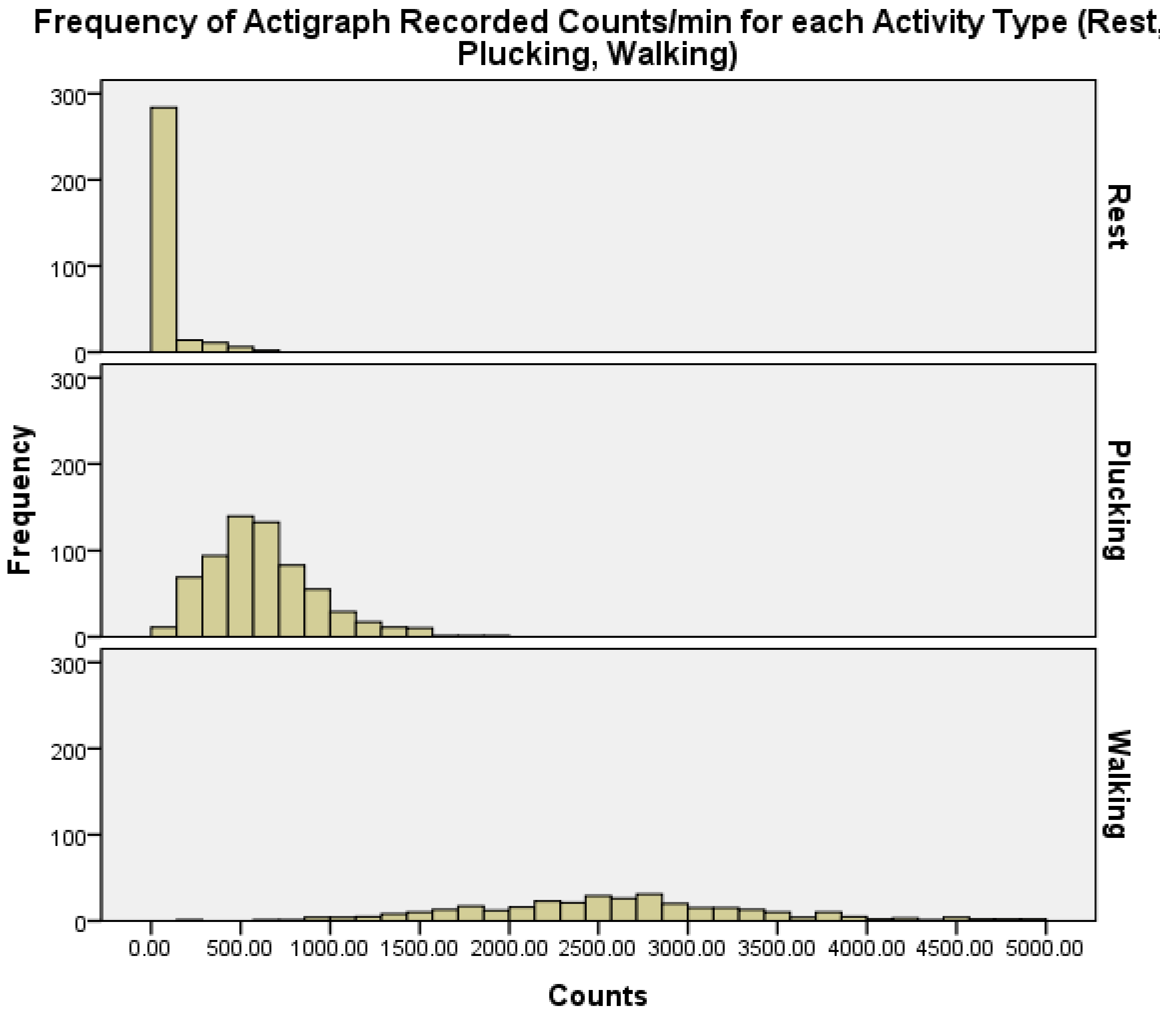

Figure 1: Distribution of counts per minute from the physical activity monitor for each level of activity (rest, plucking, and walking). Plucking and walking show normal distribution of counts, while the distribution of counts during rest is right-skewed.

Mean and Standard Deviation Physical Activity Counts for Each Activity Type

Counts

ActivityCode	Mean	N	Std. Deviation
1: Rest	47.7419	317	109.44959
2: Plucking	623.0666	655	301.72099
3: Walking	2586.9184	330	811.21502
Total	980.7419	1302	1070.49841

Table 2: Mean output in counts per minute from physical activity monitors for each period of activity (rest, plucking, and walking).

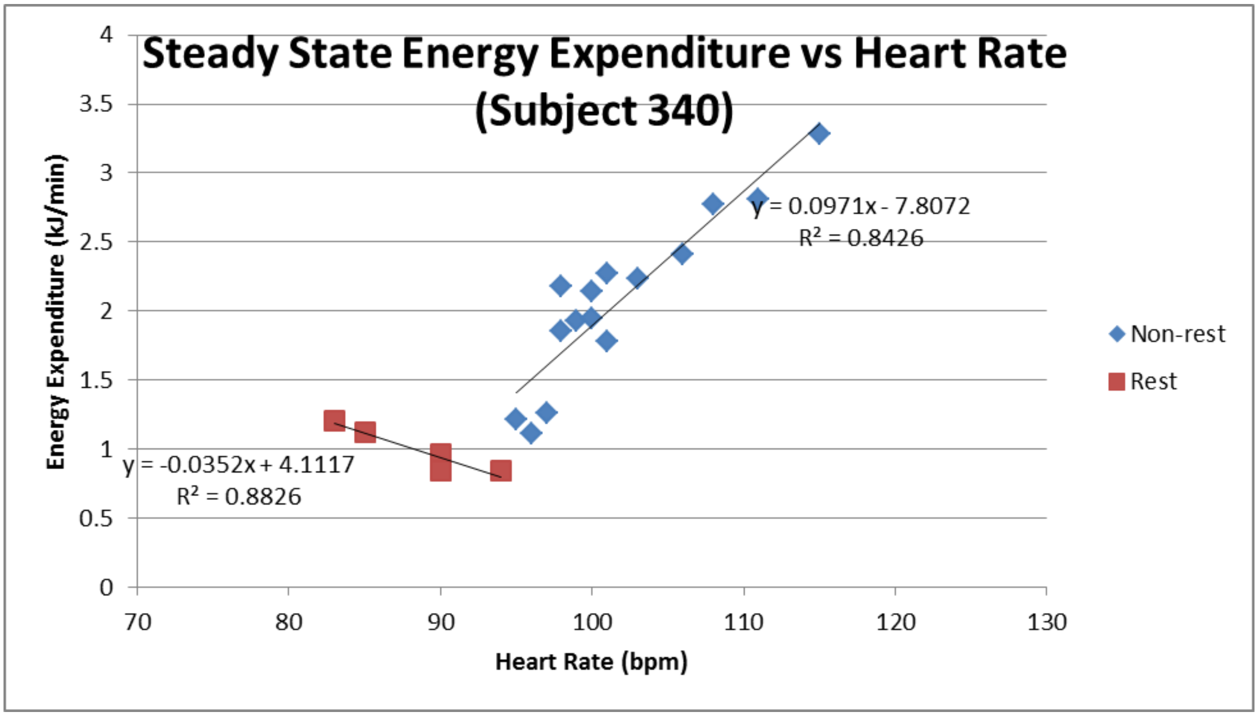

Figure 2: Individually calibrated energy expenditure prediction equation using a flex-point at 95 bpm. Above this flex-point energy expenditure is predicted according to the equation y = 0.0971*HR + 7.8072. Below the flex-point, energy expenditure is predicted according to the equation y = -0.0352*HR + 4.1117.

Group-Level Energy Expenditure Prediction Equation

Branch 1	Branch 2
Physical Activity Counts	Prediction
< 157.1 (Rest)	logEE = 0.501564 + 0.011546 * weight - 0.007846 * age
> 157.1 (Non-rest)	logEE = -20.948266 + 11.179237 * logHR - 3.61537 * BMI + 1.91938 * logHR * BMI

Table 3: Final group energy expenditure prediction equation developed. Rest activity (determined by average physical activity counts) utilizes weight and age to predict energy expenditure while non-rest activity utilizes heart rate and body mass index.

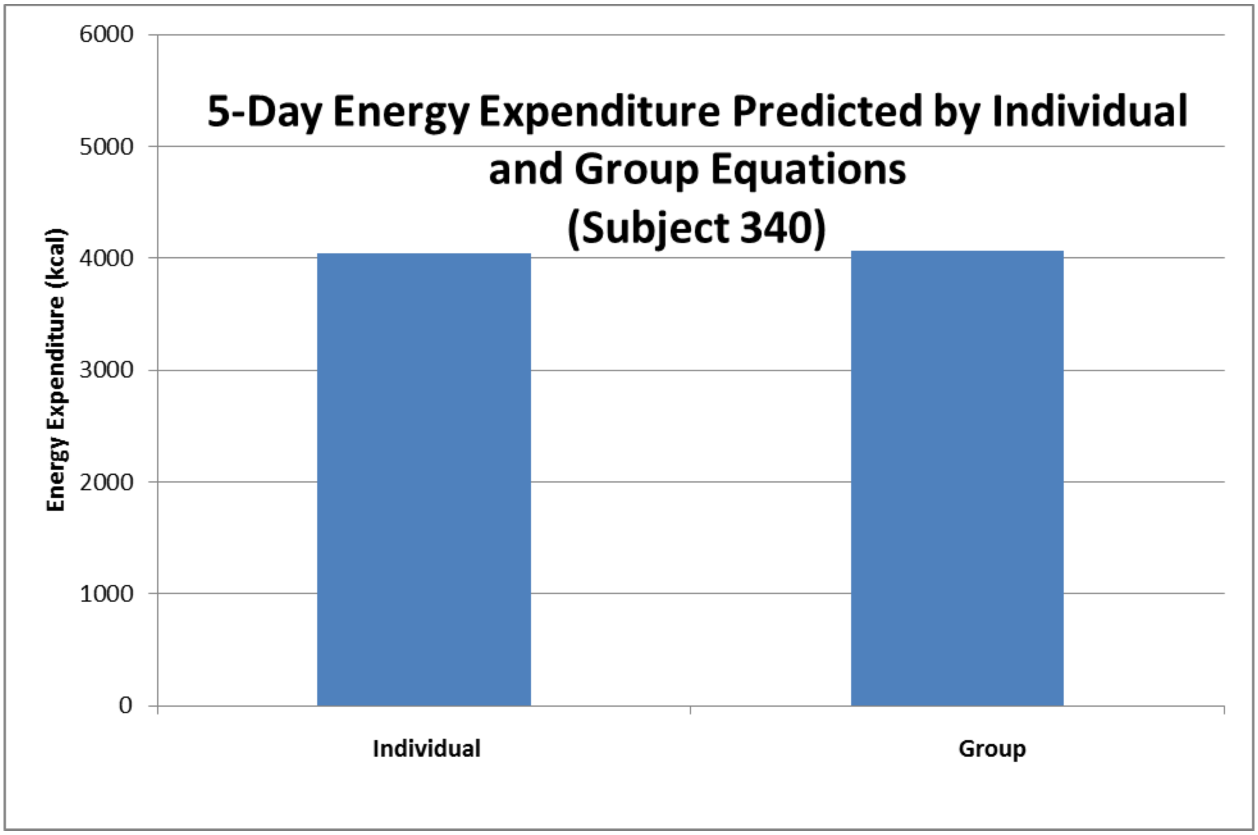

Figure 3: Comparison of total energy expenditure predicted by the two methods (individually calibrated prediction equation compared to group-level prediction equation) for a single subject over a complete 5-day work week. Energy expenditure was predicted for each minture during the monitoring period (time at work) and summed for the 5-day period. Total energy expenditure according to the indvidually calibrated equation was 4045.3 kcal, compared to 4068.2 for the group equation. The difference was not significantly different ($p<0.05$).

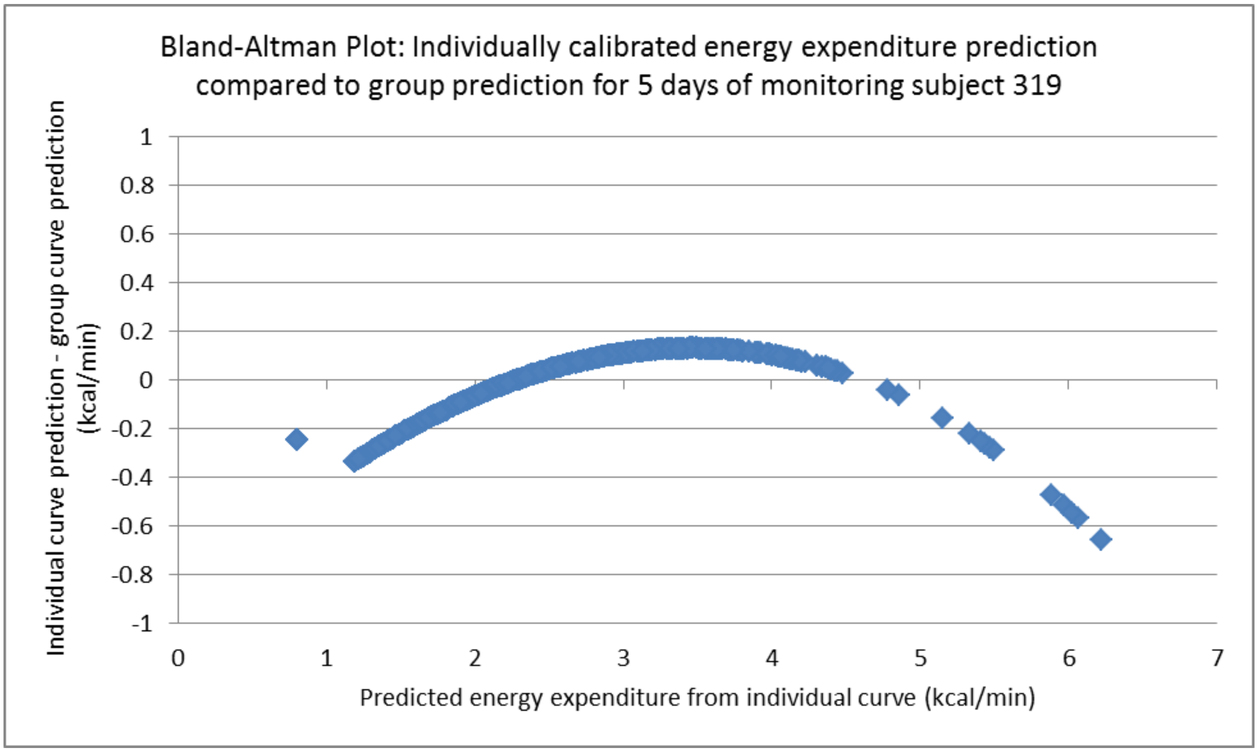

Figure 4: Plot of the difference between the individually calibrated prediction equation and the group-level prediction equation across the complete range of energy expenditure for a single subject for a 5-day monitoring period. A single subject was monitored during the work period over the course of five days with minute-by-minute energy expenditure predicted by both methodologies.

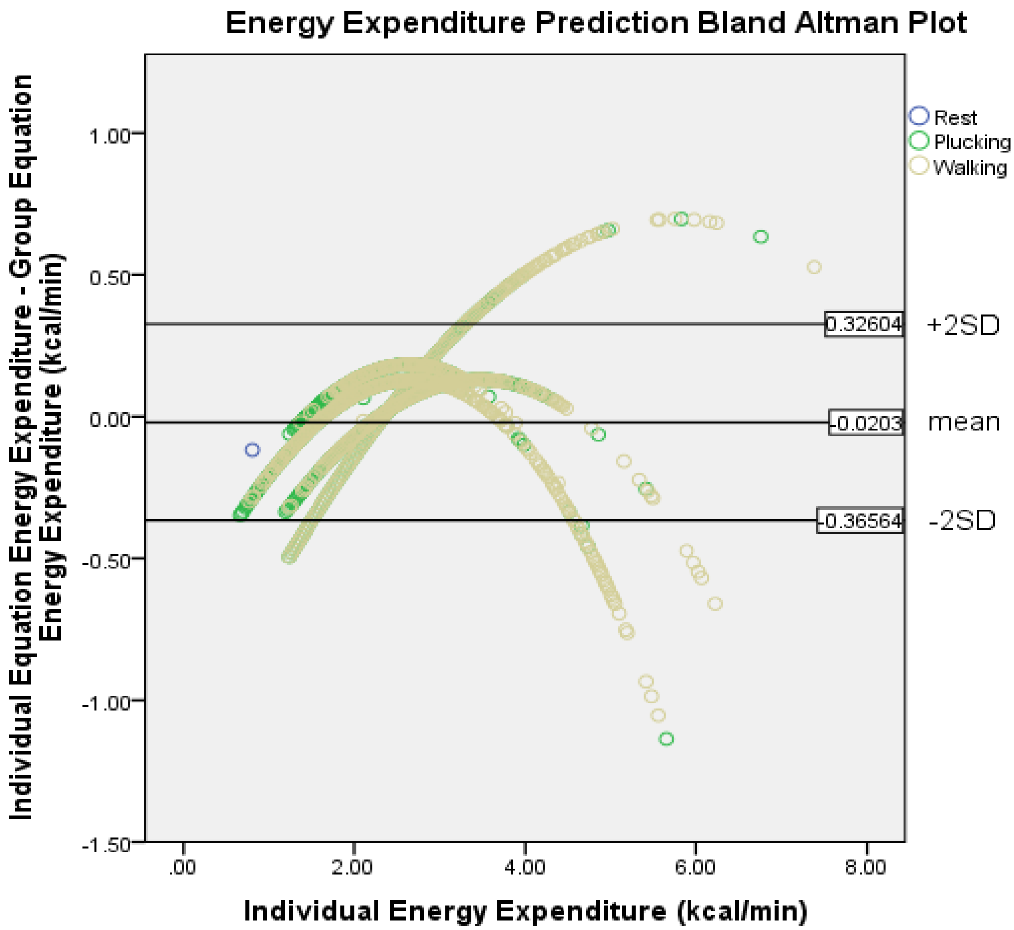

Figure 5: Bland-Altman plot comparing minute-by-minute energy expenditure for four subjects comparing group and individual prediction equations during three activity types. Activity type was determined using physical activity monitors. Energy expenditure was predicted by both methods for each minute of activity for each of the four subjects during the work day for five consecutive days.