Prediction of Non-Resting Energy Expenditure using Accelerometry

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ACADEMIC ABSTRACT

The accurate measurement of total energy expenditure is a cornerstone of metabolic research. However, there is a lack of measurement methods that are valid, objective, inexpensive, and easy to use. Accelerometry, along with validated prediction equations for resting energy requirements, may provide an opportunity to fill this void. Twenty weight stable adults (12 female, 8 male) who recently participated in a controlled feeding study comprised the study sample. Total energy requirements were assessed from the controlled feeding period in which weight stability was achieved using the intake-balance method. Resting energy expenditure was assessed using the Mifflin-St. Jeor equation. Participants wore accelerometers to objectively assess habitual physical activity. The accelerometer data obtained along with subjects' demographic and biometric data were used to predict non-resting energy expenditure (NREE) using step-wise linear regression in JMP. Bland-Altman plots and Spearman's Rho correlations were used to determine the validity of the total energy requirements obtained from the sum of the predicted non-resting energy expenditure and measured resting energy expenditure. Estimated resting energy expenditure was compared with the total energy requirements assessed using the intake-balance method from the controlled feeding period. The resulting prediction equation is as follows: 480.93 – 180.69(sex) + 0.21(Accelerometer kcals) + 617.98(BF%) = NREE. The sex was coded as 1 for females and 0 for males. This prediction model has a coefficient of determination of 0.74 (0.70 adjusted). On average, the model overestimates NREE by 76 kcals. This new model could be the key to accurately, inexpensively and objectively measuring total energy requirements.

GENERAL AUDIENCE ABSTRACT

Accurate measurement of the total amount of energy (i.e. calories) utilized by the body throughout the day, also known as total energy expenditure, is a vital component of metabolic research. However, there is a lack of measurement methods that are valid, objective, inexpensive, and easy to use. Accelerometers combined with equations designed to predict total energy expenditure may be able to fill this gap. Accelerometers are devices worn on the body that measure accelerative forces from physical activity. Twenty weight stable adults (12 female, 8 male), who recently participated in a study in which all dietary intake and exercise were closely monitored (controlled feeding study), comprised the study sample. The amount of energy needed to maintain weight (total energy requirements) was assessed from the controlled feeding period in which weight stability was achieved. Resting energy expenditure, the energy burned while the body is at rest, was assessed using an equation often used to estimate energy expenditure, the Mifflin-St. Jeor equation. Participants wore accelerometers to objectively assess habitual physical activity. The accelerometer data obtained along with subjects' demographic (age, sex) and biometric (height, weight, BMI, etc.) data were used to predict non-resting energy expenditure (resting energy expenditure subtracted from total energy expenditure). Multiple statistical tests were used to determine the validity of the total energy requirements obtained from the sum of the predicted non-resting energy expenditure (NREE) and resting energy expenditure. Estimated resting energy expenditure was compared with the total energy requirements assessed using the intake-balance method from the controlled feeding period. The resulting prediction equation is as follows: 480.93 – 180.69(sex) + 0.21(Accelerometer kcals) + 617.98(BF%) = NREE. The sex was coded as 1

for females and 0 for males. This prediction model has a coefficient of determination of 0.74 (0.70 adjusted), which means 70% of the variation in non-resting energy expenditure was explained by changes in the variables in the equation. On average, the model overestimates NREE by 76 Calories per day. This new model could be the key to accurately, inexpensively and objectively measuring total energy requirements.

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TABLE OF CONTENTS

Abstract

Academic

General Audience

Acknowledgements vi

Literature Review 1

Introduction 1

Components of Total Energy Expenditure 1

Sources of Dietary Energy 4

Energy Balance 5

Energy Intake Recommendations 6

Measurement of Energy Expenditure 7

Energy Balance and Obesity 13

Literature Review Conclusions 13

Methods 14

Table 1 18

Results 20

Table 2 21

Figure 1 22

Table 3 23

Table 4 24

Figure 2 26

Figure 3 28

Figure 4 29

Discussion 29

References 32

LITERATURE REVIEW

Introduction

Accurately measuring human energy requirements is a cornerstone of metabolic research. Total energy requirement for each person is the amount of energy intake needed to equal energy expenditure, allowing for maintenance of body weight and composition along with enough physical activity to maintain good health for the long term.[1]

Energy balance is achieved when energy intake and energy expenditure are equivalent. The amount of energy needed to maintain a stable body weight (i.e. energy requirements) can be determined under these conditions by measuring or estimating the number of calories expended. When energy intake is greater than energy expenditure, weight gain is the result. If weight gain is a desired outcome, then energy intake needs to exceed energy requirements. In contrast, when energy intake is lower than energy expenditure, weight loss is the result. If weight loss is desired, then energy intake needs to be less than energy requirements.

Components of Total Energy Expenditure

Total energy expenditure (TEE) is comprised of four components: resting energy expenditure (REE), the thermic effect of food (TEF), energy expenditure of physical activity (PAEE), and non-exercise activity thermogenesis (NEAT).

Resting Energy Expenditure

Resting energy expenditure (REE) is the minimum energy required to maintain necessary homeostatic processes while at rest.[2] Resting energy expenditure is often the largest portion of total energy expenditure, especially when physical activity levels are low. There are many factors that contribute to variations in individual REE. The most significant factor is fat free mass (FFM). Levels of FFM explained 63% of the variation in REE.[3] FFM, particularly muscle tissue, is highly metabolically active. A person with greater muscle mass burns more energy while at rest. Age and total body fat levels affect REE, explaining 6% and 2% of variance, respectively. Sex is not a significant predictor for REE.[3]

Physical Activity Energy Expenditure

Physical activity energy expenditure (PAEE) is the amount of energy burned through organized physical activity throughout a day. PAEE has more inter- and intrapersonal variation than any other contributing factor to TEE. An active lifestyle results in greater PAEE, while a sedentary lifestyle includes little to no PAEE. This is why physically active individuals burn more energy than sedentary people. Individual PAEE levels are not constant. Altering physical activity habits can quickly increase or decrease PAEE.[4]

Non-Exercise Activity Thermogenesis

The energy from any movement that is not organized physical activity is called non-exercise activity thermogenesis (NEAT).[2] NEAT and PAEE are both forms of energy burned through movement. NEAT includes everything that is not encompassed by PAEE. This includes such activity as fidgeting, walking to the mailbox, mowing the lawn, typing, etc. There is significant variance in NEAT levels between individuals. The biological factors that affect NEAT are the same as those that affect PAEE (body composition and age). NEAT is also determined by environmental factors. Some environments are more conducive to these activities (having to walk to work/school, having a lawn to mow, active job), while others are not.[5]

Thermic Effect of Food

The energy lost during digestion of food and the absorption/storage of nutrients consumed through the diet is called the thermic effect of food (TEF). Metabolic processes are not perfectly efficient, so some energy is lost as heat when nutrients are being processed. TEF is usually fairly constant between 8-15% of total energy expenditure.[2] Diet volume and composition determine how much energy is burned through TEF. Consuming more food and more energy results in a higher TEF. Different macronutrients (carbohydrates, fat, and protein) require varying amounts of energy to digest and store. The greatest thermic effect comes from protein, followed by carbohydrates, and finally fat. The thermic effect of protein is approximately three times higher than that of carbohydrates, while fats result in essentially no thermic effect.[6]

Non-Resting Energy Expenditure

Non-resting energy expenditure (NREE) is equal to resting energy expenditure subtracted from total energy expenditure. The term is used to encompass physical activity energy expenditure, NEAT, and TEF.

Sources of Dietary Energy

Dietary energy is necessary to fuel metabolic and physiological functions. This energy comes in the form of chemical energy in macronutrients (carbohydrates, fat, and protein). After digestion of food, the chemical energy can be converted to mechanical energy, thermic energy, etc. Energy need is the total amount of energy that must be consumed to maintain homeostatic processes and daily activities. Total energy intake (TEI) is the sum of all the energy consumed from all macronutrients throughout the day. This number must meet energy needs to avoid starvation. TEI represents the amount of energy that is available for all metabolic processes in the body.[7]

Carbohydrates

Each gram of carbohydrate contains 4 Calories. Carbohydrates come in many forms (sugars, starches, fibers, etc.) that all share a similar chemical makeup. If energy is needed upon ingestion, carbohydrates undergo glycolysis and are converted to energy. If energy is not needed upon ingestion, carbohydrates undergo glycogenesis and are stored as glycogen. Carbohydrates are used as energy during rest and exercise. Carbohydrates are the most readily available energy source, making it the preferred energy source, particularly for intense exercise. It is the only macronutrient that can provide quick energy, so increasing exercise intensities result in a greater need for carbohydrates.[8,9]

Fat

Each gram of fat contains 9 Calories. Fat in the diet is mostly consumed in the form of triglycerides. Like carbohydrates, triglycerides can be stored or used as energy.

Triglycerides can be broken down into free fatty acids, which are utilized as energy or stored in the liver. They can also be stored as body fat for later use. Fat is the most efficient source of energy because negligible energy is wasted during the processing of triglycerides. Triglycerides have the ability to provide steady energy over long durations. However, energy is not quickly available, making it the second option as an energy source in most scenarios. Fat is used preferentially during long bouts of low intensity exercise.[8,10]

Protein

Proteins contain 4 Calories per gram. Proteins consist of chains of amino acids. These amino acids are not efficiently used for energy and are unable to be stored for later use. They are preferentially used for other purposes, the most common being tissue formation and repair. Protein is only utilized for energy during times of starvation in which carbohydrates and fat are unavailable. The processing of amino acids into energy is incredibly inefficient. The process requires almost as much energy as is produced.[11,12] Proteins are used so sparingly (under normal conditions) that it is often ignored during calculations of energy expenditure.[13]

Energy Balance

Energy balance is a primary foundation in the field of nutritional research. When energy balance is achieved, TEE is equivalent to TEI (energy in equals energy out). Under these conditions, bodyweight maintenance is observed. This allows for the calculation of TEE given TEI and vice versa, when bodyweight is stable. Given a diet of known energy content along with weight stability, subjects' TEE can be determined. Given measurements of energy expenditure along with weight stability, subjects' TEI can be calculated.[14,15]

The concept of energy balance also allows for calculations of TEE and TEI when bodyweight is not stable. When bodyweight is increasing, TEI is greater than TEE. When bodyweight is decreasing, the opposite is true. A difference of 500 Calories per day (TEE vs. TEI) results in a gain or loss of 1lb per week.[16] The average rate of bodyweight gain/loss allows for the calculation of TEE from known TEI or vice versa.[15]

Energy Intake Recommendations

Due to extreme variations in energy expenditure between individuals, there cannot be an all-encompassing energy intake recommendation. Resting energy expenditure by itself can be accurately estimated using age, body mass, and body composition.[3] However, huge variations in PAEE cause very different TEE levels for people of the same age, body mass, body composition, etc.[4]

Physical Activity Levels

Physical activity levels (PALs) are a scale of multipliers that are used to estimate energy needs. PALs are multiplied by calculated REE to establish an estimate of energy needed to obtain energy balance. A higher PAL reflects a more active lifestyle and a lower one reflects more sedentary habits. The scale of physiologically sustainable PALs in free living adults ranges from 1.40-2.40. The average PAL for adults is approximately 1.60. PALs of 1.50-1.69 are known as sedentary to lightly active lifestyle, 1.70-1.99 corresponds to moderate activity levels, while 2.00-2.40 is indicative of a vigorously active lifestyle. A higher PAL is conducive to healthier weight and lower risk of many diseases.[17]

Measurement of Energy Expenditure

There are a variety of available methods to calculate energy expenditure, each with its own set of pros and cons. Some methods are objective, such as doubly labeled water, direct and indirect calorimetry, heart rate monitoring, the intake balance method, and accelerometry. These methods tend to be more expensive and/or less practical for everyday use, but are more accurate and precise.[18,19] Other methods are more subjective, such as estimation equations and physical activity surveys. These methods tend to be cheap and easy to use, but have lower accuracy and precision.[20-22]

Doubly Labeled Water

Doubly labeled water is heralded as the most accurate and reliable method for measuring energy expenditure, which also makes it the most expensive. It has been repeatedly shown to have accuracy within 1-2% and precision of 5-7%.[23] Doubly labeled water contains water molecules with stable of hydrogen and oxygen isotopes, ^{2}H and ^{18}O. These isotopes are consumed just like normal water. Elimination rates of both isotopes are measured. ^{2}H is lost as water and ^{18}O is lost as water and CO_2. The rate of losses of these molecules are able to be converted into an accurate approximation of total energy expenditure.[23,24] Water lost from sweating can cause small inaccuracies in this method because sweating is not directly related to metabolism.[23]

Direct Calorimetry

Direct calorimetry is another contender for gold standard of energy expenditure measurement. Direct calorimetry, as the name suggests, directly measures heat exchange from the body to the environment and vice versa. A totally insulated room is used to ensure no outside heat exchange affects the measurement. More energy expended by the body results in more heat released because all catabolic processes create heat as a by-product. This is the basic principle behind direct calorimetry. The rate of release of heat can be converted into an energy expenditure measurement.[25]

Indirect Calorimetry

Indirect calorimetry is the most frequently used energy expenditure measurement method among researchers. This method is less invasive than doubly labeled water and direct calorimetry. Indirect calorimetry is used to measure oxygen utilization and carbon dioxide production. Subjects wear a hood or mask that prevents outside air from entering. Rates of production of carbon dioxide and consumption of oxygen are measured constantly. These data are converted into an estimation of energy expenditure. Since oxygen is needed for energy production and carbon dioxide is a by-product, greater intake and production means more energy is being expended. Urinary nitrogen levels are the final part of the calculation. However, the contribution is so small, usually only 1-2% of total measured expenditure, that urinary nitrogen is usually excluded. The respiratory exchange ratio (RER) is the ratio of total carbon dioxide expelled to total consumed oxygen. This is used to determine which macronutrients (fat and carbohydrates) are being used, and in what ratio. Carbohydrate utilization results in a 1:1 ratio of oxygen consumed to carbon dioxide expelled, thus making the RER 1.0. For fat utilization, the RER is roughly 0.7. The exact ratio allows for estimate of how much of each macronutrient is being utilized. This is the only method that allows for an estimate of macronutrient utilization.[26]

Intake Balance Method

The intake balance method is by far the most labor-intensive method of all. It is based on the fact that bodyweight is stable when energy intake and expenditure are equivalent. Under conditions of weight maintenance, energy expenditure can be inferred from energy intake, and vice versa. When a diet of predetermined energy content is provided, energy expenditure can be estimated. Researchers conduct a controlled feeding diet with participants, meaning that all the subjects' food is provided and intake is measured as precisely and accurately as possible. Once a controlled diet is established that results in weight maintenance, energy expenditure is determined to be equal to the caloric content of the diet. The standard for "weight maintenance" is no greater than a +/- 1kg fluctuation for a period of 10 days. This entire process can take weeks to complete. The costs of food along with laboratory equipment and personnel can be very high. This requires a research facility with adequate funding, reliable equipment, and trained personnel to ensure accuracy of energy expenditure estimations.[27] When conducted properly, the intake balance method measures total energy expenditure within 0.3% of the gold standard, doubly labeled water. The main limitation of this method is the bodyweight variations that can come from altered hydration status. A change in the amount of water the body is holding does not reflect a change in energy intake, but bodyweight variations would still be observed. This could potentially lead to inaccurate results when interpreting weight stability.[28]

Accelerometry

Accelerometers are wearable devices that measure physical activity by registering accelerative forces. They allow for portable, objective measurement of physical activity. Accelerometers are usually attached at the hip and worn throughout the day to measure all activity. This makes accelerometers a go to measurement tool for a lot of researchers. Accelerometers can measure total physical activity, intensity of physical activity, step counts, and active/sedentary time. All of this data is used to calculate an estimate of physical activity energy expenditure.[29] Accelerometers are more convenient, cheap, and noninvasive than other objective measurement techniques. They also provide a clear boost in reliability over more subjective measurement methods.[30,31] However, accelerometers are not perfect. Accelerometers overestimate energy expenditure for treadmill walking/running by 9% and underestimate by 34% the activities of daily living when contrasted with indirect calorimetry. Activities with greater upper body motion, which are likely to be missed by hip mounted accelerometers, are underestimated by 24-64%. Accelerometers overestimated physical activity energy expenditure by 15% when compared to doubly labeled water. Accelerometers are also unable to account for weight-bearing exercise. These inaccuracies are all likely due to certain movements and static forces that cannot be registered by the accelerometer.[31]

Surveys

The use of surveys to estimate energy intake and/or expenditure is the most subjective available method. This method allows for quick data collection from a large sample of people. Quick and impersonal collection causes it to be the least accurate and precise method. These surveys consist of a set of questions pertaining to daily food intake and/or physical activity habits. Researchers use the survey answers to better understand how much energy subjects consume and/or how much energy they expend from physical activity. From this, conclusions are drawn as to how much energy a person consumes and how much he or she expends. The main problem, as previously stated, is the inaccuracies that are inevitable with such a subjective measurement method. People tend to, on average, underreport energy intake. Approximately 30% of people underreport energy intake, with intake being underreported by 15% on average.[32] Overweight and obese people present an even bigger problem, with approximately 72% of this population underreporting energy intake.[33] Participants may underreport their energy intake by as much as 800 Calories/day.[34] Physical activity surveys also suffer from similar misreporting errors. Correlations between long-term habitual physical activity recalls and accelerometer-measured physical activity were low, only 0.14-0.36. One week physical activity recalls allowed for shorter and more specific reporting, resulting in correlations between 0.50-0.53. Neither of these correlations is high enough to reasonably conclude that self-reported physical activity is a reliable way to measure physical activity.[35]

Prediction Equations

Prediction equations are likely the most commonly used method amongst researchers and health professionals. There are a variety of available equations, each created from a different study using a different sample population. The Mifflin-St. Jeor equation is one of the most common prediction equations. It was created from a sample size of 498 (247 female, 251 male) adult (aged 19-78 years) subjects who were both normal weight (n=264) and obese (n=234).[36] Every equation uses demographic and biometric variables to predict resting energy expenditure. Self-reported physical activity is used along with these other variables to predict total energy expenditure.[37,38] Mifflin-St. Jeor uses self-reported physical activity expenditure along with weight, height, age, and sex. Self-reported physical activity is converted to what is called a "physical activity level" or an "activity factor." The activity factor is a number that is multiplied by REE to come up with a prediction for total energy expenditure. The more active the subject is, the higher the activity factor.[36] Objective variables are used to estimate REE, while a subjective variable is used to predict total energy expenditure. This is why these equations, particularly the Mifflin-St. Jeor equation, predict REE accurately, but struggle to do the same with total energy expenditure.[37-39] The Mifflin-St. Jeor equation predicted REE accurately (within 10% of actual REE) 68% of the time with a bias of -1.8% for normal weight to obese women. It typically slightly underestimated REE in overweight women, which may actually be beneficial with those trying to lose weight. The Mifflin-St. Jeor equation was not able to accurately predict REE in morbidly obese subjects (BMI of greater than 45).[38] Mifflin-St. Jeor accurately predicted REE 79% of the time with -1.0% bias in overweight and obese adults. It was only consistently accurate for subjects with a BMI of less than 40.[37] No other commonly used equations significantly outperformed the Mifflin-St. Jeor equation in predicting REE in a population consisting of normal weight, overweight, and obese adults.[37-39] There is no equation that is consistently accurate in predicting REE in a morbidly obese population.[37,39] No equations were able to reliably predict total energy expenditure. This is due to inaccurate self-reported physical activity levels.[39] The subjectivity of self-reported physical activity is the only significant problem with these equations, including Mifflin-St. Jeor.

Energy Balance and Obesity

Chronic energy surplus can result in unhealthy weight gain and obesity. Obesity is an epidemic in the United States today. Obesity and associated diseases are responsible for millions of deaths annually.[40-43] Understanding treatment and prevention methods for this disease is vital for nutrition professionals. Understanding energy needs is a cornerstone to treating and preventing obesity. Avoiding or reversing chronic energy surplus can prevent weight gain or spur weight loss.

LITERATURE REVIEW CONCLUSIONS

Controlled feeding studies are able to accurately determine total energy expenditure.[28] This meant the controlled feeding study already conducted could be used to calculate energy expenditure for every subject. Weight maintenance for the subjects indicated that their daily energy intake was equal to total energy expenditure.

The current energy expenditure estimation equations, including Mifflin-ST. Jeor, were not reliable in predicting total energy expenditure. This is due to the subjectivity and inaccuracy of self-reported physical activity levels used to predict PAEE.[39] This demonstrated a clear need for an improved and more objective way to estimate habitual physical activity levels. Accelerometers are a more objective and relatively easy to use measurement that can replace self-reported physical activity.[30,31] A combination of accelerometer-measured and biometric/demographic variables could be better used to predict energy expenditure, particularly non-resting energy expenditure (NREE).

Accurate energy expenditure estimations allow for more accurate dietary recommendations for weight loss, maintenance, or gain. This is particularly important for the significant number of overweight and obese individuals. Better energy intake recommendations for weight loss in these overweight/obese individuals can be a good first step toward achieving a healthy weight. A better understanding of total energy expenditure, and thus total energy requirements, could also lead to more productive future metabolic research.

The overall goal of the current study is to determine if accelerometry and demographic/biometric variables can be used to predict non-resting energy expenditure. It is hypothesized that physical activity measured by accelerometry along with demographic and biometric variables will be predictive of non-resting energy expenditure derived from the difference of total energy expenditure using the intake-balance method and estimated resting energy expenditure from Mifflin-St. Jeor.

METHODS

Measurements

A previously conducted study was used as the basis for this study. In the previous study, 20 participants volunteered for a six week controlled feeding study. This study was carried out to determine the effects of inulin supplementation on cardiometabolic health. Participants were split into 2 separate groups; the first was given inulin and the second was given a placebo.[45] For the current study, all participants were grouped together.

Bodyweight was recorded each morning when participants picked up food for the day. Most participants were not able to make it to the lab every morning, so bodyweight was not measured every day. Bodyweight was measured on a digital scale that was accurate within 0.1kg. Height was measured by a stadiometer mounted on a scale (SCALE-TRONIX Inc.; White Planes, New York). Body fat and lean body mass was determined via dual energy x-ray absorptiometry (Prodigy Advance, GE Healthcare) by a qualified radiological technician.[45]

Dietary intake at baseline (total energy intake and macronutrient composition) was determined using food intake records over a span of 4 days. Participants were briefed on how to accurately measure and record food intake. Sizing charts were provided to help with estimating portion sizes. Returned diet records were reviewed with participants to ensure accuracy and completeness. Trained research personnel then analyzed the diet records using software called NDS-R (v. 2014) to determine energy and macronutrient content of the diet.[45]

The Mifflin-St. Jeor equation was chosen as the method for estimating participants' energy requirements. Resting energy expenditure was determined using age, height, weight, and sex. Non-resting energy expenditure was determined by self-reported physical activity. This was correlated with an activity factor, a multiplier that is combined with resting energy expenditure in order to estimate total energy expenditure.[44,45] The activity factors used come from the Mifflin-St. Jeor equation.[37] All of these data points were recorded before the study began.

The intake balance method was utilized to ensure participants were weight stable throughout the 6 week controlled feeding study. Calories provided were as close as possible to the estimated total energy expenditure using the Mifflin-St. Jeor equation. Diets were prescribed in 500 kcal increments between 1500-3000 kcals. Everything participants consumed was provided and monitored closely to ensure caloric intake was measured as accurately as possible. All foods provided were weighed to ensure optimal accuracy. Breakfast was supervised daily while other food was provided for participants to consume on their own. Returned food was weighed to determine exactly how much food, and thus how many kcals, were consumed. Bodyweight was measured daily for every participant. If daily bodyweight was not stable (varied by more than +/-3lbs), prescribed kcals were adjusted by adding /subtracting 250 kcal snacks until bodyweight stabilized. Along with bodyweight, body fat percentage was measured for each participant before and after the six weeks of controlled feeding to ensure there were no significant changes.[44,45]

Participants' self-reported physical activity levels were estimated during screening using the Godin Leisure Time Questionnaire to ensure physical activity requirements were met. Participants' physical activity habits were measured during the intervention using a triaxial Actigraph GT3x accelerometer. A triaxial accelerometer can measure acceleration in all three planes. The accelerometer was mounted on the right hip. Wear time included two separate four-day stretches (three days during the workweek and one day during the weekend) in order to adequately observe typical physical activity habits. The accelerometers recorded at 60s epochs (one measurement per minute). The data from the two four-day wear times were averaged to create one set of accelerometer data points to use for each participant. Data was analyzed using the Freedson cut-point equations.[44-46] These accelerometers were used to objectively measure variables such as total physical activity, intensity of physical activity, step counts, and active/sedentary time. A mean and standard deviation was measured for every available variable.

Participants' actual total energy expenditures were inferred from energy requirements determined via intake balance. The resting energy expenditures calculated using the Mifflin-St. Jeor equation were determined to be accurate. Actual non-resting energy expenditure was estimated by subtracting calculated resting energy expenditure from total energy expenditure. This known value for non-resting energy expenditure became the value for which the prediction model was made. The model was created to predict known non-resting energy expenditures as accurately and precisely as possible.

Participants

Twenty sedentary, overweight/obese adults served as participants in this study. The study sample consisted of 12 females and 8 males. BMI of the sample ranged from 26-38 kg/m^2 (31 +/- 3 kg/m^2). Adults aged 40-75 years (55 +/- 8 years) were eligible for inclusion in the study. Participants engaged in physical activity no more than twice per week for 20 minutes per day for the previous year. Weight stability (+/- 2.5kg) must have been maintained 6 months or more before initiation of the study. Participants had a BMI in the range from 25-40 kg/m^2. Participants had prediabetes or were at increased risk for developing diabetes. Blood pressure of ≤160/100 mmHg, total blood cholesterol of ≤300 mg/dL, and blood triglyceride levels of ≤450 mg/dL were all required for inclusion.[44,45]

Inclusion/exclusion criteria are organized into Table 1. A comprehensive list of participant characteristics can be found in Table 2.

Table 1: Participation Criteria for Inclusion/Exclusion

Inclusion Criteria	**Exclusion Criteria**
1. Population: Aged 40-75, men and women 2. Sedentary (Self-reported physical activity < 20 min/day, ≤ 2 days/week) 3. BMI: 25–40 kg/m2 4. Weight Stable for ≥ 6 months 5. Prediabetic/at risk for diabetes: ADA Screener ≥ score of 5, HbA1c value 5.7–6.4 mg/dl, FBG value 100–125 mg/dl, and/or OGTT result between 140–200 mg/dl 6. Permission from doctor for subjects with coronary heart disease (CHD) 7. Blood Pressure reading greater than 160/100 mm/Hg 8. Total Blood Cholesterol greater than 300 mg/dl 9. Blood triglycerides greater than 450 mg/dl	• Smoking • Taking diabetes medication (insulin, metformin, etc.) or diagnosed with diabetes • Past diagnoses of respiratory disease, uncontrolled CHD, IBD, various cancers, brain or blood disorders, or abuse of drugs • Taken antibiotics within three mos. • Involvement in any outside research study • Current or intended pregnancy • Currently taking antioxidant/fiber supplements or NSAIDs • Recent surgical procedure • Food allergies/intolerances or other dietary restrictions (religious or cultural)

Materials

Microsoft Excel 2011 was used to compile all available data from qualifying participants. The statistical program, JMP (JMP Pro 13. SAS Institute Inc., Cary, NC, 1989-2019). was used to conduct all statistical tests. The Freedson cut point equations were used to analyze accelerometer data.[46] No materials outside of a computer with these programs was used in the study.

Statistical Analyses

Data from all participants who completed the previous controlled feeding study was included in the analysis. Subjects' daily bodyweights were evaluated to assure bodyweight variation was not statistically significant. To do this, the slope of bodyweight vs. day was calculated for each subject. The average slope was -0.088 +/- 0.093, which was not statistically significantly different from zero. Next, the coefficient of variation for each participant's bodyweight was calculated. If the absolute value of the slope was greater than the coefficient of variation, then the slope was statistically significantly different from zero, thus meaning bodyweight was not stable. This was not the case for any of the twenty participants, meaning all of them were considered weight stable. A plot of participants' bodyweight vs. day is shown in Figure 1.

Pearson correlation coefficients were calculated for every pair of variables in order to identify potential collinearities. Collinear variables were not both able to be included in the final model. The stepwise regression analysis tested all possible combinations of variables to determine which were the best at predicting non-resting energy expenditure. One or more accelerometer variables (total physical activity, intensity of physical activity, step counts, active/sedentary time, and energy expenditure) and one or more demographic/biometric variables (height, weight, BMI, age, body composition, sex, etc.) were required for inclusion in the model. The best set of variables was used in the final prediction model.

An alpha level of 0.05 was used as one of the inclusion criterion. Adjusted R^2 (coefficient of determination) was also used to determine which potential prediction model was best. The coefficient of determination explains exactly how much of the variation in the dependent variable (non-resting energy expenditure) was explained by the variation in the predictor variables. The Statistical Applications and Innovations Group (SAIG) at Virginia Tech assisted in conducting many statistical tests.

A Bland-Altman plot was created to compare non-resting energy expenditure predictions from the model to the measured non-resting energy expenditure from the intake balance method. Bias, limits of agreement, and data point trends were all analyzed to determine how accurately the model predicts non-resting energy expenditure. A Bland-Altman plot was then created to compare non-resting energy expenditure predictions from accelerometry to the measurements using the intake balance method. The two plots were compared to ensure that the prediction model is able to more accurately predict non-resting energy expenditure than accelerometry on its own.

RESULTS

Table 2 displays all relevant participant characteristics.

Table 2: Participant Characteristics

Variable	Value
Age (years)	55 +/- 8
Sex (female, male)	12, 8
Bodyweight (lbs)	196.4 +/- 25.6
Bodyweight Variation (lbs)	5.2 +/- 1.3
Body Fat Percentage (%)	41.3 +/- 8.0
BMI (kg/m^2)	31 +/- 3
Fat-Free Mass (lbs)	122.0 +/- 3.6
Height (in)	66.4 +/- 4.0
Participant Total Energy Expenditure (kcals/day)	2357 +/- 399
Participant Non-Resting Energy Expenditure (kcals/day)	785 +/- 196
Baseline Total Energy Intake (kcals/day)	2084 +/- 539

Figure 1 below displays a graph of bodyweight vs. day for all participants.

Figure 1: Stability of Participants' Bodyweight Throughout the Intervention Period

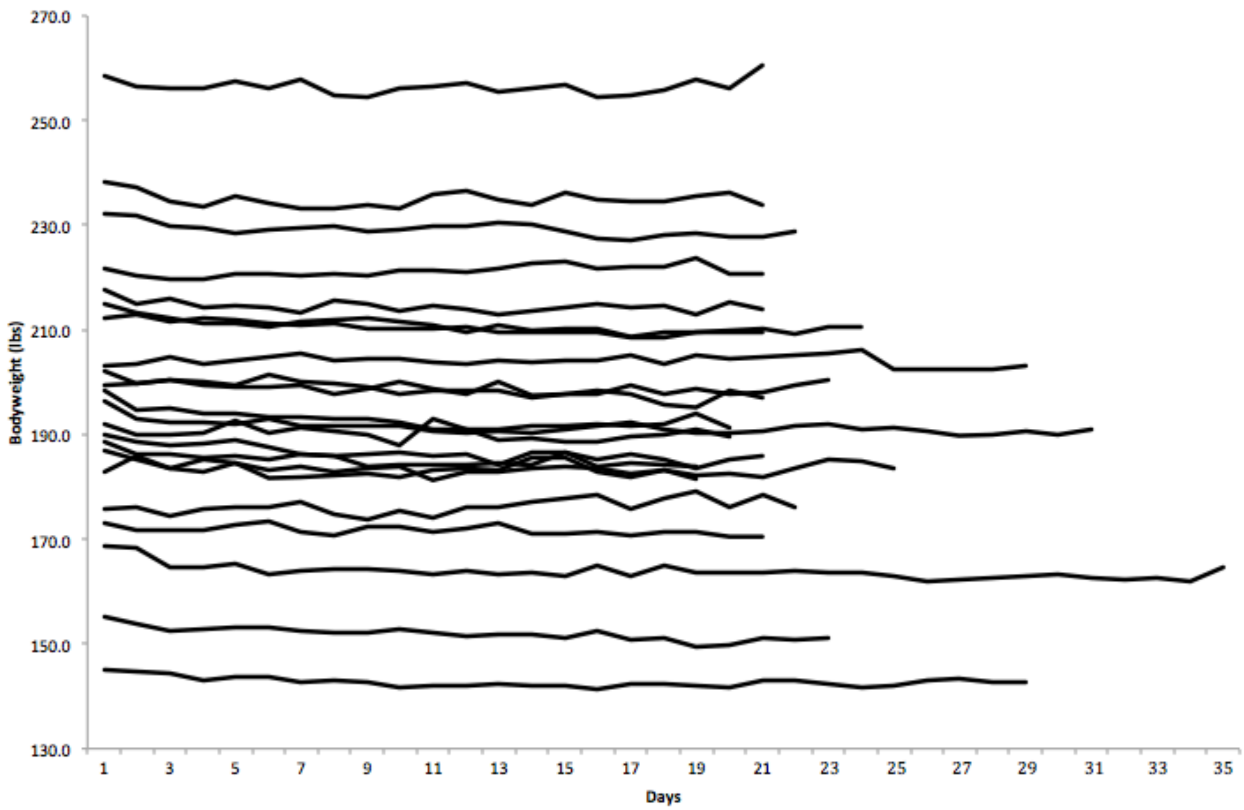

Figure 1: This line graph shows how participants' bodyweight changed throughout the controlled feeding portion of the study. Each line represents one participant. Total days for each participant represent the number of days they had their bodyweight measured in the lab.

The final prediction model includes body fat percentage (BF%), sex, accelerometer measured energy expenditure (accelerometer kcals), and a constant term. The variables included in the model along with their estimates and significance levels are included in Table 3.

Table 3: Estimate, Error, and Significance Level of Terms Included in the Prediction Model

Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**
Intercept	480.93063	239.5659	2.01	0.0599
Average Accelerometer kcals	0.2072381	0.078646	2.64	0.0168
Sex [female]	-180.6945	52.16512	-3.46	0.0028
Body Fat Percentage	617.97936	616.2246	1.00	0.3292

Table 3: The values in the Estimate column are the multipliers combined with each variable in the equation. The Standard Error column includes measures of statistical accuracy of each variable. The t Ratio and Prob>|t| columns display the statistical significance of each variable when included in the model.

This model written in the form of an equation is as follows:

$$480.93 - 180.69(\text{sex}) + 0.21(\text{Accelerometer kcals}) + 617.98(\text{BF\%}) = \text{NREE}$$

The sex term is entered as 1 for women and 0 for men. This takes into consideration the tendency for women to have lower non-resting energy expenditure than men. The units for both "Accelerometer kcals" and "NREE" are kcals/day. Body fat percentage is entered as a decimal.

The significance value for this model as a whole is <0.0001. As can be seen in Figure 2, the significance level was 0.017 for accelerometer kcals, 0.0028 for sex, 0.33 for BF%, and 0.060 for the constant term. These values represent the probability of rejecting a true null hypothesis, in this case that these variables are not correlated with non-resting energy expenditure. Accelerometer kcals and sex were able to statistically significantly predict measured NREE individually (significance of <0.05), while the constant and BF% were not (significance of >0.05). However, the addition of each of these variables, regardless of individual significance level, improved the significance level and coefficient of determination (R^2) value for the model as a whole. R^2 can be found below in Table 4.

Table 4: Summary of the Prediction Model's Ability to Predict NREE

R^2 (Coefficient of Determination)	0.742414
Adjusted R^2	0.699483
Root Mean Square Error	112.0807
Mean of Response	784.1283

Table 4: This table includes data that describes how well the model predicts actual non-resting energy expenditure.

For this model, $R^2 = 0.74$. However, adjusted R^2 is more reliable because it accounts for how many variables are used in the model. The more variables needed, the greater the decrease in adjusted R^2. The adjusted R^2 for this model is approximately 0.70, indicating 70% of the variation in non-resting energy expenditure was explained by variation in the predictors (BF%, sex, and accelerometer kcals). This R^2 value is considered strong and is comparable to the R^2 value found for resting energy expenditure predictions using the Mifflin-St. Jeor equation.[37]

The root mean square error is the square root of the average of all the errors (measured NREE subtracted from predicted NREE) squared. This is an alternate method to determine difference of predicted vs. actual values for a population. The root mean square error of 112 in this model is promising and shows that the model is able to, on average, predict non-resting energy expenditure reliably.

The mean response of this prediction model is 784 (seen in Table 4), while the mean for the measured NREE was 708. The prediction, on average, varied only 76 kcals from calculated NREE. The model underestimated NREE by as much as 121 calories and overestimated by as much as 337 calories.

Figure 2 below displays a graph that includes much of the data that was shown in Table 3. The Actual by Predicted Plot shows the actual data points on the y-axis, while the x-axis displays the predicted values. The diagonal trend line displays the correlation of the two variables (as predicted non-resting energy expenditure rises, so does measured non-resting energy expenditure). Data points in the plot represent a prediction made by the model. The horizontal line represents the mean output of the prediction model. Points gathered close to the trend line suggest an accurate prediction model. Points scattered far away from the line are indicative of an inaccurate prediction model. The points in Figure 2 are predominantly right along the diagonal line, which is indicative of a high R^2 value, in this case being 0.74 (0.70 adjusted).

Figure 2. Non-Resting Energy Expenditure Using Intake Balance vs. Predicted

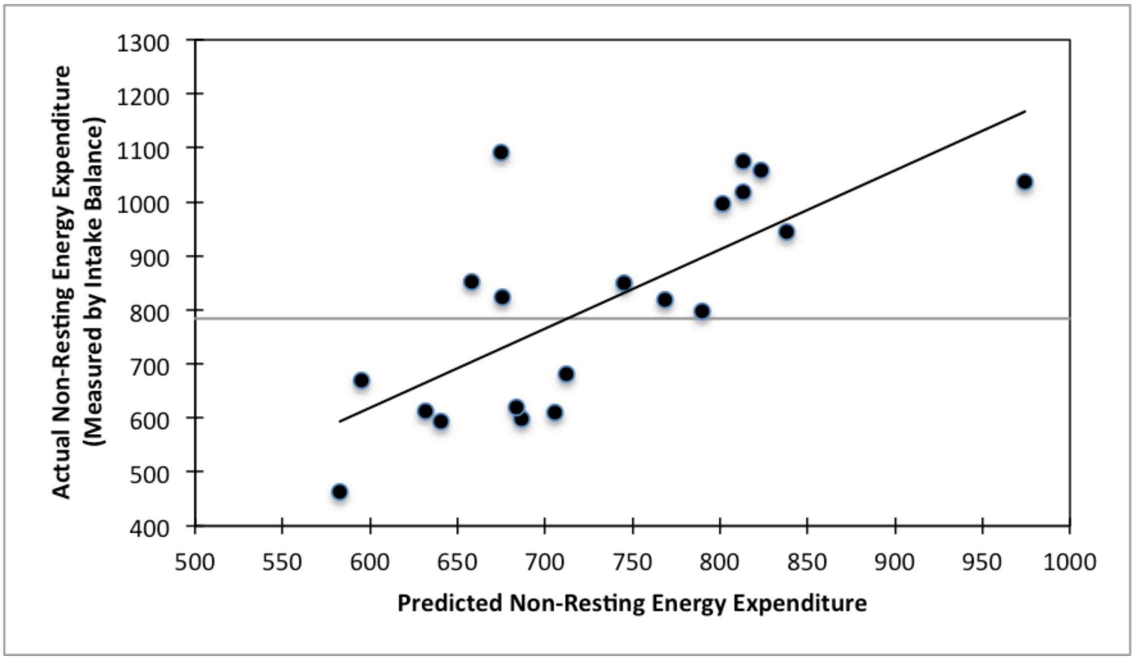

Figure 2: This plot displays the correlation between measured NREE using the intake balance method vs. the predictions made by the model. The mean NREE measured by intake balance is 784 kcals. $R^2 = 0.70$ and the p-value is <0.0001.

Figures 3 and 4 below show Bland-Altman plots for both the prediction model and accelerometer predictions of NREE vs. the NRE via the intake balance method. Figure 3 includes data from the prediction model compared to measured values. The mean daily difference, also known as the bias, between the prediction model and measured NREE showed that the model overestimates by an average of 76 kcals. The upper and lower boundary lines in the Bland-Altman plot represent +/-1.96 standard deviations from the mean daily difference, also known as the upper and lower limits of agreement. The upper limit of agreement is 336 kcals and the lower limit of agreement is -185 kcals. Ninety-five percent of predictions made by the model are expected to be overestimate by fewer than 336 kcals or underestimate by fewer than 185 kcals.

Figure 4 displays the data from accelerometer predictions of NREE vs. NREE measured via intake balance. The mean daily difference (bias) here is 286 kcals, while the upper and lower limits of agreement are 791 kcals and -220 kcals, respectively. The average output from accelerometry predictions overestimates non-resting energy expenditure by 286 kcals. Ninety-five percent of the outputs are expected to fall between a 791 kcal overestimation and a 220 kcal underestimation of true non-resting energy expenditure.

These plots display the prediction model's advantage over accelerometry. The prediction model consistently predicts non-resting energy expenditure much closer to the actual value than does accelerometry. The spread of the data points about the mean is much smaller for the prediction model than for accelerometry. The prediction model is able to, on average, predict non-resting energy expenditure 210 kcals more accurately than accelerometry (biases of 76 kcals vs. 286 kcals, respectively).

Figure 3. Bland-Altman Plot: Predicted NREE vs. NREE measured by Intake Balance

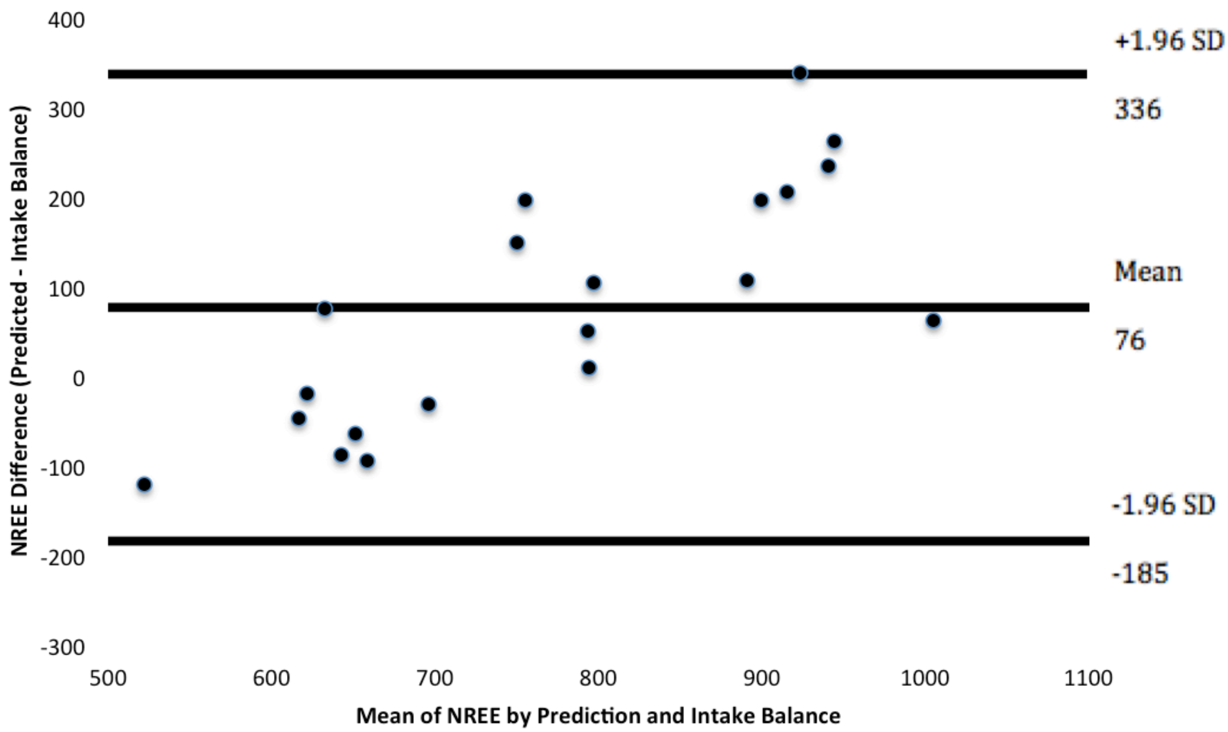

Figure 3: Non-resting energy expenditure estimated by the prediction model vs. non-resting energy expenditure measured via the intake balance method.

Figure 4. Bland-Altman Plot: NREE Measured by Accelerometry vs. NREE Measured by Intake Balance

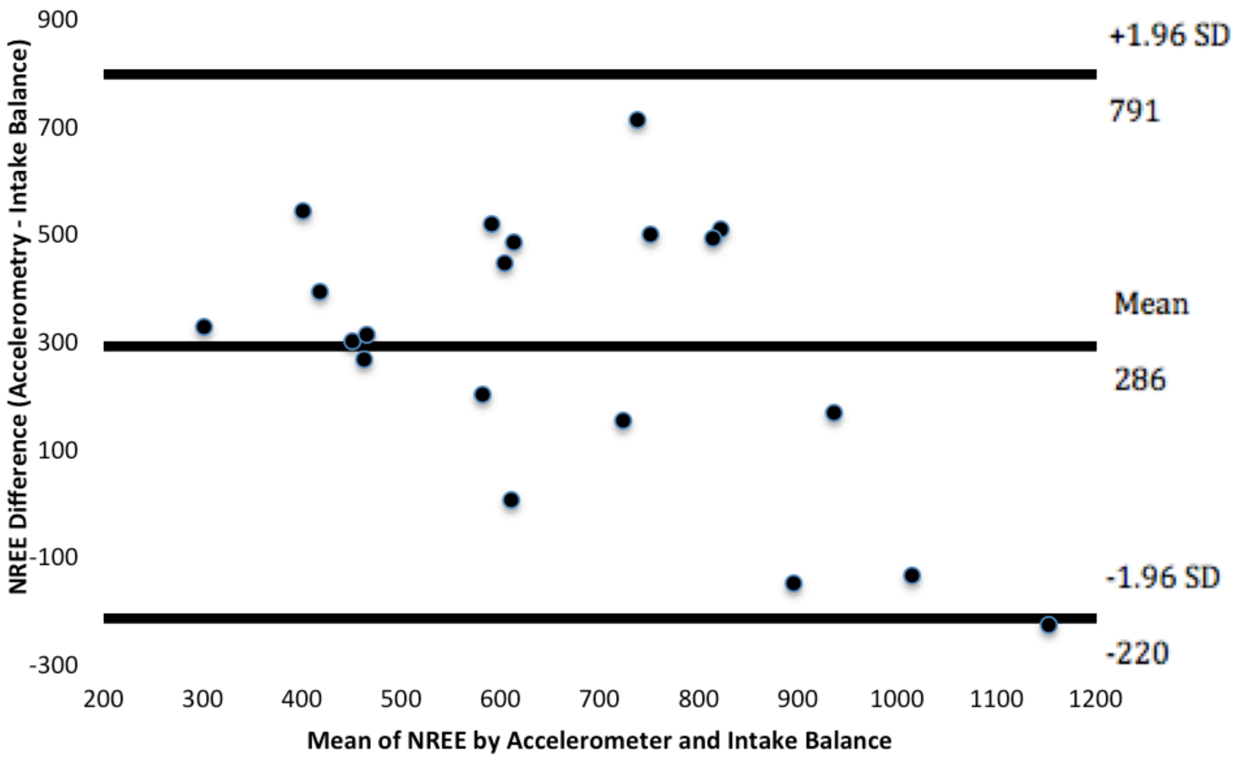

Figure 4: Non-resting energy expenditure estimated by accelerometry vs. non-resting energy expenditure measured via the intake balance method.

DISCUSSION

The model created from this study is a cheap, easy, and objective way to predict non-resting energy expenditure. The model uses REE estimations from the Mifflin-St. Jeor equation. The problem with Mifflin-St. Jeor is subjectivity when estimating non-resting energy expenditure. This new model avoids the subjectivity of self-reported physical activity, thus creating an entirely objective method to estimate total energy expenditure.

The model gives researchers in the field of nutrition the ability to easily and accurately predict resting energy expenditure along with NREE and total energy expenditure. Total energy expenditure is equivalent to total energy intake, so accurately predicting total energy expenditure allows for accurate predictions of total energy needs. Total energy needs are the basis for determining how many kcals need to be consumed in the diet. Better understanding total energy needs allows for more accurate diet prescriptions for weight loss, maintenance, or gain.

This model has advantages over other prediction methods in that it is cheap, objective, and easy to use. Other objective methods are not cheap and are often not easy to use for untrained personnel. This model can be used by anyone with tools available to measure the predictor variables. It is also far cheaper than objective methods such as both forms of calorimetry and doubly labeled water. The objectivity gives this model an advantage over other cheap and easy methods. Other prediction methods, such as the Mifflin-St. Jeor and physical activity surveys, have subjective methods for predicting non-resting energy expenditure. The coefficient of determination for this model is 0.70, which is the same R^2 value for the Mifflin-St. Jeor equation's predictions for resting energy expenditure. Resting energy expenditure predicted by Mifflin-St. Jeor is considered consistently accurate, which is an encouraging sign for this new model. Another advantage comes from participants' weight stability throughout the study protocol. Energy consumed was equivalent to energy expended, so the all data from this study is accurate.

The main limitation for the study was its sample size and homogeneity. The sample size was small, only consisting of 20 participants. The statistical power of such a limited sample size is not ideal. The sample population was sedentary, overweight, middle aged or older, and almost completely Caucasian. The prediction model may not be as accurate with those who are more active, average weight, younger than middle age, or those who are not Caucasian. Participants were all from the same rural area, so the model does not account for environmental factors of other areas, particularly urban settings. The model also had the tendency to underpredict very low NREEs and overpredict higher NREEs. The tendency to overestimate higher values could create a problem with predicting non-resting energy expenditure in very active populations. Accelerometers were only worn for 8 total days throughout a 6-week study. Accelerometers are also unable to accurately measure energy expended from static or weight-bearing exercises. These accelerometer shortcomings could potentially yield inaccurate physical activity data.

The model seems adequate to serve its intended purpose, but there is still much more research to be done. This is a step in the right direction in the field of nutrition research because it is the first accurate, objective, cheap, and easy to use method to predict non-resting energy expenditure. Research moving forward should incorporate work with a much larger and more diverse sample population. Future work could also be done to combine multiple samples from different geographic locations. This would allow for a better sample of people from various cultures with different environmental factors affecting non-resting energy expenditure. This new research would likely allow for more reliable extrapolation to the general population.

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