THE INFLUENCE OF BODY CIRCUMFERENCE MEASUREMENTS AND BODY COMPOSITION ON ESTIMATING RESTING METABOLIC RATE IN HEALTHY ADULTS

by

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ABSTRACT

Measurement of resting metabolic rate (RMR) is an important factor for weight management. Previous research has reported several variables to estimate RMR such as body size, percent fat (%BF), age, and sex; however, little is known regarding the effect of circumference measures in estimating RMR. **PURPOSE:** The purpose of this study was to develop a model to estimate RMR using waist circumference (WC), an easily obtainable measure, and cross-validate it to previously published models. **METHODS:** Subjects were 140 adult men and women, ages 18-65 years. RMR was measured through indirect calorimetry, %BF was measured through air displacement plethysmography, and fat mass and fat-free mass were determined from %BF and weight. Other variables collected were: weight, height, age, sex, ethnicity, body mass index, WC, hip circumference, waist-to-hip ratio, waist-to-height ratio, and %BF estimated from bioelectrical impedance analysis. Subjects were randomly divided into derivation and cross-validation samples. A multiple regression model was developed to determine the most accurate estimation of RMR in the derivation sample. The cross-validation sample was used to confirm the accuracy of the model and to compare the accuracy to published models. **RESULTS:** The best predictors for estimating RMR were body weight, r = 0.70, *p* = 0.031, age, r = -0.30, *p* = 0.012, and sex, r = 0.51, *p* = 0.018. Other factors failed to account for significant variation in the model. The derived equation for estimating RMR is: RMR (kcal/day) = 843.11 + 8.77(weight) – 4.23(age) + 228.54(sex, M = 1, F = 0), R^2 = 0.68, SEE = 173 kcal/day. Cross-validation statistics were: $R^2 = 0.54$, $p \leq 0.05$, SEE =

199 kcal/day, and total error = 198 kcal/day. In published models, R^2 ranged from 0.47 to 0.57, SEE ranged from 192 to 213 kcal/day, and total error ranged from 212 to 1311 kcal/day. **CONCLUSIONS:** Cross-validation to published models for estimating RMR were similar to those of the derived model; however, the total error in the derived equation was lower than any of the previously published models. Several published models considerably overestimate RMR compared to the current model. The results of this study suggest that RMR can be reasonably estimated with easily obtainable measures which allow for estimation and implementation of RMR for weight management in clinical practice.

I. LITERATURE REVIEW: THE RELATIONSHIP BETWEEN VARIABLES USED IN RESTING METABOLIC RATE EQUATIONS AND THE PREDICTION OF ENERGY EXPENDITURE IN NORMAL WEIGHT AND OBESE INDIVIDUALS

Obesity rates have been on a steady rise for the past three decades in the United States. More than one-third (36.5%) of US adults are currently obese (Centers for Disease Control and Prevention, 2016). This is alarming considering the association between obesity and risk of chronic disease and premature death (Centers for Disease Control and Prevention, 2016). Clearly, addressing this obesity epidemic is challenging and complicated (Bezner, 2015; Bouton, 2014). Thus, a wide variety of strategies targeting the many levels of influence on human behavior – individual, interpersonal, organizational, community, and policy – are required (McLeroy, Bibeau, Steckler, & Glanz, 1988). At the individual level, in particular, one fairly successful strategy is prescription of daily energy intakes with consideration of daily energy expenditures to create appropriate caloric deficits for safe and optimal weight loss (Jensen et al., 2014).

Daily energy expenditure is comprised of three components: basal metabolic rate (BMR), thermic effect of feeding, and energy expenditure during physical activity (McArdle, Katch, & Katch, 2015). Of these, the largest component, accounting for 60 to 80%, is BMR (Madden, Mulrooney, & Shah, 2016). BMR is the minimal amount of energy required to sustain life's vital functions, such as breathing, blood circulation, temperature control, and cellular growth (McArdle et al., 2015). Measurement of BMR, however, involves a fairly stringent testing protocol requiring a 12 to 18-hour fast prior to testing (McArdle et al., 2015). A well-accepted alternative to BMR is resting metabolic rate (RMR). The protocol for measuring RMR is less stringent, requiring only a 3 to 4-hour fast prior to testing, and produces only slightly higher values (Haugen, Melanson, Tran, Kearney, & Hill, 2003; McArdle et al., 2015). Therefore, RMR and BMR are often considered to be physiologically equivalent (Cunningham, 1991; McArdle et al., 2015) and, herein, RMR will be used.

RMR can be accurately and reliably measured using indirect calorimetry systems, including whole-room calorimeters, doubly labeled water, and metabolic carts (Conway, Irwin, & Ainsworth, 2002; King, McLaughlin, Howley, Bassett, & Ainsworth, 1999; Nieman, Trone, & Austin, 2003; Phang, Rich, & Ronco, 1990; Sun & Hill, 1993; Tissot et al., 1995). Measurement of RMR using these systems is often impractical, as these systems are fairly expensive, require trained personnel to operate, and can only accommodate one person at a time. In addition, accurate measurement of RMR requires well-controlled laboratory conditions that are quite demanding and burdensome to the subject being tested (Horner et al., 2001). In light of these challenges, estimation of RMR from prediction equations is well accepted as a suitable proxy for measurement of RMR (Sabounchi, Rahmandad, & Ammerman, 2013).

Prediction of RMR has been investigated since the early 1900s (Harris & Benedict, 1918) and a number of prediction equations have been developed. Though they vary in number of predictors, they all include some measure of body size (body weight) or composition (fat mass, FM, and/or fat-free mass, FFM). The equations that contain body weight either use body weight by itself or body weight with a combination of other easily obtainable anthropometric (height) and/or demographic (age and/or sex) measures (Madden et al., 2016; Siervo et al., 2013; Willis et al., 2016). The equations that contain either FM or FFM typically do so without the addition of any other measures (Cunningham, 1991; Mifflin et al., 1990; Nelson, Weinsier, CL, & Schutz, 1992). Research is discordant on whether prediction equations that include body weight or body composition as a key predictor are more accurate.

The accuracy of these predication equations, regardless of whether they include body weight, FM or FFM, also depends on the population in which they are applied (Sabounchi et al., 2013). Overall, the accuracy rate is lower in obese individuals than non-obese individuals (Frankenfield, 2013). Specifically, subnormal values are observed in the obese population when estimating RMR using body weight (Heymsfield et al., 2012). Given that fat mass has a substantially lower mass-specific energy expenditure than FFM, prediction equations using body composition (specifically, FFM) instead of body weight are more accurate (Sabounchi et al., 2013) and should be used when predicting RMR in obese individuals (Heymsfield et al., 2012). However, an accurate measure of body composition may be difficult to attain for some settings where indirect calorimetry is unavailable. Thus, clinical settings, with limited resources, may prefer prediction equations that use body weight, as it is easily attainable.

To date, research has yet to develop and validate one single prediction equation that is best suited for all populations. Perhaps they never will. However, the need remains to continue to develop and identify a set of accurate equations that can be applied to different populations in different settings, as the accuracy of prediction equations is essential for effective programs that use the energy balance approach to weight management. For instance, when estimating RMR, a prediction equation that overestimates the energy requirements may lead to a daily caloric surplus, thereby resulting in weight gain. On the other hand, a prediction equation that underestimates the energy requirements may result in a daily caloric deficit, possibly leading to rapid, unhealthy weight loss (Madden et al., 2016). Thus, accurate RMR prediction equations targeted to available resources within settings and populations will ensure a more precise estimation of daily energy expenditure, which in turn will allow for the optimization of appropriate, individualized treatments (Psota & Chen, 2013). The purpose of this review is to examine the research pertaining to the accuracy of RMR prediction equations, compare the accuracy of the equations that include body weight to the accuracy of the equations that include body composition, and determine which equations are best suited for normal weight and obese populations. This review will: 1) be helpful to researchers and practitioners in identifying the best prediction equation to use given their resources for assessing body composition, and 2) guide future research focused on improving accuracy of prediction equations.

Methods

Search Strategy

The research articles for this review were identified by accessing the PubMed, SPORTDiscus, and Medline databases for all available dates through August 1, 2017. These databases were searched using key words “resting metabolic rate,” “basal metabolic rate,” “prediction equation,” “fat distribution,” “body composition,” and “circumference.” References from review articles and meta-analyses were used to identify additional studies.

Selection Criteria

For initial evaluation, the title and abstracts from 300 potential articles were reviewed. Articles were included if they: (1) were written in English; (2) were published in peer-review journals; and (3) investigated, to some extent, the accuracy of BMR or RMR prediction equations in healthy non-obese and obese adults. Articles were excluded if they did not meet all criteria. From this initial evaluation, 32 met the initial selection criteria. Further evaluation of articles for this review limited the inclusion criteria to the investigation of: RMR measured using indirect calorimetry and a measure of body size and/or composition (e.g., weight, waist circumference, percent body fat) included in the prediction equation of interest. Articles were excluded if they did not meet these criteria. On the basis of the inclusion criteria, studies were either identified as ‘excluded’ or ‘full text reviewed and applicable’. After final evaluation, 10 studies met the criteria for inclusion in this review.

Results

Body Weight

Body weight is the main variable when predicting RMR using anthropometric and demographic measures. It is either used as the sole predictor (Mifflin et al., 1990; Owen et al., 1987, 1986) or in combination with other predictors. With regards to the latter, body weight may be used in combination with: height (Lazzer, Agosti, Silvestri, Derumeaux-Burel, & Sartorio, 2007; WHO/FAO/UNU, 1985); age (Livingston & Kohlstadt, 2005; WHO/FAO/UNU, 1985); height and age (Harris & Benedict, 1918); age and sex (Müller et al., 2004); and height, age, and sex (Mifflin et al., 1990). The most widely used prediction equations involving body weight are discussed in this section.

Body weight alone. Body weight is an easily obtainable measure that requires no special equipment other than a scale, and, thus prediction equations using body weight alone are often preferred in settings with limited resources. However, there is conflicting research regarding the accuracy of RMR prediction equations using body weight as the sole predictor. Owen et al. (1986) developed and tested a body weight-based RMR prediction equation on 44 women ranging in age (18-65 yr) and body mass index (BMI, 18.2-49.6 kg/m^2). Body weight, body surface area, lean body mass, body cell mass, and FFM by densitometry as well as by measurement of skinfold thickness were highly correlated with measured RMR (R^2= 0.50 to 0.61) and with each other (R^2> 0.71). Because of the latter, Owen et al. was unable to identify which variable truly reflected "the active protoplasmic tissue that is thought to dictate RMR" (Owen et al., 1986, p.2). Nevertheless, body weight alone was used to derive the RMR prediction equation for several reasons. Body weight: 1) was highly related to RMR (R^2= 0.55) and stepwise inclusion of additional variables did not improve the prediction of RMR, 2) was correlated with the other measures of body size and composition (R^2> 0.71), 3) can be measured with a fair degree of accuracy, and 4) can be easily obtained. Indeed, results revealed this equation to be fairly accurate, as it predicted RMR within -236 to 487 kcal/24 h of the measured RMR. In a follow-up study involving only men (n=60) of varying ages (18-82 yr) and BMI (20.4-58.7 6 kg/m^2), Owen et al. (1987) reported similar results. Measures of body size and composition were highly correlated with measured RMR (R^2= 0.52 to 0.61) and with each other (R^2> 0.72). Again, body weight alone was used to derive the RMR prediction equation; and results revealed equation to be somewhat accurate, as it predicted RMR within -432 to 522 kcal/24 h of the measured

RMR. Following these two studies, Owen (1988) published a review suggesting that predicting RMR using body weight alone, without additional predictors, was acceptable.

In a study with a much larger sample, the predictive power of body weight by itself was not supported. Specifically, Mifflin et al. (1990) investigated the accuracy of body weight alone, as well as with other measures, in predicting RMR based on a sample of 498 apparently healthy men and women of varying ages (19-78 yr) and BMI (17-42 kg/m^2). In this group, about half were classified as normal weight (129 men and 135 women) and about half as obese (122 men and 112 women). Analysis revealed that body weight contributed to an R^2 of 0.56. When additional variables (i.e., height, age, and sex) were added to the prediction equation, R^2 increased substantially to 0.71, and thus, led the authors to conclude that adding height, age, and sex builds on the predictive power of body weight in determining RMR. In short, Mifflin et al. suggested that an RMR prediction equation using body weight with additional metrics is more accurate than one using body weight alone.

Body weight and height. Given the limited predictive power of body weight alone, researchers have explored the relevance of adding other easily obtainable measures, such as height, to RMR prediction equations. Decades old research has shown that the use of height in addition to body weight when predicting RMR does not significantly improve the accuracy of the prediction (WHO/FAO/UNU, 1985). More recent research, however, has shown otherwise. For example, Lazzer et al. (2007) developed an RMR prediction equation from a random sub-sample of 91 RMR measurements in severely obese women (BMI 40-≥ 50 kg/m^2), aged 19-60 yr. Data analysis revealed body weight as a significant determinant of RMR, explaining 54% of the variance (R^2=0.54). Height alone explained 31% of the variance (R^2=0.31), and when combined with body weight, increased the variance to 66% (R^2=0.66). Additionally, results revealed the correlation coefficient between predicted RMR and measured RMR to be R^2= 0.70, with RMR predicted accurately in 60% of the subjects. In this study, the prediction accuracy was defined as the percentage of subjects whose predicted RMR were within ±5% of their measured RMR. The remaining 40% consisted of an overestimation in 25% of the subjects and an underestimation in 15%. Given the high degree of accuracy and use of easily obtainable anthropometric measures, the authors concluded that this prediction equation is appropriate for obese women. Nevertheless, because of the discordance in literature, it is unclear whether using height is additive to the predictive power of body weight when predicting RMR.

Body weight and age. When body weight is used in combination with age, the accuracy of the prediction of RMR has been shown to improve (Livingston & Kohlstadt, 2005; WHO/FAO/UNU, 1985). For instance, Livingston & Kohlstadt (2005) developed RMR prediction equations using body weight alone as well as body weight and age based on a sample of 655 men and women of varying ages (18-95 yr) and body weights (33-278 kg). Analysis revealed that body weight alone contributed to an R^2 of 0.67 for women and 0.73 for men. When age was added to the prediction equation, R^2 increased to 0.71 for women and 0.77 for men, resulting in improvements in RMR estimation. In this study, the contribution of height in addition to body weight and age to RMR variance was also investigated. Results showed that in terms of contribution to the explained RMR variance, the correlation was weak (e.g., 0.07 for women) between weight and age, but strong (e.g., 0.32 for women) between weight and height, thereby suggesting a significant overlap in body weight and height. To this end, these results indicate that body weight in combination with age, but not height, will strengthen the accuracy of RMR prediction.

Body weight, age, and sex. The inclusion of sex to body weight and age when predicting RMR has also been investigated. Muller et al. (2004) developed prediction equations from a sample of 388 males and 658 females with a mean age of 44.2 ± 17.3 yr and BMI of 27.1 ± 7.7 kg/m^2. The prediction equations derived from this sample were then validated on another sample including 410 males and 649 females with very similar anthropometric data (age 44.1±17.4 yr, 26.8±7.1 kg/m^2). Further, there were no significant differences between these two samples in any of the measured variables. Results revealed that 73% of the variance (R^2= 0.73) in RMR was explained by body weight, age, and sex. In addition, when predicted RMR was compared with measured RMR, the mean deviation was 9.55 ± 205.41 kcal/day. Furthermore, data analysis revealed that deviations between measured and predicted RMR varied between BMI subgroups. For instance, the deviations were higher in the obese groups and lower in the nonobese groups. In light of this, the researchers suggested that RMR predictions can be improved with the use of BMI group-specific equations. Based on these results, authors concluded that prediction equations using body weight, age, and sex are acceptable when predicting RMR.

Body weight, height, age, and sex. Two of the first RMR prediction equations developed and still commonly used today are the Harris-Benedict equations. Harris & Benedict (1918) developed RMR prediction equations from data gathered on 136 men, 103 women, and 94 new-born infants. Two equations were developed, one for males and for females. The variables in these equations included body weight, height, and age.

Contrary to Livingston & Kohlstadt (2005), results indicated that both body weight and height had independent significance as bases for the prediction of RMR. Though these equations remain fairly popular, their level of accuracy has been questioned. The population studied by Harris & Benedict (1918) were subjects of normal weight and in presumably good health. Thus, it is of no surprise that when applied to overweight and obese populations, these equations have overestimated RMR (Feurer, Crosby, Buzby, Rosato, & Mullen, 1983; Livingston & Kohlstadt, 2005; Pavlou, Hoefer, & Blackburn, 1985). In fact, regardless of the populations in which these equations have been applied, the Harris-Benedict equations have been shown to overestimate RMR by an average of ≥15% (Cunningham, 1980, 1982; Daly et al., 1985; Mifflin et al., 1990; Owen, 1988; Owen et al., 1987, 1986). Considering the limited population in which the equations were derived from and their consistent overprediction, caution should be exercised when using the Harris-Benedict equations. Thus, other gender-based equations have since been developed, with some showing a fair degree accuracy. For example, Mifflin et al. (1990) also developed an RMR prediction equation using body weight, height, age, and sex. The authors found that body weight alone contributed to an R^2 of 0.56 when predicting RMR, but when height, age, and sex were added to body weight, R^2 increased substantially to 0.71. Therefore, authors concluded that although body-weight prediction equations are simpler than equations that use body weight, age, height, and sex, they are less accurate in predicting RMR.

Body Composition

Although prediction equations that use body weight alone or body weight in combination with other easily obtainable measures are often preferred by facilities for practical reasons, the use of body composition may increase the accuracy of the prediction. Body composition is comprised of two components: FFM and FM. Equations involving FFM, FM, and both FFM and FM as predictors of RMR are discussed in this section.

FFM alone. The reflection of metabolically active tissue (FFM) in the body has been shown to be highly related to RMR and, thus, the best single predictor of RMR (Cunningham, 1980, 1982; Mifflin et al., 1990; Nelson et al., 1992; Ormsbee et al., 2009; Owen et al., 1987, 1986; Ravussin & Bogardus, 1989). Cunningham (1991) conducted a review of numerous studies examining the relationship between RMR and FFM (Bernstein et al., 1983; Cunningham, 1980; Dore, Hesp, Wilkins, & Garrow, 1982; Garrow & Webster, 1985; Kashiwazaki, Suzuki, & Inaoka, 1988; Mifflin et al., 1990; Owen, 1988; Ravussin & Bogardus, 1989). Examination of these studies including a wide range of adults with varying body weights confirmed a primary correlation between RMR and FFM. With FFM explaining ~85% of the individual variation in RMR, Cunningham concluded that FFM can serve as a reasonable surrogate for the representation of metabolically active tissue that continues to alter measurement in healthy individuals. Further, in obese women, there is a potential contribution of FM to RMR predictions, whereas in nonobese individuals, this individual contribution is not supported.

FFM and FM. Research is consistent in that FFM is highly correlated with RMR and, thus, a significant predictor of RMR, but when FM is used as a covariate, changes in body composition are better accounted for. Research by Nelson et al. (1992), tested the relative contribution of FFM and FM to RMR. To determine this contribution, researchers collected data in a laboratory as well as combined data from published data sets that included FFM, FM, and RMR for each subject. The RMR prediction equations were derived from a sample of 213 subjects, 81 of whom were lean and 132 obese (percent body fat >20% for males and >30% for females). These prediction equations were then tested on a data set of 1067 subjects with varying body weight (54.9-131.9 kg) and percent body fat (10.7-50.7%). Results revealed (1) the equations which include FFM as an independent variable were able to predict RMR within 3% of the measured RMR; (2) for adult subjects, RMR is linearly related to FFM; (3) FFM and FM can explain 75% of the variability in RMR, with FFM explaining the largest variability and FM explaining very little of the remaining variance; (4) FFM has a metabolic rate 6-7 times greater than that of FM; and (5) when adjustments are made for FFM when predicting RMR, the influence of sex is negated, however, when FM is included as a covariate, sex exhibits a significant effect on RMR. In short, RMR prediction equations that use FFM as an independent variable are accurate, but the equations that use both FFM and FM are valuable in accounting for changes in RMR that occur with a change in both FFM and FM. These changes in body composition are commonly seen throughout weight loss programs and should be accounted for when predicting RMR.

More recent research by Lazzer et al. (2007) also investigated the contribution of FFM and FM to RMR. In agreement with other research, the major determinants of RMR in this study population were body weight (R^2= 0.54) and FFM (R^2=0.39). Interestingly, of the remaining variables studied, FM exhibited the strongest relationship with RMR (R^2= 0.36), which can most likely be explained by the severely obese population being studied (BMI 40-≥ 50 kg/m^2). Based on these correlations, an RMR prediction equation including both FFM and FM was developed and a <-2% difference was found between predicted and measured RMR. Therefore, authors suggested that FM should be included with FFM when predicting RMR in obese cohorts.

Body Weight-Based Equations vs. Body Composition-Based Equations

Numerous studies have investigated the accuracy of RMR prediction equations using body weight and/or body composition. The debate of whether to use body weight or body composition when predicting RMR will be discussed in this section.

In 1980, Cunningham tested the hypothesis proposed originally by Harris and Benedict (1918), using the subjects from their classic study, that metabolically active tissue (i.e., lean body mass or FFM) is the single best predictor of RMR. Of the variables tested, including sex, age, height, body mass, and estimated FFM, FFM was found to be the best single predictor of RMR. Cunningham found the influence of sex and age in the prediction equation with FFM to be negated and, thus, proposed a simple linear equation to best estimate RMR with the sole predictor being FFM.

In a subsequent study by Owen (1988), the elimination of the influence of sex when predicting RMR using FFM was confirmed. Owen found that when using his body-weight equations, gender differences along with differences in athletes and non-athletes emerged. An explanation for the gender differences resides in the differences in body composition between males and females. "As body mass increases, the relative proportion of stored triglycerides is greater in women than in men. Thus, per unit mass, relatively more inert triglycerides are stored subcutaneously as fat in women than in men, and the energy requirements per unit of fat mass are less than the energy requirements per unit of fat-free mass" (Owen, 1988, p. 506). Therefore, when RMR is corrected for FFM, the influence of sex is eliminated when predicting RMR. As for the differences in athletes and non-athletes, when RMR is corrected for FFM, the influence of training is also eliminated.

Despite the elimination of the influence of sex and training when predicting RMR using FFM, Owen suggests that body weight alone is a reasonable predictor of RMR. Although FFM was found to be highly related with RMR, it yielded values comparable to body weight alone. Thus, since body weight is a more easily and accurately measured variable than FFM, as well as highly correlated with RMR, it is the preferred predictor when estimating RMR.

As previously mentioned, Mifflin et al. (1990) investigated the accuracy of prediction equations using body weight alone, as well as prediction equations including other variables (i.e., height, age, sex, FFM, BMI, percent ideal body weight, and waist-to-hip ratio). Analysis of these measured variables and their respective influences on RMR revealed that FFM was most highly correlated with RMR (R^2= 0.64), with body weight and height also demonstrating high R^2 values of 0.53 and 0.48. Although FFM was most highly correlated with RMR, the trained personnel and equipment required to measure FFM is impractical for most settings. Thus, for more practical use in many different settings, Mifflin et al. derived prediction equations including variables that are routinely measured by a physician (i.e., body weight, height, age, and sex). In the body-weight prediction equation, weight contributed to an R^2 of 0.56. When height, age, and sex were added to the RMR prediction equation, R^2 increased substantially to 0.71. Therefore, authors concluded that although RMR is determined largely by FFM, body weight is also highly correlated with RMR and, thus, a reasonable independent RMR predictor. Further, the addition of height, age, and sex increases the predictive power of the body weight equation when predicting RMR and the use of commonly collected variables enhances the practicality of use of this equation in settings with limited resources.

A limitation presented by Mifflin et al. (1990) was the measure of body composition. The Jackson-Pollack skinfold method was used because of its recommended use with large, heterogenous populations, however, trained personnel are required for accurate measurements and it has been suggested that the skinfold method should not be used to assess the body composition of obese individuals (Heyward & Stolarczyk, 1996). Therefore, while the Mifflin-St. Jeor equations accurately predicted RMR in normal-weight and moderately overweight individuals, caution should be exercised when using these equations with obese individuals.

Discussion

A precise estimation of RMR is critical for calculating daily energy expenditure. This is of specific significance for health professionals prescribing realistic goals for daily energy intake in relation to the energy balance approach for successful weight management. Although RMR can be accurately measured via indirect calorimetry, this requires expensive equipment, trained personnel, and stringent pretest instructions that the client must adhere to. These requirements make it difficult for measurements to be obtained, and thus, RMR prediction equations are commonly used. Research on RMR prediction equations has been investigated since the beginning of the 20th century. Upon review of this research, these prediction equations fell into one of two main categories: predictions based on body weight or predictions based on body composition.

The prediction equations based on body weight either include prediction of RMR using body weight as an independent variable or body weight in combination with other anthropometric or demographic variables. Anthropometric variables such as body weight and height, and demographic variables such as sex and age, are easily obtainable measures that do not require expensive equipment or trained personnel to collect. This makes body-weight prediction equations desirable in most settings. However, body weight does not account for specific changes in body composition, therefore, RMR prediction equations based on body weight may result in a decrease in accuracy of prediction when compared to equations that use body composition to predict RMR.

RMR prediction equations based on body composition include FFM, FM, or both FFM and FM. The main advantage of using body composition-based equations to predict RMR is that with varying amounts of metabolically active tissue from person to person, differences observed in energy expenditure can be accounted for between individuals of the same body weight but with different chemical compositions. However, accurate measures of body composition can be difficult to obtain and require costly equipment, and thus, in most settings, body-weight based equations are preferred.

In summary, the relationship between RMR and several variables were studied to determine the most accurate predictors of RMR. FFM and body weight were found to be highly correlated with RMR, and thus, significant predictors of RMR. While, in some cases, prediction equations using body composition were shown to be more accurate than equations using body weight, especially in obese cohorts, not all settings are equipped to obtain accurate body composition measurements to utilize these equations. Regardless of the prediction equation used, health professionals need to be aware of the under- or overprediction of selected RMR prediction equations, and account for this when prescribing energy intakes. Further studies are needed to investigate the accuracy of using easily obtainable measures (e.g., waist and/or hip circumference) to first, predict body composition and second, RMR.

Purpose

Therefore, the purpose of the present study is to develop an equation which uses measures that are easily obtained but also highly correlated with body composition (i.e., waist circumference (WC), hip circumference (HC), waist-to-height ratio (WHR), and waist-to-hip ratio (WHtR)) to more accurately predict RMR in normal weight and overweight/obese individuals than previously developed equations.

Limitations

Limitations presented in this study include the test subjects self-report of adhering to the strict testing protocols. There is also a chance for human measurement error during the circumference measurements, although this error will be minimized by taking duplicate measures at each site and retesting if these measurements are not within 5 mm. Also, the same researcher will take all measurements. Additionally, the limitations of RMR prediction equations, in general, need to be considered. RMR predictions are limited to the study population in which the equation was derived from. Therefore, when determining the appropriate prediction equation to use, the population the equation will be applied to should be considered. Also, the accuracy of the equation should be noted and adjustments for prescription of energy intake should be made according to the specific metabolic reactions of the individual. RMR prediction equations can only provide estimates of RMR and, thus, for precise determination of RMR, direct metabolic measurement via indirect calorimetry should be used.

Delimitations

Delimitations presented in this study include the exclusion of children and adults aged ≥ 70 years. These populations were chosen to be excluded due to the significant changes in resting metabolic rate that occur with growth and development in children and aging in older adults. Similarly, people with diagnosed diseases were chosen to be excluded due to the varying effects that diseases have on resting metabolic rate.

Operational Definitions

In this study, subjects will be defined as underweight if BMI < 18.5 kg/m^2, normal weight (lean) if BMI 18.5-24.9 kg/m^2, overweight if BMI 25.0-29.9 kg/m^2, and obese if BMI ≥30.0 kg/m^2. Additionally, the line of best fit is a trend line that best represents the estimated RMR from the predictive model and the line of identity is a line where y = x, or the predictive model perfectly estimates the measured RMR from indirect calorimetry. Further, standard error of estimation (SEE) is the average amount of error around the line of best fit and total error is the average amount of error around the line of identity.

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II. THE INFLUENCE OF BODY CIRCUMFERENCE MEASUREMENTS AND BODY COMPOSITION ON ESTIMATING RESTING METABOLIC RATE IN HEALTHY ADULTS

More than two-thirds (70.7%) of adults in the United States are overweight or obese (Centers for Disease Control and Prevention, 2016). Obesity is a complex condition and is influenced by many factors including genetics, inactivity, diet, social and economic issues, and metabolic diseases (Hernandez & Blazer, 2006). In light of this, a substantial amount of research is currently being directed towards the education and treatment of obesity. Unfortunately, to date, there has been little evidence of success in resolving this severe public health crisis. However, one lifestyle treatment strategy, in particular, that has been successful is the prescription of daily energy intakes with consideration of daily energy expenditures to create appropriate caloric deficits for safe and optimal weight loss (Jensen et al., 2014).

Daily energy expenditure is comprised of three components: basal metabolic rate (BMR), thermic effect of feeding, and energy expenditure during physical activity (McArdle et al., 2015). Of these, the largest component, accounting for 60 to 80%, is BMR (Madden et al., 2016). BMR is the minimal amount of energy required to withstand vital life-sustaining functions, such as respiration, blood circulation, temperature control, and cellular growth (McArdle et al., 2015). Measurement of BMR, however, involves a fairly stringent testing protocol requiring a 12 to 18-hour fast prior to testing (McArdle et al., 2015) as well as an overnight stay on bedrest to eliminate the effect of physical exertion on metabolic expenditure. Thus, a well-accepted alternative to BMR is resting metabolic rate (RMR). The protocol for measuring RMR is less stringent, more practical for the general population, and may be more suitable for clinical testing purposes, as it requires only a 3 to 4-hour fast prior to testing and produces only slightly higher values (Haugen et al., 2003; McArdle et al., 2015). Specifically, RMR values are approximately 3-6% higher than BMR values (Kopelman, 2000). Therefore, RMR and BMR are often considered to be physiologically similar (Cunningham, 1991; McArdle et al., 2015) and, herein, RMR will be used.

RMR can be accurately and reliably measured using indirect calorimetry systems, including whole-room calorimeters, doubly labeled water, and metabolic carts (Conway et al., 2002; King et al., 1999; Nieman et al., 2003; Phang et al., 1990; Sun & Hill, 1993; Tissot et al., 1995). Measurement of RMR using these systems, however, is time consuming and requires expensive equipment and trained personnel to operate. In addition, the testing environment must be well-controlled and the test subject must adhere to stringent testing protocols (i.e., ≥12-hour fast and ≥24-hour abstention from physical activity, alcohol, and caffeine) for accurate measurement (Horner et al., 2001). Thus, estimating RMR using prediction equations is more practical and often preferred over measuring, especially in settings with limited resources such as clinics and fitness centers. Additionally, health professionals including personal trainers, coaches, dietitians, physicians, and exercise physiologists benefit from these prediction equations as they offer a quick and inexpensive method of estimating RMR which can then be accounted for when prescribing appropriate caloric deficits for weight loss programs.

Predicting RMR has been investigated since the early 1900s (Harris & Benedict, 1918) and is still an active area of research today. To date, many different RMR prediction equations exist, and though they differ in number and type of variables used, they all include some measure of body size or composition (fat mass (FM), and/or fat-free mass (FFM)). Research is discordant on whether body weight-based or body composition-based RMR prediction equations are more accurate. For instance, Owen (1988) and Mifflin et al. (1990) investigated the accuracy of RMR prediction equations that used body weight alone, as well as equations that used body composition variables. While both studies found FFM to be the most highly correlated with RMR, they also agreed that body weight was highly correlated and a more easily obtainable measure. Therefore, authors concluded that when compared to body composition-based equations, body weight-based equations display a fair level of accuracy and are more practical for use in many different settings.

Body-composition based RMR equations also present a challenge in diverse populations due to the increase in measurement error exhibited in overweight/obese individuals (Bottaro, Heyward, Bezerra, & Wagner, 2002; Burton & Cameron, 2009; Mifflin et al., 1990). Due to the reduced accuracy presented in commonly used body composition assessments (i.e., skinfold measurements) in the obese population, more credible measures of body composition, such as dual-energy x-ray absorptiometry or air displacement plethysmography, are suggested for use with overweight and/or obese populations. However, the equipment required for these measures is not available in all settings and can be difficult for facilities to acquire. Thus, one more economic, easily administered and accessible method of measuring body composition is bioelectrical impedance analysis (BIA), which sends a low electrical current throughout the body to estimate total body fat (Yacoob Aldosky, Yildiz, & Hussein, 2018). The present study will evaluate the ability to use a BIA device to estimate percent body fat and, therefore, aid in a simple and easy prediction of RMR with a body-composition based equation.

Another inexpensive and simple method to estimate body fat is through simple anthropometric measurements. Specifically, waist circumference (WC) has been found to be closely associated with visceral adipose tissue and central adiposity (Turcato et al., 2000) and measures of body mass index (BMI) and WC (Lee, 2016), waist-to-hip ratio (WHR; Pimenta et al., 2016) and waist-to-height ratio (WHtR; Swainson, Batterham, Tsakirides, Rutherford, & Hind, 2017) have been examined for use of surrogates to body fat percentage. If simple anthropometric measurements can be used as surrogates for body fat percentage when predicting RMR, this will eliminate the need for invasive methods (e.g., computed tomography or dual-energy X-ray absorptiometry [DXA] scans), expensive equipment (e.g., DXA or BOD POD), and trained personnel, and allow for more accurate predictions of RMR in diverse populations.

Very few studies have examined the effect of body circumference measurements in estimating RMR (Karhunen et al., 1997; Khalaj Hedayati & Dittmar, 2011; Rodríguez et al., 2002). Karhunen et al. (1997) studied a population of obese, non-diabetic, Caucasian women and did not find waist and hip circumferences to be significant predictors of RMR. Consequently, Rodríguez et al. (2002) studied a population of Caucasian children and adolescents and found that WC accounted for additional significant variance in RMR in the obese children and adolescents, but only by 2.5%. Only one study, to our knowledge, found abdomen and hip circumferences to be signficiant predictors of RMR and included these measures in derived RMR prediction equations (Khalaj Hedayati & Dittmar, 2011). A limitation presented in Khalaj &

Dittmar's (2011) study, however, is the sample of elderly participants (aged ≥ 60 years) of German origin in which the equations were derived from. This population, limited in both age and ethnicity, presents a challenge in the reliability of the derived equations to predict RMR in more diverse populations.

In lieu of the observed limitations presented in previous research regarding body circumferences and RMR, there is a need to further investigate the effects of circumference measurements in estimating RMR in a more reflective population of the U.S. containing a wide variety of ages and ethnicities. Therefore, the primary purpose of the present study is to develop an equation which uses measures that are easily obtained but also highly correlated with body composition, such as WC, HC, WHR, and/or WHtR, to more accurately predict RMR in normal weight and overweight/obese individuals than previously developed equations. If RMR can be predicted with an equation in which the most complex measures require the use of an inexpensive and easily accessible tape measure, practitioners and various health professionals will be able to offer this estimation to patients quickly and easily with no additional burden. This quick and easy estimation could eliminate a barrier for many individuals who need an accurate estimation of RMR for the calculation of an appropriate energy balance but may not have the time or money to have this measurement obtained. Additionally, if physicians routinely include an estimation of RMR to patients, an opportunity will be presented for patients to ask questions and physicians to provide education on proper weight loss or weight management strategies. The addition of routine health counseling in physical exams, if needed, might be a step towards reducing current and/or preventing increasing obesity rates in the U.S.

Previously published RMR prediction equations focused on in this study were developed by Harris & Benedict (1918), Mifflin et al. (1990), Owen et al. (1986), Owen et al. (1987), Nelson et al. (1992), and Lazzer et al. (2010). These equations were chosen based on the diverse populations studied (i.e., nonobese and obese) as well as a combination of different variables used in the prediction equations (i.e., weight alone, weight with age and sex, weight with age, sex, and height, FFM alone, and FFM with FM). One common limitation presented in all of these studies was the lack of a cross-validation within their own respective studies to determine the accuracy and reliability of predicting RMR with the developed models in an independent, random sample. Thus, a secondary purpose of the present study is to determine the accuracy of the derived model by cross-validating the predicted RMR values with the measured RMR values obtained from indirect calorimetry from the cross-validation sample. The predicted RMR values from the derived model will also be compared to the predicted RMR values from several previously published models in order to determine which model presents the least amount of total error, therefore, representing the most accurate and least biased equation. The equations evaluated are presented in Table 1.

Methods

Participants

Prior to initial data collection, a pilot study was conducted on eight participants. Overall, data was collected from 163 participants. After excluding participants from the pilot study and those who did not reach the steady-state criteria for RMR, 140 participants were included in this study. Participants included instructors, students, and employees recruited from Texas State University as well as residents in the greater part of the San Marcos, TX area. Descriptive characteristics of the participants can be found in Tables 2 and 3. The population studied included 51 men and 89 women, ranging in age from 19 to 65 years (32.02 ± 1.05, mean ± SE). One individual was classified as underweight (BMI <18.5 kg/m^2), 70 classified as normal weight (BMI 18.5-24.9 kg/m^2), 44 classified as overweight (BMI 25.0-29.9 kg/m^2) and 25 classified as obese (BMI ≥ 30 kg/m^2). Additionally, ethnicity was identified by participants as follows: 80 Caucasian (57%), 29 Hispanic (21%), 18 African American (13%), 6 Asian (4%), and 7 Other (5%).

Participants were screened for eligibility and excluded if <18 or >70 years of age; had experienced significant weight loss (>11 kg) in the past 3 months; were currently ill; or diagnosed with any major metabolic or organ disease (e.g., diabetes, cancer, heart disease, chronic respiratory diseases, autoimmune diseases, neurological diseases, stroke, thyroid dysfunction), and/or any other health issues that may influence RMR.

The Texas State University Institutional Review Board approved the research protocol for this study prior to subject recruitment and data collection. An electronic comprehensive medical health appraisal was completed prior to the visit and sent via email to the test administrator for review of inclusion and exclusion criteria to determine study eligibility. Pre-test instructions were also sent with these forms to be followed by the subjects including: ≥2-hour abstention from nicotine, ≥12-hour fast (water acceptable until ≤3 hours before scheduled time of visit), ≥24-hour abstention from physical activity, caffeine, and alcohol consumption, avoiding applying any lotions or skin creams before testing, and obtaining ≥6 hours of sleep the night before the test. Subjects were also encouraged to eat a well-balanced meal (i.e., a meal including carbohydrates, fats and protein) around 6-8 p.m. the evening before the study and bring a snack (e.g., a granola bar or sandwich) with them to consume after the tests. On the day of the visit to the laboratory, procedures were verbally explained to the participant and any questions/concerns were discussed. If the participant wished to participate, then he/she signed the consent form. Additionally, participants signed a document stating they adhered to study pre-test instructions, and all participants in the study reported adherence to the instructions. Measurements obtained in the Exercise Physiology Laboratory, in chronological order, were as followed: height and weight; indirect calorimetry (oxygen consumption (VO_2), carbon dioxide production (VCO_2), and respiratory quotient (RQ)); body composition; and waist and hip circumference. Anthropometric measures (i.e., height, total body weight, fat percentage, lean percentage, weight of body fat, weight of fat-free mass, waist and hip circumference) and measured RMR (kcal/day) were provided to the participants after the visit for their own personal records.

Height and Weight

Participants were instructed to remove their shoes and both height and weight were measured on a digital scale with an integrated stadiometer (Seca 703 S Wireless Column Scale with Integrated Stadiometer, Seca GmbH & Co. KG, Hamburg, Germany). Height was measured to the nearest 0.1 cm and weight to the nearest 0.5 kg. The body weight (kg) and height (cm) obtained from the scale were used to calculate the participant's body mass index (BMI) in kg/m^2 and then categorize population based on health risk (American College of Sports Medicine (ACSM), 2018).

Oxygen Consumption, Carbon Dioxide Production, and Respiratory Quotient.

RMR was measured using an open-circuit indirect calorimetry system (ParvoMedics TrueOne® 2400, Sandy, UT). A gas and flow calibration were performed every 4 hours during testing, as recommended by the manufacturer (ParvoMedics TrueOne® 2400, Sandy, UT). The testing room was isolated aside from the participant and administrator. Additionally, the temperature of the room was controlled at 20-25℃, the noise level was kept to a minimum, and the room was dimly lit. Upon the participant's arrival to the lab, the equipment and procedures were explained, and any questions regarding the test were answered. After signing the consent form, the participant was fitted with a facemask (7450 Series Reusable V2 Oro-Nasal Mask, Hans-Rudolph Inc., Shawnee, KS) that covered their mouth and nose. The participant was required to wear the facemask for the duration of the resting metabolic rate measurement. While wearing the facemask, the participant was instructed to lie motionless in a comfortable supine position on a padded table. Further, the participant was instructed to relax as much as possible while remaining awake and was given a pillow and/or blanket if needed.

The resting measurement was approximately 40 minutes in duration and the facemask was worn the entire time. Because the participants walked to the testing site from the parking lot, the first 30 minutes were used as a rest period to allow adequate recovery from physical activity. Following the 30-minute rest period, VO_2 and VCO_2 were measured and recorded for ≥10 minutes with the final 5 minutes of data used for steady-state analysis. Steady-state was reflected as achievement of a 5-minute period with ≤10% coefficient of variation (CV) for VO_2 and VCO_2, in accordance with recommended protocol (Compher, Frankenfield, Keim, & Roth-Yousey, 2006). CV was calculated as: CV= [(Standard Deviation of collected VO_2/Mean) x 100]. If the CV was >10% after 5 minutes, then another minute was added until a 5-minute continuous period with ≤10%

CV for VO_2 and VCO_2 was achieved.

During the measurement, the metabolic cart recorded averages of variables (VO_2, VCO_2, and RQ) and displayed these averages on the computer display screen every 30 seconds. During data collection, the test administrator entered the recorded VO_2, VCO_2, and RQ into an Excel sheet every 30 seconds to determine the CV. RMR was calculated from the average 5-minute steady-state VO_2 and caloric equivalent (determined by the average 5-minute steady-state RQ) and then extrapolated to 24-hour RMR using the following equation: RMR = (average VO_2 x average caloric equivalent x 1440 min/day). Test results were then printed and the RMR was recorded by the administrator for later analysis.

Body Composition

Determination of Body Composition by Air Displacement Plethysmography.

Body composition was assessed via air displacement plethysmograph (BOD POD® Express, COSMED USA, Inc., Concord, CA). The air displacement plethysmograph requires an extensive calibration process which was completed within 24 hours of testing a participant and the integrated digital scale was calibrated at least once a week. Additionally, participants were instructed to wear proper attire for the body composition testing: For men, either, a form-fitting swim suit or single-layer compression shorts without padding and, for women, either a form-fitting swim suit, or single-layer compression shorts without padding and a single-layer jog bra without padding. The participant also wore a swim cap during testing to compress the hair on the head. Before the measurements were taken, a short volume calibration was performed by placing a company-issued, certified 50-Liter cylinder in the air displacement plethysmograph.

After the volume calibration, one of the five two-compartment density models was selected by the test administrator. Determination of the selected model was based on the participant's ethnicity, sex, and/or BMI (Table 4). Next, the participant's sex, age (years), and height (feet and inches) was entered into the BOD POD kiosk. The participant was instructed to change into the proper attire, remove any glasses, jewelry, and shoes, and step on the scale to be weighed. After obtaining the weight measurement, the participant was instructed to enter the air displacement plethysmograph for three, 40-second volume measurements. If for any reason the participant wanted to end the test early, the participant was made aware of the emergency stop button that would immediately open the chamber door and terminate the test. While inside the chamber, the participant was to limit movement as much as possible, breathe normally, and sit back comfortably. The test administrator opened and closed the air displacement plethysmograph door between each test, but the participant remained inside the chamber the entire time. After the three measurements were taken, the participant was then able to exit the air displacement plethysmograph, gather belongings, and change into his/her preferred attire. Measurements recorded and used for analysis included percent body fat, FFM in pounds, and FM in pounds.

Determination of Body Composition by Bioelectrical Impedance Analysis (BIA). Body composition was also measured using a bioelectrical impedance analysis monitor (Fat Loss Monitor, HBF-306C, OMRON Healthcare Inc., Bannockburn, IL). Prior to testing, the participant was asked if they had a pacemaker or other implanted device and if so, the participant did not participate in BIA, as recommended by the manufacturer. For all participating subjects, the athletic level on the monitor was set to normal. The test administrator manually entered the participant's measured height (cm) and weight (kg) along with their age (years), and sex into the monitor. The participant then placed both hands on the monitor by holding the grip electrodes, stood with both feet slightly apart, and held their arms straight out at a 90-degree angle to their torso. The administrator then pressed the start button on the monitor. Within approximately 10 seconds, the body fat percentage was displayed on the monitor screen and the body fat percentage was recorded by the administrator.

Waist and Hip Circumference

During the waist measurement, the participant stood with arms at their sides, feet together and abdomen relaxed (i.e., avoiding sucking in the abdominal wall). A horizontal measure was taken at the narrowest part of the torso (above the umbilicus and below the xiphoid process). During the hip measurement, the participant stood with their feet together and a horizontal measure was taken at the maximal circumference of the buttocks (ACSM, 2018). Both measurements were taken according to ACSM's protocol: The tape was placed directly over the skin surface for the waist and over the spandex-like material for the hip, without compressing the subcutaneous adipose tissue; A Gulick-type spring-loaded tape measure (Gulick II Tape Measure Model 67020, FitnessMart, Gays Mills, WI) was used for both measurements with the handle extended to the same mark, indicating proper tension, each trial; Duplicate measures were taken at each site and retested if these measurements were not within 5 mm; The measurement sites were rotated through to allow time for skin to regain normal texture (ACSM, 2018). Test results were recorded by the administrator.

Statistical Analysis

This study developed a model to estimate RMR (kcal/day). Observations were randomly divided into two samples: a validation (n = 70) and cross-validation (n = 70) sample. Prior to initial data collection, a pilot study was conducted in order to determine the test-retest reliability of the RMR measures. This pilot study also examined the time constraints and likelihood of undue participant discomfort or stress during the testing measurements. Based on the pilot study data from eight participants, the Chronbach Alpha coefficient for the RMR measures was 0.96 for two trials. Using the Spearman-Brown formula, the estimated test-retest reliability for one trial is 0.92. Using a criteria of 0.80 to define high reliability, it was determined that one measure of RMR would be highly reliable; consequently, each subsequent participant's RMR was measured only once. The eight participants tested during the pilot study were not included as participants in either the derivation or cross-validation samples.

The validation sample was used to develop the prediction models for estimating RMR. The models were then applied to the cross-validation sample to determine the prediction accuracy. Other published models for estimating RMR were also applied to the cross-validation sample to compare the accuracy of the models derived in this study with those of previous investigations. The derived models and raw data were compared to the models in Table 1. All models were also compared to the measured values obtained via indirect calorimetry.

Statistical analyses were performed using Stata Software, version 15.0 (StataCorp LLC, College Station, TX). Multiple regression utilizing a step-down ordering of variables was used to develop generalized equations for predicting RMR, which was the dependent variable. The independent variables were: weight (kg), height (cm), BMI (kg/m^2), age (yr), sex, ethnicity, WC (cm), HC (cm), WHR (WC/HC), WHtR (WC/height), measurements from the BOD POD® including FFM (kg), FM (kg), and percent body fat, and percent body fat estimated from BIA. Homogeneity of intercept and slope between men and women were also examined. Additionally, a multivariate analysis of variance (MANOVA) indicated no significant mean differences between the two samples for the dependent or independent variables.

Variables added to the model that prove to be significant predictors ($p < 0.05$) remained in the model as the other variables were tested. Analysis of partial F-tests for testing full and restricted models was used to determine the contribution and significance of each variable and second-order partial correlations were calculated for the final predictors included in the derived equation. Data are reported as mean ± SE and statistical significance set at $p \leq 0.05$.

Results

The first stage of the analysis was to divide the 140 participants tested into two randomly selected samples of 70 participants each. Participants were assigned a random number for sorting, then assigned another random number for selection into either the derivation sample or cross-validation sample. MANOVA indicated no significant mean differences between the two samples for the dependent or independent variables, Wilk's Lambda = 0.89, $F(12, 125) = 1.35$, $p = 0.20$. The descriptive characteristics of the two samples are summarized in Tables 2 and 3. In addition, based on BMI, approximately 50% of participants were normal weight, 31.4% were overweight, 17.9% were obese, and 0.7% were underweight. Two of the participants did not undergo BIA testing to estimate percent body fat, as recommended by the manufacturer, due to having a pacemaker or implanted device.

Since each participant was assigned to one and only one sample, all variables met the assumption of independence. In the derivation sample, the Shapiro-Wilk test for normality indicated that the distribution of the measures of the dependent variable, RMR, was not significantly different from normal, $z = 0.77$, $p = 0.22$, indicating that RMR met the assumption of normality. The Pearson Product-Moment correlations between RMR and the independent variables are reported in Table 5. To develop the derived model for estimating RMR, the regression analysis began with FFM, as this was the predictor variable with the highest correlation with RMR ($r = 0.77$), and the remaining variables were added to the model separately. Each variable was added or deleted from the model based on its separate contribution in accounting for significant additional variation in RMR.

FFM (kg) was a significant predictor of RMR, $F(1, 68) = 100.91$, $p < 0.0001$, $R^2 = 0.60$, standard error of estimation (SEE) = 191.4 kcal/day. Body weight (kg) was also a significant additional predictor, $t(67) = 2.20$, $p = 0.031$. With both FFM and body weight as predictors, the model R^2 increased to 0.62 and SEE decreased to 186.2 kcal/day. To test for homogeneity of intercepts between men and women, sex was added to the model, and accounted for significant additional variation in RMR, $t(66) = 2.42$, $p = 0.018$. However, when sex was added as a predictor, FFM no longer accounted for significant additional variation in RMR, $t(66) = 1.12$, $p = 0.27$; consequently, FFM was removed as a predictor variable. With body weight and sex as the two predictors, the model R^2 increased to 0.65 and SEE decreased to 180.1 kcal/day. To test for homogeneity of slopes between men and women, the interaction between body weight and sex was added to the model. This predictor did not account for significant additional variation in RMR, $t(66) = 0.70$, $p = 0.486$, and was dropped from the model. This analysis indicates that body weight is a significant predictor of RMR, but FFM does not account for additional variation in RMR after sex is added to the model. Further, the addition of sex to the model indicates that men and women have significantly different estimates of RMR, but the slopes of the lines-of-best-fit between males and females do not significantly differ.

In the next stage of the analysis, after body weight and sex were included in the model, WC (cm) was added as the next predictor, and accounted for significant additional variation in RMR, $t(66) = 2.05$, $p = 0.044$. With body weight, sex, and WC as predictors, the model R^2 increased to 0.66 and SEE decreased to 176.0 kcal/day. After these three predictors were included in the model, the following variables were added separately, but failed to account for significant additional variation: height (cm), $t(65) = 0.85$, $p = 0.400$, BMI (kg/m^2), $t(65) = 0.84$, $p = 0.404$, HC (cm), $t(65) = 0.20$, $p = 0.839$, WHR (cm), $t(65) = 0.12$, $p = 0.903$, WHtR (cm), $t(65) = 0.71$, $p = 0.477$, FM (kg), $t(65) = 0.40$, $p = 0.689$, percent body fat estimated from BOD POD® analysis, $t(65) = 0.03$, $p = 0.976$, percent body fat estimated from BIA, $t(65) = 1.64$, $p = 0.106$, and ethnicity $t(65) = 0.89$, $p = 0.377$.

The last predictor to be added to the model and tested was age (years). Age accounted for significant additional variation in RMR after body weight, sex, and WC were in the model, $t(65) = 2.57$, $p = 0.012$. In addition, after age was added as a predictor, WC no longer accounted for significant additional variation, $t(65) = 1.01$, $p = 0.317$, and was dropped from the model. The addition of age as a predictor, along with body weight and sex, increased R^2 to 0.68 and SEE decreased to 173.0 kcal/day. To test for the homogeneity of slopes between men and women based on the relationship between age and RMR, the interaction between age and sex was added to the model. This predictor did not account for significant additional variation in RMR, $t(65) = 1.59$, $p = 0.116$, and was dropped from the model. Also, a test for a quadratic relationship between RMR and body weight indicated that the relationship between these two variables is linear and not quadratic $t(65) = 0.45$, $p = 0.651$. Lastly, a test for a quadratic relationship between RMR and age indicated that the relationship between these two variables is also linear and not quadratic $t(65) = 1.14$, $p = 0.258$.

The generalized prediction equation that resulted from the preceding analysis is: RMR (kCal/day) = 843.11 + (8.77 x body weight, kg) + (228.54 x sex, male = 1; female = 0) - (4.23 x age, years). The regression coefficient for sex indicates that for any persons with the same body weight and age, men have an average RMR 228.54 kcal/day higher than women. Similarly, the regression coefficient for age indicates that for any persons with the same body weight and sex, RMR will decrease by an average of 4.23 kcal/day per year. Further, the sex (male = 1, female = 0) can be combined with the coefficients to simplify the equation and yield different coefficients for men and women:

For men: RMR (kCal/day) = 1071.65 + 8.77 (wt) - 4.23 (age)

For women: RMR (kCal/day) = 843.11 + 8.77 (wt) - 4.23 (age)

To demonstrate the contribution of each predictor within the derived equation, second-order partial correlations were calculated for the variables in the equation. These correlations represent the association between each predictor and RMR, controlling for the relationship between RMR and other predictors. The second-order correlation for body weight was 0.70 ($p < 0.001$), sex was 0.51 ($p < 0.001$), and age was -0.30 ($p = 0.012$). This result indicates that body weight was the most substantial independent predictor of RMR, while sex was more substantial than age.

In the last stage of the analysis, the derived model was applied to the cross-validation sample to test for accuracy and validity. In the cross-validation sample, RMR estimated from the derived model was moderately related to measured RMR, with $R^2 = 0.54$, SEE = 199.1 kcal/day, and total error = 198.0 kcal/day. This relationship is illustrated in Figure 1. The predicted values from the newly derived equation and previously published RMR prediction equations by Nelson et al. (1992), Harris & Benedict (1918), Owen et al. (1986), Owen et al. (1987), Mifflin et al. (1990), and Lazzer et al. (2010) were also compared to the measured values obtained in the cross-validation group via indirect calorimetry to determine the prediction accuracy of each model. Nelson et al. (1992) published two equations which were evaluated: one equation includes only FFM and we have labeled this equation Nelson et al. (1), and the other equation includes both FFM and FM and we have labeled this equation Nelson et al. (2). Additionally, the Owen et al. equation examined includes the Owen et al. (1986) RMR prediction equation for women as well as the Owen et al. (1987) RMR prediction equation for men. The relationship between measured and estimated RMR from these equations are illustrated in Figures 2 through 7. A comparison of the cross-validation statistics from all models evaluated is presented in Table 6. Cross-validation of the other published models for estimating RMR were similar to those of the derived model in the current study, with R^2 ranging from 0.47 to 0.57, and SEE ranging from 192 to 213 kcal/day; however, the total error in the derived equation (198 kcal/day) was lower than any of the other published models, which ranged from 212 to 1311 kcal/day. Additionally, several of the other published models considerably over-estimated RMR, and the error increased as RMR increased.

Discussion

In the present study, the derivation sample was used to develop a new RMR prediction equation which was then validated using the cross-validation sample. The newly derived equation includes simple anthropometric and demographic measures (body weight, age and sex), is applicable to a diverse population, and exhibited less total error than previously published models. Variables collected for the derivation of the new equation included: body weight, height, age, sex, ethnicity, BMI, WC, HC, WHR, WHtR, measurements from the BOD POD® including FFM, FM, and percent body fat, and percent body fat estimated from BIA. After analysis, predictors that accounted for significant variation in RMR were body weight ($R^2 = 0.70$), sex ($R^2 = 0.51$), and age ($R^2 = -0.30$). Initially, simple anthropometric measurements such as WC, HC, WHR, and WHtR were collected with the intent to be used as surrogates for body fat percentage when predicting RMR. However, these findings suggest that FFM was a significant predictor of RMR as a sole variable ($R^2= 0.60$), but when body weight and sex were included in the prediction, FFM no longer accounted for significant additional variation. In lieu of these data, body composition measurements are unnecessary for accurate predictions of RMR and, thus, collection of simple measures of WC and HC and/or more complex measures (e.g., body fat percentage via dual-energy X-ray absorptiometry or air displacement plethysmography) might not be as useful as body weight and sex when predicting RMR.

The elimination of body composition measurements when predicting RMR also reduces the concern for accurate measures of body composition for this purpose, especially in the overweight/obese populations. Further, the inclusion of simple and commonly collected anthropometric and demographic variables (i.e., body weight, sex, and age) enhances the feasibility to accurately predict RMR in not only clinical settings, but also by practitioners in the field. Expensive equipment and trained personnel are not required for these simple measurements and, thus, personal trainers, coaches, dietitians, physicians, exercise physiologists, and other health professionals can effortlessly and accurately predict RMR with the use of a scale using the newly derived equation.

The equations derived by Mifflin St.-Jeor (1990) had the highest coefficient of determination observed ($R^2 = 0.57$) and a smaller SEE than the derived equation, but greater total error compared to the derived equation. This result indicates greater systematic error than the derived model, and as seen in Figure 2, the estimated values from this equation included noticeable overestimation of RMR. This overestimation could possibly be due to some demographic differences between the sample in the Mifflin et al. (1990) study and the sample in the present study. The mean age in the Mifflin et al. (1990) sample (44.5 ± 14.1) was more than ten years older than the cross-validation sample in the present study (32.02 ± 12.41). Studies have shown significant declines in RMR with increasing age (Bosy-Westphal et al., 2003; Luhrmann, Edelmann-Schafer, & Neuhäuser-Berthold, 2010) and, thus, the derivation of the Mifflin St-Jeor equations from an older study population could explain why those equations overestimated RMR in younger participants from the cross-validation sample.

As seen in Figure 2, the equation derived by Harris & Benedict (1918) had a similar correlation to the derived equation ($R^2 = 0.55$) and smaller SEE, but greater total error. In agreement with previous research (Daly et al., 1985; Frankenfield, 2013; Mifflin et al., 1990; Owen et al., 1987; Willis et al., 2016), estimation of RMR from the Harris-Benedict equation resulted in considerable overestimation of RMR. Additionally, the line of best fit for this model suggests the higher the measured RMR, the greater the overprediction. A possible explanation for this widely observed overprediction is the significant increase in the obesity rates (Hales, Carroll, Fryar, & Ogden, 2017) and life expectancy of humans in the U.S. adult population observed from the 1900s to present (Arias, Heron, & Xu, 2017). In lieu of this, the Harris-Benedict equation is not reflective of the current U.S. population and, therefore, it is difficult to generalize the Harris-Benedict equation to this population.

The Owen et al. equation had the lowest coefficient of determination compared to the derived equation ($R^2 = 0.47$) and greater SEE and total error. This indicates greater systematic error in the Owen et al. equation. As seen in Figure 5, the Owen et al. equation mostly underestimated lower measured RMR values and mostly overestimated higher measured RMR values. So, although the Owen et al. equations use only body weight, and thus, are simpler than the proposed equation, caution should be used when predicting RMR in individuals on either extreme end of the weight spectrum due to the increased error in the prediction model.

The Nelson et al. equations produced almost identical correlation values and SEE to the derived equation, but they both exhibited greater total error. Although the difference in total error is only approximately 32 kcal/day, the derived equation exhibits an advantage over the Nelson et al. equations because of the simple variables included (body weight, age, and sex), whereas, the Nelson et al. equations include more complex, body composition variables (FFM and/or FM). Additionally, the Nelson et al. (2) equation seemed to have a similar trend as the Owen et al. equation and underestimates lower RMR values and overestimates higher RMR values.

The Lazzer et al. equation had an almost identical coefficient of determination ($R^2 = 0.54$) and SEE (198.2 kcal/day) with the derived equation, however, the total error was inappropriate for accurate estimation (1311.2 kcal/day). As seen in Figure 6, the Lazzer et al. equation overestimated RMR in almost 100% of the participants. This large systematic error could be due to the severely obese (BMI $\geq$ 30 kg/m^2) sample from which that equation was derived. Additionally, the method in which body composition was measured could also have an effect on the results. Lazzer et al. (2010) measured body composition via BIA and estimated the participant's FFM via prediction equations. Previous research has suggested that BIA fail to work properly in obese participants due to the increased amount of total body water and extracellular water present in obese individuals (Coppini, Waitzberg, & Campos, 2005) and, thus, this may present a limitation in the Lazzer et al. equation which uses FFM estimated from BIA.

In summary, the predictive value of the derived equations was very similar in some ways when compared to the six previously published equations, however, the derived equation had the lowest total error, thus, representing the most accurate and least biased equation. One strength of the newly developed equation was the sample studied, which included a wide variety of ages (19 to 65 years) and BMI (50% normal weight, 31.4% overweight, and 17.9% obese), thus reflecting a diverse population and allowing for generalizability of the model. Further, the assessment of the predictive performance of the derived model using cross-validation on an independent, random sample (the cross-validation sample) confirmed the derived equation can be generalized to an independent data set. The previously published models examined did not report cross-validation and, therefore, there is no published data on how accurate the equations would predict RMR in a random, independent sample. Lastly, the simple demographic (sex and age) and anthropometric (body weight) variables included in the derived equation are currently routinely collected in both field and clinical settings and, thus, present no additional challenge for physicians or personal trainers to obtain.

Limitations

The limitations of this study must also be considered. Prediction equations offer a quick and easy approximation of energy expenditure, but direct metabolic measurement via indirect calorimetry is the preferred method for precise and accurate measures of RMR. Additionally, the derived equation resulted in an R^2 of 0.54, indicating that only 54% of the variance in RMR can be accounted for by the variables included in the newly derived equation. Consequently, 46% of the variability in RMR is unaccounted for and cannot be explained by the variables examined in this study. Future studies might consider examining additional variables, such as diet, fitness/physical activity level, and/or aerobic capacity, to determine if those variables may account for some of the unexplained variability presented in RMR in this study. Also, our sample population was mainly Caucasian (57%) so future studies might consider the effect of race/ethnicity on energy expenditure and collect data from a more racially diverse sample.

Tables

Table 1

Resting Metabolic Rate (kcal/day) Prediction Equations Evaluated

Reference	Population Tested	Sex	Prediction Equation
Derived Equation	Men (n = 27) and women (n = 43)	Men	1071.65 + 8.77 (wt) - 4.23 (age)
		Women	843.11 + 8.77 (wt) - 4.23 (age)
Lazzer et al. (FFM) (2010)	Obese (n = 7, 368)	Men	20 (FFM) - 2 (age) + 830
		Women	20 (FFM) - 2 (age) + 841
Nelson et al. (FFM) (1992)	Nonobese (n = 81) and obese (n = 132)	Men/Women	1265 + 93.3 (FFM)*
Nelson et al. (FFM & FM) (1992)	Nonobese (n = 81) and obese (n = 132)	Men/Women	108 (FFM) + 16.9 (FM)*
Mifflin-St. Jeor (1990)	Normal weight (n = 264)	Men	10 (wt) + 6.25 (h) - 5 (age) + 5
	and obese (n = 234)	Women	10 (wt) + 6.25 (h) - 5 (age) - 161
Owen et al. (1987)	Lean and obese (n = 60)	Men	879 + 10.2 (wt)
Owen et al. (1986)	Lean and obese (n = 44)	Women	795 + 7.18 (wt)
Harris & Benedict (1918)	Men (n = 136) and women (n = 103)	Men	66.5 + 13.75 (wt) + 5.0033 (h) - 6.76 (age)
		Women	655 + 9.56 (wt) + 1.85 (h) - 4.68 (age)

Note. Wt= weight (kg); h= height (cm); age (yr); FFM= fat-free mass; FM= fat mass.
*Indicated result converted from kJ/day to kcal/day using 4.184 equivalency.

Table 2

Anthropometric Data and Resting Metabolic Rate from Indirect Calorimetry

	All (n = 140)	Derivation Group (n = 70)	Cross-Validation Group (n = 70)
Age (yr)	32.02 ± 1.05	33.8 ± 1.52 [19 - 65]	30.24 ± 1.43 [19 - 64]
Height (cm)	169.19 ± 0.81	167.82 ± 1.18 [150.6 - 193]	170.57 ± 1.10 [151.6 - 193]
Weight (kg)	75.34 ± 1.53	75.8 ± 2.43 [44.4 - 164]	74.88 ± 1.86 [47.55 - 123.1]
WHtR (cm)	0.46 ± 0.01	0.47 ± 0.01 [0.36 - 0.75]	0.45 ± 0.01 [0.37 - 0.68]
BMI (kg/m^2)	26.15 ± 0.43	26.72 ± 0.72 [18.26 - 54.42]	25.59 ± 0.47 [19.05 - 37.58]
WC (cm)	78.14 ± 1.05	78.94 ± 1.65 [56.4 - 130.65]	77.34 ± 1.29 [60.65 - 122.8]
HC (cm)	101.34 ± 0.79	101.59 ± 1.32 [81.3 - 151.75]	101.10 ± 0.89 [88.45 - 119.6]
WHR (cm)	0.77 ± 0.01	0.77 ± 0.01 [0.64 - 0.96]	0.76 ± 0.01 [0.65 - 1.09]
$\%BF_{ADP}$	27.89 ± 0.80	29.30 ± 1.12 [11.1 - 49.7]	26.48 ± 1.14 [3.9 - 43.9]
$\%BF_{BIA}$	25.05 ± 0.76[a]	26.49 ± 1.09 [8.1 - 49.5]	23.56 ± 1.03 [5.7 - 38.8][b]
FM (kg)	21.47 ± 0.92	23.04 ± 1.48 [7.5 - 81.7]	19.89 ± 1.08 [2.9 - 46.6]
FFM (kg)	53.88 ± 1.07	52.89 ± 1.49 [33.9 - 82.7]	54.88 ± 1.54 [32.2 - 85]
RMR_M (kCal/day)	1462.81 ± 24.93	1443.11± 35.78 [623.61 - 2091.2]	1482.506 ± 34.81 [882.46 ± 2331.07]

Note. MANOVA indicated no significant mean differences between the two samples for the dependent or independent variables. Values are mean ± SE [minimum - maximum values]. WHtR = waist-to-height ratio; BMI = body mass index; WC = waist circumference; HC = hip circumference; WHR = waist-to-hip ratio; $\%BF_{ADP}$ = percentage body fat measured from air displacement plethysmography; $\%BF_{BIA}$ = percentage body fat measured from bioelectrical impedance analysis; FM = fat mass; FFM = fat free mass; RMR_M = measured resting metabolic rate.

[a]BIA data was not collected for two participants due to implanted devices and, therefore, n = 138. [b] n = 68.

Table 3

Anthropometric Data and Resting Metabolic Rate from Indirect Calorimetry for Men and Women in Different Groups

	Derivation Group		Cross-Validation Group	
	Men (n = 24)	Women (n = 46)	Men (n = 27)	Women (n = 43)
Age (yr)	32.79 ± 1.98	34.33 ± 2.07	29.63 ± 2.09	30.63 ± 1.94
Height (cm)	177.25 ± 1.41	162.89 ± 1.07	179.98 ± 1.01	164.66 ± 0.83
Weight (kg)	86.05 ± 2.87	70.45 ± 3.12	86.96 ± 2.92	67.30 ± 1.54
WHtR (cm)	0.48 ± 0.01	0.47 ± 0.01	0.47 ± 0.01	0.44 ± 0.01
BMI (kg/m^2)	27.45 ± 0.94	26.34 ± 0.98	26.83 ± 0.87	24.80 ± 0.52
WC (cm)	84.25 ± 2.08	76.16 ± 2.17	84.20 ± 2.42	73.03 ± 1.03
HC (cm)	101.72 ± 1.59	101.52 ± 1.84	101.59 ± 1.45	100.80 ± 1.13
WHR (cm)	0.83 ± 0.01	0.75 ± 0.01	0.83 ± 0.02	0.72 ± 0.01
$\%BF_{ADP}$	23.70 ± 1.49	32.22 ± 1.33	19.69 ± 1.73	30.74 ± 1.08
$\%BF_{BIA}$	19.83 ± 1.37	29.97 ± 1.22	17.33 ± 1.56	27.67 ± 0.95[a]
FM (kg)	20.99 ± 1.89	24.11 ± 2.02	18.01 ± 2.15	21.08 ± 1.12
	64.88 ± 1.67	46.63 ± 1.37	68.69 ± 1.56	46.21 ± 0.87
RMR_M (kCal/day)	1687.41 ± 42.94	1315.65 ± 37.99	1706.55 ± 52.81	1341.83 ± 30.58

Note. MANOVA indicated no significant mean differences between the two samples for the dependent or independent variables. Values are mean ± SE. WHtR = waist-to-height ratio; BMI = body mass index; WC = waist circumference; HC = hip circumference; WHR = waist-to-hip ratio; $\%BF_{ADP}$ = percent body fat measured from air displacement plethysmography; $\%BF_{BIA}$ = percent body fat measured from bioelectrical impedance analysis; FM = fat mass; FFM = fat free mass; RMR_M = measured resting metabolic rate.

[a]BIA data was not collected for two participants due to implanted devices and, therefore, n = 41.

Table 4

Two-compartment Body Density Models Used for BOD POD® Assessment

Name	Percent Body Fat Equation	Population
Siri	%fat = (4.95/Db - 4.50)*100	General Population[a]
Schutte	% fat= (4.374/Db - 3.928)*100	African American Males
Ortiz	%fat = (4.83/Db - 4.37)*100	African American Females
Brozek	%fat = (4.57/Db - 4.142)*100	Lean and Obese Individuals[b]

Note. Db= body density. [a]General population includes underweight individuals (BMI < 18.5 kg/m^2) and overweight individuals (BMI 25.0-29.9 kg/m^2) who are non-African American. [b]Lean defined as BMI 18.5-24.9 kg/m^2 and obese defined as BMI $\geq$ 30 kg/m^2.

Table 5

Pearson Correlations Between Resting Metabolic Rate and Independent Variables

Variables	RMR_M (kcal/day)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Height (cm)	0.63*	1.00											
(2) Weight (kg)	0.72*	0.55*	1.00										
(3) BMI (kg/m^2)	0.55*	0.15	0.90*	1.00									
(4) WC (cm)	0.58*	0.33*	0.91*	0.92*	1.00								
(5) HC (cm)	0.52*	0.27*	0.88*	0.91*	0.81*	1.00							
(6) WHR (cm)	0.41*	0.27*	0.57*	0.55*	0.79*	0.29*	1.00						
(7) FM (kg)	0.41*	0.13	0.82*	0.90*	0.86*	0.90*	0.47	1.00					
(8) FFM (kg)	0.77*	0.78*	0.81*	0.57*	0.62*	0.54*	0.45*	0.34*	1.00				
(9) $\%BF_{ADP}$	0.03	-0.24	0.43*	0.64*	0.60*	0.65*	0.32*	0.84	-0.15	1.00			
(10) $\%BF_{BIA}$	-0.07	-0.34*	0.40*	0.65*	0.56*	0.64*	0.25	0.77*	-0.13	0.90*	1.00		
(11) Age	-0.18	-0.13	0.03	0.11	0.22	0.01	0.37*	0.18	-0.15	0.31*	0.45*	1.00	
(12) WHtR (cm)	0.39*	-0.02	0.76*	0.92*	0.94*	0.76*	0.75*	0.86*	0.38*	0.72*	0.71*	0.29*	1.00

Note. BMI = body mass index; WC = waist circumference; HC = hip circumference; WHR = waist-to-hip ratio; FM = fat mass; FFM = fat-free mass; $\%BF_{ADP}$ = percentage body fat measured from air displacement plethysmography; $\%BF_{BIA}$ = percentage body fat estimated from bioelectrical impedance analysis; RMR_M = resting metabolic rate measured by indirect calorimetry; WHtR = waist-to-height ratio.

*$p < 0.05$

Table 6

Cross-Validation Statistics for the Compared Models

Model	R^2	SEE (kCal/day)	Total Error (kCal/day)
Derived Equation	0.54	199.1	198
Harris & Benedict (1918)	0.55	196.4	268.1
Owen et al. (1988)	0.47	212.7	219.4
Mifflin et al. (1990)	0.57	192.0	212.3
Lazzer et al. (2010)	0.54	198.2	1311.2
Nelson et al. (1) (1990)	0.54	199.6	229.8
Nelson et al. (2) (1990)	0.54	199.6	230.5

Figures

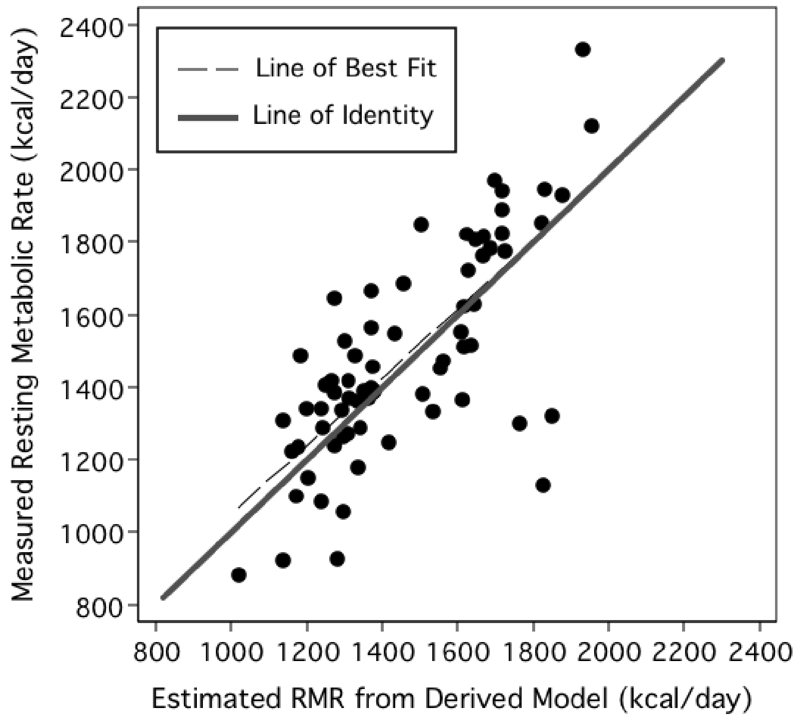


Figure 1. Relationship Between Measured Resting Metabolic Rate (RMR) and Estimated RMR from Derived Model. RMR was measured using indirect calorimetry and predicted using the newly derived equation: For men: RMR (kCal/day) = 1071.65 + 8.77 (weight) - 4.23 (age). For women: RMR (kCal/day) = 843.11 + 8.77 (weight) - 4.23 (age).

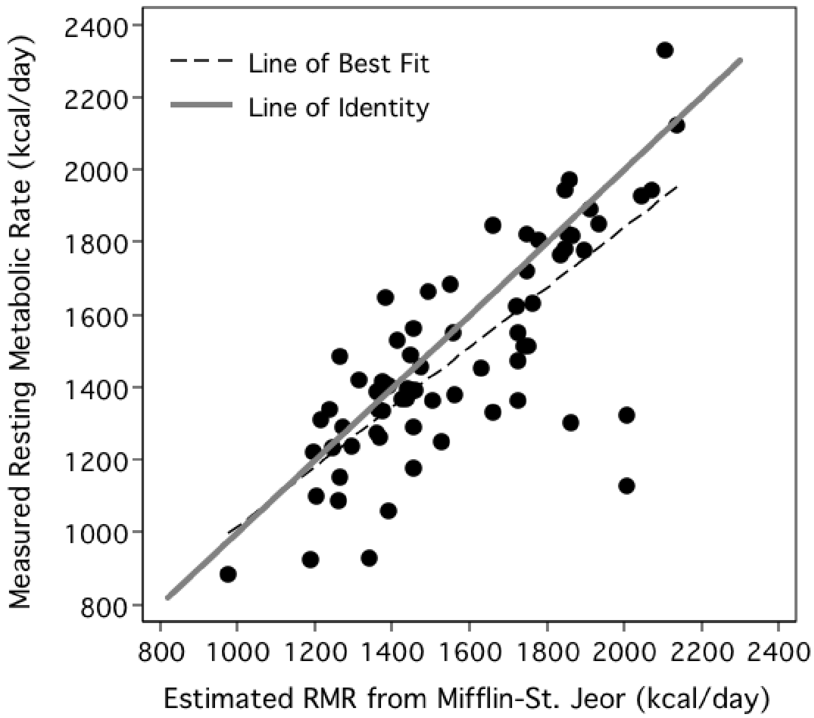


Figure 2. Relationship Between Measured Resting Metabolic Rate (RMR) and Estimated RMR from Mifflin-St. Jeor Equation. RMR was measured using indirect calorimetry and predicted using the Mifflin St-Jeor equation: For men, RMR (kcal/day) = 10(weight) + 6.25(height) – 5(age) + 5. For women, RMR (kcal/day) = 10(weight) + 6.25(height) – 5(age) + 161.

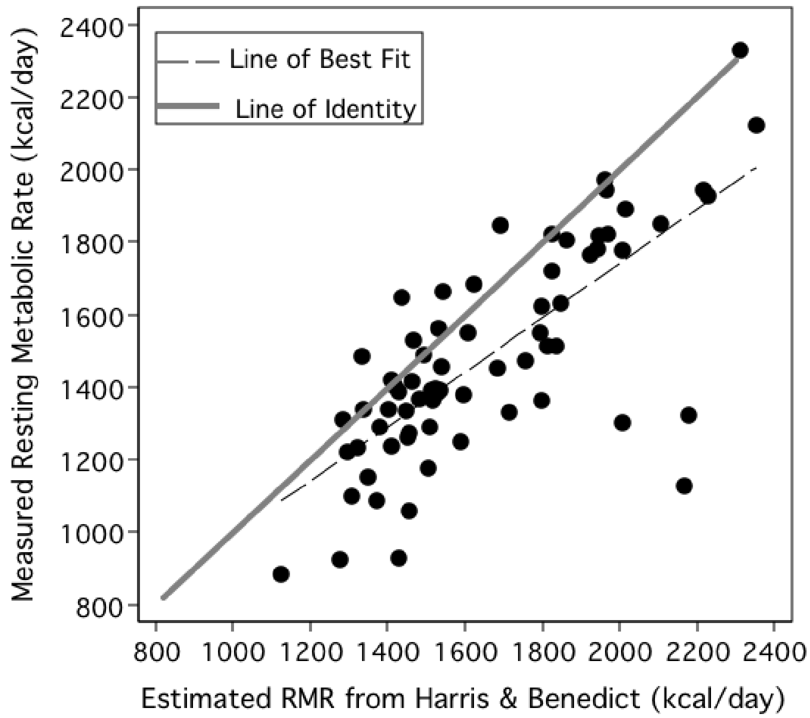


Figure 3. Relationship Between Measured Resting Metabolic Rate (RMR) and Estimated RMR from Harris & Benedict Equation. RMR was measured using indirect calorimetry and predicted using the Harris & Benedict equation: For men, RMR (kcal/day) = 66.5 + 13.75(weight) + 5.0033(height) – 6.76(age). For women, RMR (kcal/day) = 655 + 9.56(weight) + 1.85(height) – 4.68(age).

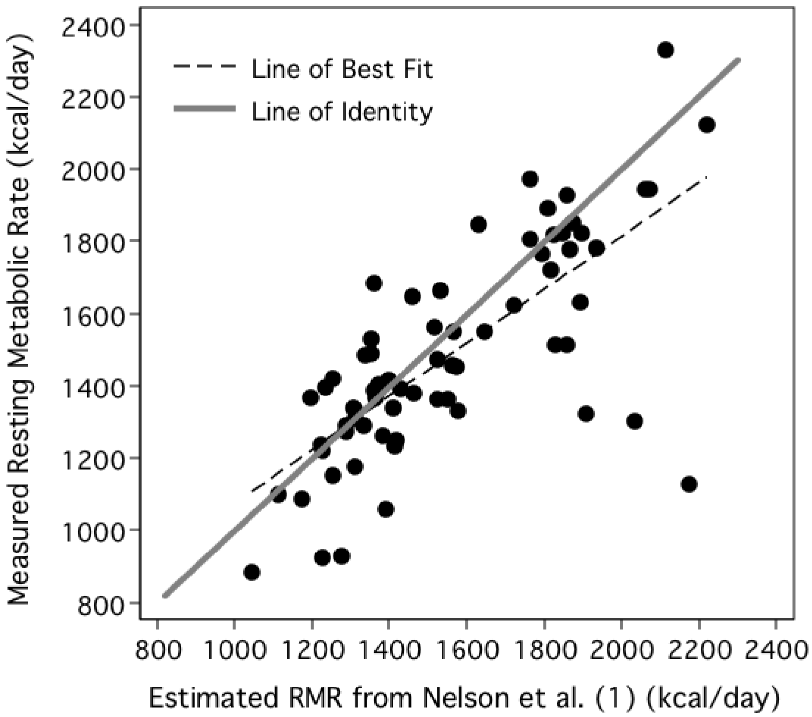


Figure 4. Relationship Between Measured Resting Metabolic Rate (RMR) and Estimated RMR from Nelson et. al (1) Equation. RMR was measured using indirect calorimetry and predicted using the Nelson et al. (1) equation: RMR (kcal/day) = 1265 + 93.3(FFM).

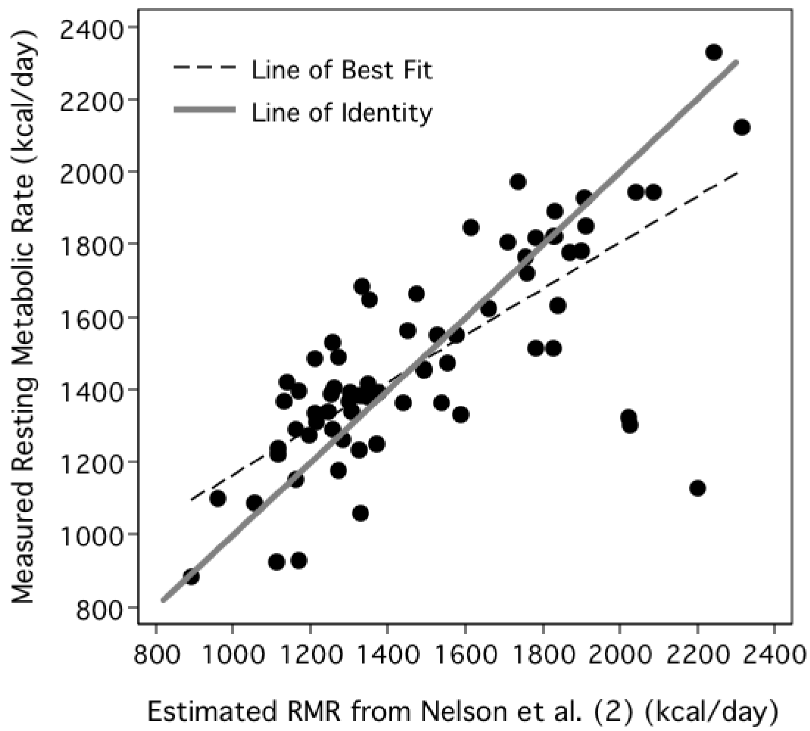


Figure 5. Relationship Between Measured Resting Metabolic Rate (RMR) and Estimated RMR from Nelson et. al (2) Equation. RMR was measured using indirect calorimetry and predicted using the Nelson et al. (2) equation: RMR (kcal/day) = 108(FFM) + 16.9(FM).

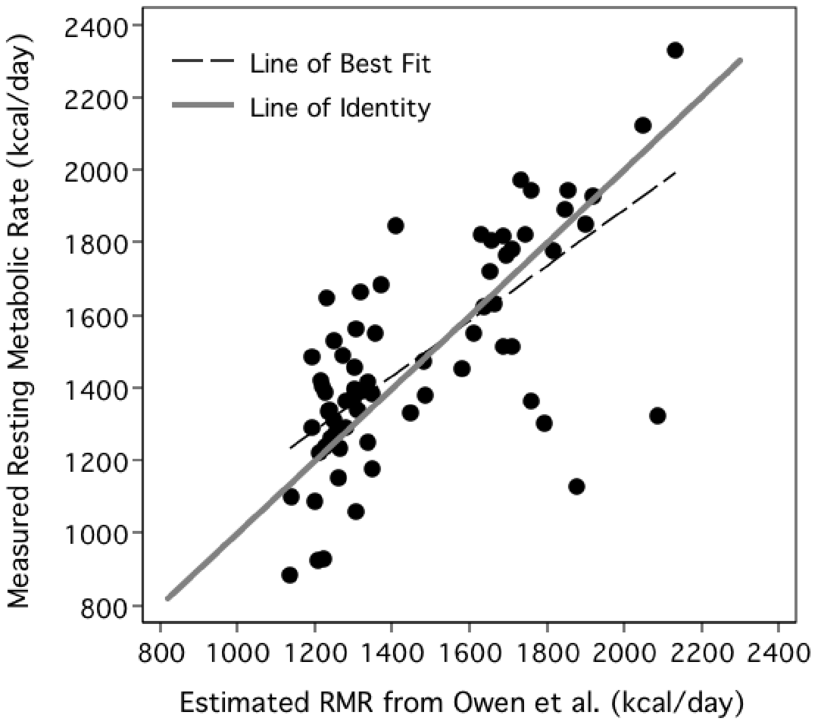


Figure 6. Relationship Between Measured Resting Metabolic Rate (RMR) and Estimated RMR from Owen et. al Equation. RMR was measured using indirect calorimetry and predicted using the Owen et al. equations: For men, RMR (kcal/day) = 879 + 10.2(weight). For women, RMR (kcal/day) = 795 + 7.18(weight).

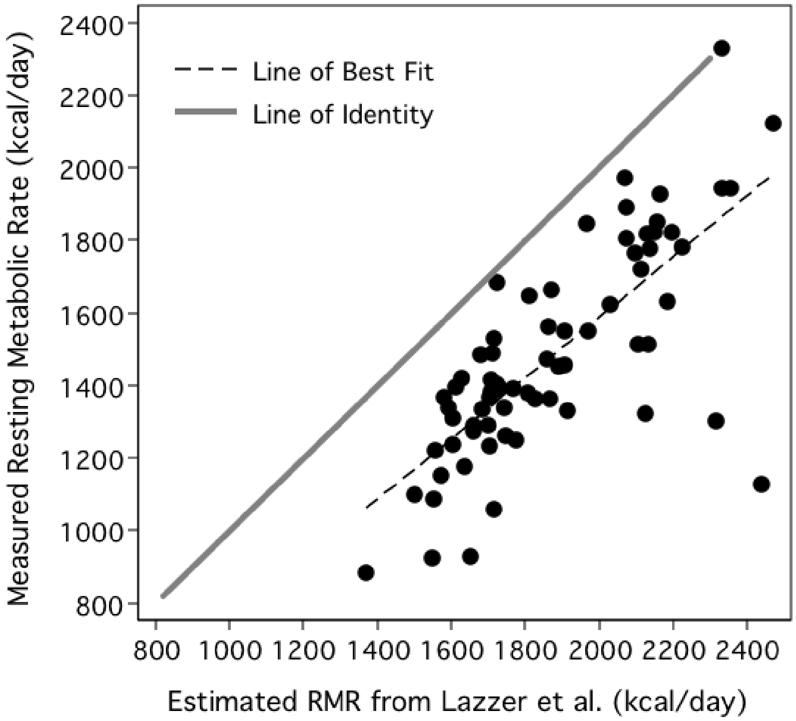


Figure 7. Relationship Between Measured Resting Metabolic Rate (RMR) and Estimated RMR from Lazzer et. al Equation. RMR was measured using indirect calorimetry and predicted using the Lazzer et al. equation: For men, RMR (kcal/day) = 20(FFM) – 2(age) + 830. For women, RMR (kcal/day) = 20(FFM) – 2(age) + 841

APPENDIX SECTION

APPENDIX A: DATA COLLECTION SHEET

Date: _______________

Age: _______________ Sex: _______________

Race/Ethnicity: ☐ Caucasian ☐ African American
☐ Hispanic ☐ Asian
☐ Other: ________________

For administrator use only Subject # _______

IC: RMR (kcal/day): ________________

Digital scale: Height (cm): _________ Body weight (kg): _________
Height (ft) ______ (in) ________ Body weight (lb): _________

BMI (kg/m^2): ___________ BMI Classification: ______________

Body density model: _____________________

Tape measure: WC- Trial 1 (cm): _________ HC- Trial 1 (cm): _________
WC- Trial 2 (cm): _________ HC- Trial 2 (cm): _________
WC- Trial 3 (cm): _________ HC- Trial 3 (cm): _________

WC- Average (cm): _________ HC- Average (cm): _________

Bod Pod: BF %: _________ Lean %: _________

Fat mass (lb): _________ Fat-free mass (lb): _________

Total body weight (lb): _________ Est. RMR (kcal/day): ________

BIA: BF%: ________

APPENDIX B: RESULTS SHEET

Name: ____ Date: _________________

Indirect Calorimetry:

Resting Metabolic Rate (kcal/day): _____________

Digital scale:

Height (cm): __________

Body weight (kg): __________

BMI (kg/m^2): ____________
*Classification on information sheet

Tape measure:

Waist circumference (cm): __________
*Classification on information sheet

Hip circumference (cm): __________

Bod Pod:

Body Fat Percentage: __________
*Classification on information sheet

Lean Fat Percentage: __________

Fat mass (lb): __________
*weight of fat

Fat-free mass (lb): __________
*weight of muscles, bones, organs, etc.

Total body weight (lb): ____________

Handheld Fat Loss Monitor (Bioelectrical Impedance Analysis):

Body Fat Percentage: _________

Note: Research has shown the Bod Pod to be considered the gold standard for measurement of body composition; range of measurement error= ± 1 to 2.7%.

Information on Resting Metabolic Rate (RMR)

Resting Metabolic Rate (RMR) is the measure of resting energy expenditure in our body (in Calories/day). Resting metabolic rate refers to the amount of energy (in the form of calories) used by the body in a given period of time when the body is at complete rest. This energy is merely used to maintain the basic body functions like keeping the heart beating, lungs breathing, and maintaining a normal body temperature.

Information on Body Composition

Body Fat: A certain amount of fat is necessary for good health. Fat plays an important role in protecting internal organs, providing energy, and regulating hormones. The minimal amount of "essential fat" is approximately 3-5% for men, and 12-15% for women. When we drop below the minimal recommended levels of essential fat, we negatively affect the delivery of vitamins to the organs, the ability of the reproductive system to function, and overall well-being. However, if too much fat accumulates over time, health may be compromised (see table below). Thus, a body composition within the recommended range suggests you have less risk of developing obesity-related diseases such as diabetes, high blood pressure, and even some cancers (American College of Sports Medicine, 2016).

Fat Free Mass: Fat free mass is everything except fat. It includes muscle, water, bones, and internal organs. Muscle is the "metabolic engine" of the body that burns calories (fat) and plays an important role in maintaining strength and energy. Healthy levels of fat-free mass contribute to physical fitness and may prevent conditions such as osteoporosis.

ACSM Body Composition (% Body Fat) for Men and Women

Male	AGE				
Fitness Category	**20-29**	**30-39**	**40-49**	**50-59**	**60+**
Essential Fat	2- 5	2- 5	2- 5	2- 5	2- 5
Excellent	7.1 - 9.3	11.3 - 13.8	13.6 - 16.2	15.3 - 17.8	15.3 - 18.3
Good	9.4 - 14	13.9 - 17.4	16.3 - 19.5	17.9 - 21.2	18.4 - 21.9
Average	14.1 - 17.5	17.5 - 20.4	19.6 - 22.4	21.3 - 24	22 - 25
Below Average	17.4 - 22.5	20.5 - 24.1	22.5 - 26	24.1 - 27.4	25 - 28.4
Poor	>22.4	>24.2	>26.1	>27.5	>28.5
Female	**AGE**				
Fitness Category	**20-29**	**30-39**	**40-49**	**50-59**	**60+**
Essential Fat	10 - 13	10 - 13	10 - 13	10 - 13	10 - 13
Excellent	14.5 - 17	15.5 - 17.9	18.5 - 21.2	21.6 - 24.9	21.1 - 25
Good	17.1 - 20.5	18 - 21.5	21.3 - 24.8	25 - 28.4	25.1 - 29.2
Average	20.6 - 23.6	21.6 - 24.8	24.9 - 28	28.5 - 31.5	29.3 - 32.4
Below Average	23.7 - 27.6	24.9 - 29.2	28.1 - 32	31.6 - 35.5	32.5 - 36.5
Poor	>27.7	>29.3	>32.1	>35.6	>36.6

Taken from ACSM'S Health-Related Physical Fitness Assessment Manual, Second Ed. 2008. pg 59.

What Can You Do with Your Results? The results from your body composition assessment can be used to identify risks, personalize your exercise program or evaluate how well your current exercise and nutrition program is working for you. If you find that you are within a healthy range, continue your exercise and dietary behaviors. If you find that your body composition has room for improvement, take a closer look at what you can do to make positive changes to your current level of activity and diet. Use more than just the scale to assess body composition. Remember, it is possible for the number on the scale to remain constant but experience changes in fat mass and lean mass. Changes in body composition take time and a dedicated effort, but the positive impact on health and quality of life is worth the effort. Participation in regular exercise and physical activity along with a healthy balanced diet are the key to reaching and maintaining a healthy body composition.

Information on Waist Circumference

According to the American College of Sports Medicine (2016), the measurement of waist circumference provides insight to increased risk of obesity-related illness due to the location of excess fat. Waist circumference should be at or below 102 cm (or 40 in) for men and 88 cm (or 35 inches) for women. Android obesity, classified as excess weight located in the trunk area, places an individual at greater risk for high blood pressure, metabolic syndrome, type 2 diabetes, high cholesterol, coronary artery disease and premature death (see table below).

Risk Criteria for Waist Circumference in Adults	Waist circumference (cm)	
Risk Category	**Women**	**Men**
Very low	<70 cm	<80 cm
Low	70-89 cm	80-99 cm
High	90-110 cm	100-120 cm
Very high	>110 cm	>120 cm

Taken from ACSM'S Guidelines for Exercise Testing and Prescription, Tenth Ed. 2018. Pg 73.

Information on Body Mass Index (BMI)

BMI is used to assess weight relative to height and is calculated by dividing weight in kilograms (kg) by height in meters squared (kg m-2). A BMI of 25 or higher is classified as overweight while a BMI of 30 or greater is classified as obese (see table below). While BMI may give an individual a general idea of increased risk for obesity-related health problems, it fails to distinguish the composition of that weight.

Classification of Disease Risk Based on BMI	
	BMI (kg/m^2)
Underweight	<18.5
Normal	18.5-24.9
Overweight	25.0-29.9
Obesity class I	30.0-34.9
Obesity class II	35.0-39.9
Obesity class III	≥40.0

APPENDIX D: COMPREHENSIVE MEDICAL HEALTH APPRAISAL

HEALTH HISTORY SCREEN INFORMATION

Participant Full Name: **Date information obtained:**

Age: **Occupation:**

Email: **Phone Number:**

Race/Ethnicity (choose/highlight one): **Caucasian** **African American**

Hispanic **Asian** **Other: ________________**

Answer questions below. Highlight Y or N and type in answer if needed.

Y N Are you currently ill?

Y N Have you ever experienced claustrophobia (i.e., fear of confined/tight spaces)?

Y N Have you experienced significant weight loss (>24 lb) in the past 3 months?

Y N Do you have a pacemaker?

Do you have any other medical conditions?

	Yes	No
Diabetes		
Chronic Respiratory diseases		
Autoimmune conditions		
Stroke		
Seizures		
Other neurological conditions		
Kidney or liver disease		
Heart Disease		
Thyroid condition		
Cancer in the last 5 years		
Other medical conditions not already addressed		

If yes, describe other medical conditions:

____

____

What prescription medications do you take, if any?

Medication:	Dosage:	For:

If you don't qualify for this study, would you be interested in participating in other studies as they become available? Yes No

Additional Comments:

APPENDIX E: PRE-TEST INSTRUCTIONS FOR VISIT

Pre-test Instructions for Laboratory Testing

Before you participate in this study, you need to first be made aware of what to expect, what to do before testing, and what to wear to the test.
*Note- the health appraisal form must be completed and sent back to Kristi Chase at klc280@txstate.edu to evaluate if you meet the criteria for participation in this study before scheduling the lab visit. When you arrive to the lab, the consent form will be reviewed with you and any questions you have will be answered. After, if you wish to participate in the study, you will sign the consent form and be given a copy.

What to expect?

When you arrive, you will be introduced to the primary investigator, Kristi Chase, who will explain the equipment and answer any questions that you may have. If you have no further questions and wish to participate, you will then sign the consent form. After that the following measurements, in chronological order, will be obtained: how much oxygen you are consuming and how much carbon dioxide you are producing will be measured through a facemask that will cover your nose and mouth; height, weight, waist and hip circumference will be measured; and body composition (i.e., body fat percentage, fat-free mass, and fat mass) will be measured. The visit should last approximately one hour. At the end of the visit, all body measures recorded (i.e., height, body weight, fat percentage, lean percentage, weight of body fat, weight of fat-free mass, waist and hip circumference) and measured resting metabolic rate (i.e., a measure of the minimum number of calories required for your body to survive while at rest) will be provided to you to keep for your own personal records.

What to do before testing?

Prior to the visit to the laboratory, we ask that you:

1. Avoid physical activity, caffeine, and alcohol 24 hours before the test.
2. Fast for at least 12 hours before the test (i.e., do not eat food or drink anything other than plain water – no coffee).
3. Eat a well-balanced meal (i.e., a meal including carbs, fats, and protein) around 6-8 pm the evening before the study.
4. Drink plenty of water up until 3 hours before the test (i.e., drink plenty of water during the 21-hour period before the test, **but you should not drink any fluids 3 hours before testing**).
5. Avoid nicotine for at least 2 hours before the test.
6. Get at least 6 hours of sleep the night before the test.

Measuring body composition requires the subject to:

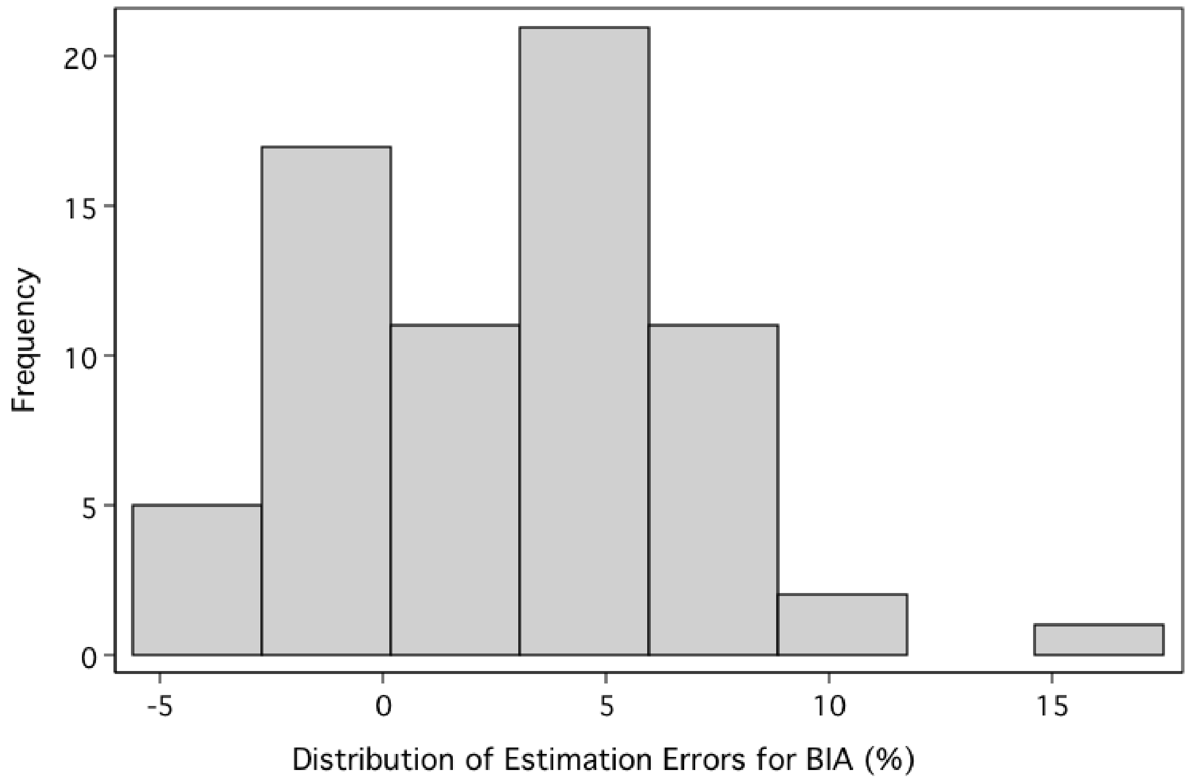
7. Avoid applying any lotions or skin creams before testing.
8. Wear proper clothes (note- regular clothes can be worn during the RMR measurement portion of the visit, therefore, the clothing listed below can either be worn under your regular clothes or brought with and changed into before the body composition test):
    - ***Women* should wear a form-fitting Speedo® or other Lycra®/spandex-type swimsuit or single-layer compression shorts and sport bra (with padding removed).**
    - ***Men* should wear a form fitting Speedo® or other Lycra®/spandex-type swimsuit or single layer compression shorts (with padding removed).**

What to bring?

1. We encourage you to bring a snack! After the lab visit, we recommend that you eat something (i.e., a granola bar, sandwich, etc.) before you leave the lab.

If you have any questions, please email Kristi Chase at klc280@txstate.edu or call 512-245-1915.

APPENDIX F: COMPARISON OF BIA AND BOD POD®



Error Distribution of Bioelectrical Impedance Analysis (BIA) Device When Estimating Percent Body Fat. The error distributions of BIA when estimating percent body fat can be seen here. The BOD POD® was used as the criterion measure to which BIA was compared. From the entire sample of 140 participants, the correlation between the measured percent body fat values from the BOD POD® and those estimated from the BIA was 0.90. The accuracy of the BIA measures can be summarized as: R^2 = .80, SEE = 4.25 percent, and Total Error = 5.09 percent.

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