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Prediction of percent body fat measurements in Americans 8 years and older

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Abstract

BACKGROUND/OBJECTIVES—Although numerous equations to predict percent body fat have been published, few have broad generalizability. The objective of this study was to develop sets of equations that are generalizable to the American population 8 years of age and older.

SUBJECTS/METHODS—Dual-emission X-ray absorptiometry (DXA) assessed percent body fat from the 1999–2006 National Health and Nutrition Examination Survey (NHANES) was used as the response variable for development of 14 equations for each gender that included between 2 and 10 anthropometrics. Other candidate variables included demographics and menses. Models were developed using the Least Absolute Shrinkage and Selection Operator (LAASO) and validated in a ¼ withheld sample randomly selected from 11 884 males or 9215 females.

RESULTS—In the final models, R^2 ranged from 0.664 to 0.845 in males and from 0.748 to 0.809 in females. R^2 was not notably improved by development of equations within, rather than across, age and ethnic groups. Systematic over or under estimation of percent body fat by age and ethnic groups was within 1 percentage point. Seven of the fourteen gender-specific models had R^2 values above 0.80 in males and 0.795 in females and exhibited low bias by age, race/ethnicity and body mass index (BMI).

CONCLUSIONS—To our knowledge, these are the first equations that have been shown to be valid and unbiased in both youth and adults in estimating DXA assessed body fat. The equations developed here are appropriate for use in multiple ethnic groups, are generalizable to the US population and provide a useful method for assessment of percent body fat in settings where methods such as DXA are not feasible.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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INTRODUCTION

Although classic definitions of obesity emphasize adiposity, in practice a body mass index (BMI: weight in kg/height in m²) of 30 kg m⁻² is currently the measure most often used to diagnose obesity. As BMI does not distinguish fat from lean tissue, some misclassification of obesity (defined as excess adiposity) is inevitable. Adiposity can be accurately assessed in humans in many research and clinical settings, but the most accurate techniques are often not feasible outside these setting because they require relatively expensive equipment, trained technicians and a high level of subject cooperation. Numerous equations have been developed to predict percent body fat that use anthropometric measurements that are feasible to collect in home, school and other community settings.¹⁻⁸ Most of these equations were developed in small or moderately sized samples that were recruited by convenience and usually limited to a specific and narrowly defined group. It is well known that associations between anthropometric measurements and percent body fat can differ importantly by gender, age and race/ethnicity; and therefore, it is necessary to match these characteristics between the sample in which an equation was developed and the individuals to which it is applied.

In the last 7 years, five groups of investigators have developed equations to predict percent body fat using data from the 1999–2004 National Health and Nutrition Examination Survey (NHANES) in youth^{4,5} and in adults.^{6–8} All used percent body fat measured by dualemission X-ray absorptiometry (DXA) as the criterion measure and included demographic and anthropometric measures in prediction equations. Four of these groups studied at most only 3 of the 10 anthropometric measurements available in NHANES. Zanovec et al.⁶ examined equations that included *either* BMI *or* waist as the only anthropometric variables, whereas Li et al.⁷ used BMI and triceps skinfold. Dugas et al.⁴ examined BMI (with exponents of $\frac{1}{2}$, -1 and -2) and body weight in selected combinations. Zanovec *et al.*⁶ and Li et al.⁷ studied only linear, main effects. All of these studies combined data across gender in their analyses. Heo *et al.*⁸ stratified by gender, age group and race/ethnicity to create 18 equations using only BMI −1. None of the four papers mentioned above performed internal or external validation of the equations developed or examined potential bias in the estimates across key subgroups.

The fifth set of equations for prediction of percent body fat developed from the 1999–2004 NHANES were developed by Stevens *et al.* in youth 8–17 years of age, and were intended for use by investigators in the Childhood Obesity Prevention and Treatment (COPTR) Consortium.^{5,9} Explanatory variables in the gender-specific equations were limited to those collected by the COPTR investigators, which included demographics plus four anthropometric measurements (height, weight, waist circumference and triceps skinfold). Forward and backward selection was used to develop equations in 2/3 of the sample, and the remaining 1/3 of the sample provided internal validation. Bias across race/ethnic groups and BMI categories was examined and influenced the selection of the final equations.

None of the five studies fully tapped the potential of the NHANES data. The purpose of this study was to systematically construct equations to predict percent body fat studying all 10 of the anthropometric measurements in NHANES, as well as subsets, using strategies that

thoroughly search for and accommodate much more complex relationships than equations previously developed. We included candidate variables in non-linear forms and interactions and performed term selection using the Least Absolute Shrinkage and Selection Operator $(LASSO)$ technique.¹⁰ We strived to develop multiple gender-specific equations, each of which used a different set of variables and each of which is appropriate for use in individuals 8 years of age and older. In addition, we used data from the 1999–2006 NHANES, adding 2 years of information to that included in previous work.

MATERIALS AND METHODS

Data for this study were from the 1999–2006 NHANES. The NHANES used a complex, multistage, probability, sampling design to provide a representative sample of US noninstitutionalized children and adults.¹¹ Race and ethnicity were self-reported and categorized as non-Hispanic Whites, non-Hispanic Blacks, Mexican Americans, other Hispanics and other race/ethnicities. We followed the NCHS (National Center for Health Statistics) recommendation to not separately analyze the other Hispanic or the other race/ethnicities groups due to small sample sizes.¹²

Girls over 12 years of age were asked the age when their first menstrual period occurred. Using this information, we created a dichotomous variable indicating the presence or absence of menarche. Age was used as a continuous variable and as a dichotomous variable indicating youth $(8-19)$ or adult (20 years). Ten anthropometrics were measured using standardized procedures:11 height, weight, triceps and subscapular skinfolds, waist, maximal calf, arm and thigh circumferences, and upper arm and upper leg lengths.

DXA measurements were obtained on participants 8 years of age or older using a Hologic QDR-4500 A fan-beam densitometer (Hologic, Inc., Bedford, MA, USA). Data were adjusted as described by Schoeller $et al.¹³$ Participants were excluded from DXA measurement if pregnant, had amputations other than fingers and toes, had self-reported history of radiographic contrast material use in past 7 days or participation in nuclear medicine studies in the past 3 days, weighed over 300 pounds or had a height over 6'5". The imputation of missing DXA measurements is described in technical documents.¹² In the text that follows we call both imputed and measured DXA assessed percent body fat 'observed', for the purpose of differentiating observed values from the values predicted using the equations developed here. Unresolved IRB issues concerning the reporting of pregnancy test results to minors resulted in no DXA data in females 8–17 years of age in 1999. Since NHANES data were weighted by 2-year increments, there are no public use DXA data available for girls 8–17 years from the 1999–2000 survey. In addition, DXA data were available for individuals $\frac{70 \text{ years}}{20 \text{ years}}$ of age only in the 1999–2004 surveys.

Analytic sample

There were 31 194 men and women 8 years and older in the 1999–2006 NHANES data with a positive survey weight. After exclusions, the analysis sample included 21 099 participants (exclusion details in Supplementary information 1). Here we use the term 'eligible sample' to indicate the sample from which we generalize to the population of Americans who are 8 years of age; females who were not pregnant, did not give birth in the last year and were not

currently breastfeeding; amputees if they had lost no more than fingers and toes; and those who were $\frac{300}{200}$ pounds and less than $6'5''$. Because 22% of the eligible sample was excluded in our analysis, we adjusted the sampling weights as recommended by NCHS¹² when more than 10% of the eligible sample is excluded and missing is not completely at random (details of method in Supplementary information 2).

Analysis plan

In this work, we distinguish variables (for example, race/ethnicity and weight) from terms (for example, squared terms and interaction terms). The variables used were age, race/ ethnicity, menarche status (females only), the 10 NHANES anthropometric variables and BMI (called a variable here). We selected terms to study based on our review of terms used in published equations and our own exploratory analyses (terms in Supplementary information 3). The maximum number of terms tested was 1335 for males and 1402 for females. We conducted model selection with 14 different subsets of candidate variables (models A–N), chosen based on the combinations of variables we judged most likely to be generally available in other studies and with the specific variables measured in selected large cohort studies (The Atherosclerosis Risk in Communities study, the Coronary Artery Risk Development in Young Adults study and the Fels Longitudinal study). For comparison, we examined BMI alone in the linear form (model O). All analyses took into account survey design and multiple imputation.

The following steps outline our approach:

Step 1. Create development and validation data sets and adjusted sampling weights—We used the PROC SURVEYSELECT procedure in SAS (SAS/STAT 9.2 User's Guide, 2011) to create the development or fitting data set containing a random sample of $\frac{3}{4}$ of the sample. The remaining ¼ of participants constituted the validation data set. All analyses were stratified by gender.

Step 2. Generate models in development data set—We used the LASSO technique to select models for this project because it can incorporate multiple imputation, accommodates sampling weights, handles large numbers of terms and is computationally efficient.¹⁰ Precautions were taken to prevent overfitting. We compared the adjusted R^2 in the model selected by LASSO with the minimal cross-validation error (CVmin) to that of the model with cross-validation error that was up to, but not more than 1 standard error (s.e.) larger than the minimum (CVmin+1 s.e.).¹⁴ If the difference between the adjusted R^2 was at least 0.01, then we chose (CVmin+1 s.e.) as the final model. If not, we examined additional models that further increased the cross-validation error in increments of 0.25 s.e. and selected the model with the largest SE that had an adjusted R^2 that was reduced by up to 0.01 compared with the CVmin model. In the rare instance when the R^2 was the same to the third decimal place between two such candidate models, we chose the model with the larger s.e.

Step 3. Evaluate equations in the validation data sets—The estimates for the intercept and coefficients for the terms in models calculated in the fitting data set were used

to calculate the predicted percent body fat in the validation data set. Then, gender-specific univariate regression models were run using the predicted percent body fat as the only independent variable and DXA as the dependent variable. We compared models created in the full, gender-specific fitting data with those created in subsets of the fitting data formed by age and race/ethnicity groups, and the more generalizable model was preferred if the R^2 was reduced by 0.02 or less compared with the model developed in a subset. Models with root mean square error (RMSE) estimates <3 percentage points of body fat were considered as excellent, whereas those with RMSE between 3 and 4 were considered as good. Mean signed differences (MSD) were calculated as the percent body fat from an equation minus percent body fat by DXA, overall and by age group, race/ethnicity and BMI category. We also estimated differential bias within categories of age, ethnicity and BMI by calculating the differences in MSD values (for example, the MSD in youth minus the MSD in adults). An MSD calculated within a subgroup or category that was outside the bounds of ± 1 body fat percentage point was considered biased.¹

Step 4. Obtain and examine final equations in a data set that included both the fitting and validation data sets—To estimate the coefficients with greater precision, we ran the models by gender (and over age and race/ethnicity subgroups) in the combined fitting and validation data. Performance statistics were calculated using models in the full data.

RESULTS

The sample was predominantly White and over half were either overweight or obese (Table 1). DXA-measured (or imputed) body fat averaged 27.3% in males and 38.4% in females. As expected, skinfold thickness tended to be greater in females, whereas height, weight and circumferences tended to be greater in males.

Supplementary information 4 shows results from 14 models (A–N) developed in the fitting sample and applied to the validation sample with R^2 calculated overall and within age, race/ ethnicity subgroups in males and females. An example of the application of the rules used to select among the models is given in Supplementary information 5. In males, the BMI only comparison model (model O) had the lowest R^2 (0.436) overall and in the age- and race/ ethnicity-specific results. Several models produced R^2 values >0.8 both overall (models A, B, D, F, G, H and I) and within subgroups of males. Performance tended to be superior in boys compared with adult males and in Whites compared with Blacks and Mexican Americans. When applied to the data stratified by both race/ethnicity and age category, the $R²$ values tended to be lowest in Mexican American men and highest in Mexican American boys with the median difference in the R^2 in those two groups across the 14 models being 0.1245 (model O was not included in these estimates).

In the overall estimates, only one model in females produced an R^2 over 0.8, however, 7 of the 14 chosen models produced estimates over 0.79 and 11 of the 14 models had R^2 values over 0.75. Similar to males, performance of the equations was generally stronger in younger than in older females (exception was models K and N). Different from males, R^2 values tended to be higher in Blacks than in Mexican Americans, with results in Whites varied.

Performance tended to be less strong in Black and Mexican American women compared with the other subgroups. In both males and females, models that included a skinfold measurement tended to perform better than those that did not.

We compared the R^2 estimates of equations developed in the full gender-specific fitting sample (over age and ethnic groups) with that of equations developed using data only from the age or race/ethnic group to which they were applied in the validation step. In males (Figure 1), the age and race/ethnic-specific R^2 values were within \pm 0.02. In girls (Figure 2), the age-specific analyses for model E in White girls, K and N in Black girls and A in Mexican American girls estimate produced R^2 that was slightly better than the overall female equation. In contrast, the R^2 was over 0.02 larger in the equation developed in all females than the race/ethnic-specific equations in Mexican American girls for models B, D, K, M and N.

We explored systematic differences in the prediction of percent body fat in subgroups categorized by age, ethnicity and BMI by examining MSD. As an illustration, the results of this analysis for BMI (model O) are shown in Figure 3. For both genders, the point estimate of the bias by age was outside the limit of ± 1 percentage point of body fat and statistically different from zero $(P_{0.05})$. Examination of MSD by ethnic groups showed that percent body fat was overestimated by BMI in Blacks in both males and females. Within BMI categories, BMI overestimated percent body fat in normal weight males and underestimated percent body fat in obese males by an amount only slightly exceeding 1 percentage point (−1.02 and 1.07 percentage points, respectively). BMI overestimated percent body fat in underweight women and underestimated percent body fat in overweight women by more than 1 percentage point. Similar analyses done examining equations A–N showed no systematic differences by age group or ethnicity that was as large as 1 body fat percentage point. There were also no systematic differences that large by BMI categories in women. However, in men four final models underestimated percent body fat in the underweight groups (K, L, M and N) deviating by −1.33 (CI: −2.38, −0.29), −1.09 (CI: −2.12, −0.05), −1.26 (CI: −2.06, −0.46) and −1.66 (CI: −2.58, −0.75) percentage points, respectively.

We also examined differential bias by categories within age, ethnicity and BMI. We found no evidence of differential error as large as 1 percentage point by age (young versus old) or ethnicity (White versus Black and White versus Mexican American). There were also no differential error estimates as large as 1 percentage point between normal weight and overweight participants or between normal weight and obese participants.

We combined the fitting and validation samples and recalculated the coefficients using the models that had been selected in the fitting data. Tables 2 and 3 show the R^2 and RMSE estimates for the full data. As expected, the R^2 and RMSE estimates were generally intermediate between those found in the fitting data and the validation data (fitting results not shown). Most of the RMSE estimates for developed equations were between 3.5 and 2.5 percent body fat, indicating good to excellent performance. The terms and coefficients for selected, better performing equations are presented in Supplementary information 6.

DISCUSSION

In this work, we developed 28 equations for the prediction of percent body fat in children and adults. For the final gender-specific models, the adjusted R^2 ranged from 0.664 to 0.845 in males and from 0.748 to 0.809 in females. BMI alone produced an R^2 of 0.430 in males and 0.656 in females. The addition of triceps and subscapular skinfolds to the candidate variables of demographics, height weight and BMI improved performance more than the addition of up to four circumference measurements. R^2 values for each set of variables were higher in males than in females, and in youth than in adults. Our examination of the performance of equations within age and race/ethnicity subgroups provided evidence that the equations can be applied with relatively good validity across a wide range of age, race/ ethnic and BMI groups and within youth, adults, BMI categories and three race/ethnicities. Equations A, B, D, F, G, H and I performed strongly in both males (adjusted R^2 0.805) and females (adjusted R^2 0.795). Four models (K, L, M and N) underestimated percent body fat in men by more than 1 percentage point in the underweight group, indicating that that these models should be used with caution if estimates in underweight men are of special interest. Otherwise, the bias by subgroups was within acceptable limits and equations developed within age and race/ethnicity groups did not notably outperform equations developed in the entire gender group in terms of the amount of variance explained.

Our model selection used cutoffs for decision making that were directed by expert judgment. We generally avoided decision making based on P -values.¹⁵ The cut point of 1 s.e. for LASSO was taken from Hastie *et al.*¹⁴ In addition, we used the limit of a reduction in R^2 of 0.01 for dropping terms. This was an arbitrary, a priori decision based on our judgment that a reduction of this size was small and therefore tolerated in order to have a more parsimonious model. We used a larger bound of a reduction of 0.02 in the R^2 to select a more generalizable model over a model fit in a subgroup, and therefore with reduced generalizability. In the former instance, the penalty of retaining more terms was considered to be less of a sacrifice compared with the penalty inflicted by having to apply different equations in different subgroups. Here, the four equations in females that exceeded this bound in a subgroup were at the maximum over 0.02 by only 0.002, an amount we consider trivial. For that reason, we feel comfortable recommending the use of the more general equation in the identified subgroups. For the evaluation of systematic bias, we called biased values outside the range of ± 1 percentage body fat from the DXA-measured mean and 2 percentage points between model-predicted percentage body fat by categories. To put this into perspective, the span in average percentage body fat in Non-Hispanic Whites, 18–29 years of age at a BMI of 18.5 versus 40.0 kg m−2 was approximately 21 percentage points in the 1999–2004 NHANES.⁸

Truesdale (unpublished, 2015) and Cui *et al.*¹ used MSD to detect differential trends in the underestimation or overestimation of percent body fat by published prediction equations within key subgroups when they were applied to the NHANES data matched to the development data on the criteria of gender, age and ethnicity. Truesdale et al. examined seven equations developed in children and found that six had differential systematic errors in the estimation of percent body fat that varied between the normal weight and obese by more than 2 percentage points. Cui *et al.*¹ found that more than $2/3$'s of 26 sets of equation

developed in adults, when applied to NHANES, showed systematic bias between normal weight and obese men and women that were larger than 2 percentage points. Both studies also found instances of systematic differences of this magnitude by gender, age and race/ ethnic categories. The bias in these estimates could be adequately large to produce misleading results across groups studied. Nevertheless, weaknesses in the assessments of differential errors by Cui and Truesdale include inability to control for subtle differences in the protocols for and operationalization of measurement of anthropometrics as well as potential differential error in the NHANES DXA measures. In the equations developed here in NHANES data, none showed a systematic difference in the estimation of percentage body fat in normal weight compared with obese participants that was as large as 0.5.

The R^2 values of the equations developed here are not the largest currently published in the literature, even though these equations may well be the most complex published to date. There are several reasons why other investigators may have reported larger R^2 values with more simple equations. Several reports, including those by Dugas *et al.*⁴ Zanovec *et al.*⁶ Heo *et al.*⁸ and Li *et al.*⁷ that used the NHANES data to produce percent body fat prediction equations, reported R^2 values with males and females combined and included gender in their models, and therefore the very large differences in percent body fat between men and women were captured as part of the variance explained by the model, and the range of percent body fat was extended. Both of these attributes would increase the R^2 . Freedman *et* al. showed that the R^2 for BMI alone as a predictor of percent body fat was 0.55 in an analysis across genders, and the estimate increased to 0.79 with the addition of gender to the model. Most likely, the gender-specific R^2 for BMI would have been even lower than 0.55. As currently advocated in the literature, 16 we produced separate equations by gender, although this tended to lower the R^2 . Another reason that other published R^2 values may be higher is that they included alternative anthropometric measures. For instance, hip circumference was not available in the NHANES, and it might have explained additional variance. Finally, the estimate of R^2 attained could vary importantly by the sample examined. Equations developed for youth by Stevens et al.⁵ using the 1999–2004 NHANES data had a higher R^2 than shown here for equations developed for youth in the 1999–2006 NHANES. However, when the current equations are applied to the 1999–2004 data, they produce higher R^2 estimates than shown in this work, and higher estimates than previously published by Stevens *et al.*⁵

A limitation of this as well as other work in this field is potential error in the criterion method. Different DXA systems and software produce somewhat different percent body fat measurements. The correction applied to the DXA data here¹³ was developed in adults, and may not be applicable to participants of all size, fatness and age. Finally, a four compartment model may have provided a more accurate criterion.

Our analytic approach is a strength of this work, and we know of no other study that has used LASSO to identify models for the prediction of percent body fat. LASSO has the advantage of being able to handle a large number of terms, and in fact, the number of terms can exceed the number of observations.¹⁰ Given current technology, the complexity of the equations developed here does not limit their feasibility. We credit this complexity as a key to the prediction of percent body fat estimates that (using our limits) are unbiased over age,

race/ethnicity and BMI subgroups and explain variance in criterion percent body fat measures equally well as estimates developed exclusively in those specific subgroups. We see these attributes, along with the use of a large sample of superb generalizability, as major advantages of our approach. To assist investigator and personal use of our equations, we developed the American Body Composition Calculator (ABCC) [\(http://ABCC.sph.unc.edu](http://ABCC.sph.unc.edu)), which facilitates use of SAS to calculate percent body fat for multiple subjects in an existing data set and use of hand-entered data to perform calculations for a single individual. It is our hope that the equations for prediction of percent body fat produced in this work will leverage research that will improve understanding of the role of obesity in health and disease and promote its prevention and treatment.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Figure 1.

Differences in R^2 values between equations developed in all males in the fitting sample versus equations developed in age- and race/ethnic-specific subgroups of the fitting sample $(R^2$ all males – R^2 subgroup). R^2 values are for the prediction of criterion percent body fat from DXA and were calculated in age- and ethnic-specific subgroups of the validation sample using the different equations developed in the fitting sample. Letters represent results for models shown in the footnote of Table 2 with the point estimate at the center of the letter. NHANES 1999–2006.

Figure 2.

Differences in R^2 values between equations developed in all females in the fitting sample versus equations developed in age- and race/ethnic-specific subgroups of the fitting sample (R^2 all females – R^2 subgroup). R^2 values are for the prediction of criterion percent body fat from DXA and were calculated in age- and ethnic-specific subgroups of the validation sample using the different equations developed in the fitting sample. Letters represent results for models shown in the footnote of Table 3 with the point estimate at the center of the letter. NHANES 1999–2006.

Figure 3.

MSD between percent body fat measured by DXA compared with values predicted using BMI in the cross-validation data set within subgroups by age, ethnicity and BMI category: BMI predicted percent body fat minus percent body fat from DXA. A value above zero indicates that the equation developed in the full fitting sample had a higher R^2 in the validation sample than the equation developed in boys only, and values below zero indicate that the equation developed in the full fitting sample had a lower R^2 compared with the equation developed in boys only. The letters on the plot identify result from different equations with the point estimate at the center of the letter. NHANES 1999–2006.

Table 1

Description of the weighted analysis sample from 1999–2006 NHANES

 α ²Number in sample without application of sampling weights.

 b
Average of five imputed values.

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Model D; age, race, height, wight, BMI, triceps, waist, calf circumference, arm circumference; Model E; age, race, height, wight, and thight, wight, BMI, triceps, waist, calf circumference; Model D; age, race, height, weig triceps, subscapular, waist and calf circence; Model G: age, race, height, weight, weight, ticeps, subscapular, waist and arm circumference; Model H: age, race, height, BMI, triceps, subscapular and arm circumference; Mode high circumference, arm length Abbreviations: BMI, body mass index; NHANES, National Health and Nutritional Health and Nutrition Examination Survey; RMSE, root mean square error. Model A: age, race, height, weight, BMI, triceps, subscapular, waist, calf and leg length; Model B: age, race, height, weight, RMI, triceps, subscapular, waist, calf circumference, arr circumference, arm circumference and thigh circumference; Model C: age, race, height, weight, weight, subscapula Model D: age, race, height, weight, BMI, triceps, waist, calf circumference, arm circumference and thigh circumference; Nodel E: age, race, hoight, weight, weight, weight, ealf circumference, arm circumference and thigh ci Model D: age, race, height, BMI, triceps, waist, calf circumference, arm circumference and thigh circumference; Nodel E: age, race, height, weight, weight, waist, calf circumference, arm circumference and thigh circumferen and leg length; Model B: age, race, height, BMI, triceps, subscapular, waist, calf circumference, arm circumference and thigh circumference; Model C: age, race, height, BMI, subscapular, waist, calf circumference, arm circ and waist, Model J: age, race, height, BMI, waist and arm circumference; Model K: age, race, height, and arm circumference; Model L: age, race, height, waist, Model Mi age, race, height, weight, weight, weight, BMI and tri veps, ingia w ran ago, 19 mhs System weight and BMI; Model O: BMI.

 ${}^{\it 2}$ All candidate variables were retained by the selection process for all models. All candidate variables were retained by the selection process for all models.

an and weight and BMI; Model O: BMI, Waist, and circumference Model K: age, race, height, (weight) BMI and am circumference; Model L: age, race, height, weight, weight, and triceps; Model N: age, race, height, Walsley, The BMI, triceps and waist; Model J: age, race, height, weight, BMI, waist, arm circumference Model K: age, race, height, weight bilips, Model I: age, race, height, age, and waist; Model M: age, and waist; Model M: age, race, circumference; Model D: age, race, height, weight, BMI, triceps, waist, calf circumference, arm circumference, and thigh circumference; Model E: age, race, height, weight, waist, calf circumference, arm circumference; Mode Avoicviations, Dwy mass muck, Attack, length, leg length and menses; Model B: age, race, height, bleight, Reight, the subscapular, waist, calf circeps, subscapular, waist, calf circept, eage, height, BMI, waist, calf circumference, and thigh circumference; Model D: age, race, height, weight, BMI, triceps, waist, calf circumference, am circumference, and thigh circumference; Model E: age, race, height, weight, weight, weight, waist, calf circumference, am circu weight, BMI, triceps, subscapular, waist and calf circumference; Model G: age, race, height, wist and arm circumference; Model H: age, race, height, weight, BMI, triceps, subscapular, arm circumference Model E age, race, h weight, BMI, triceps, subscapular, waist and calf circence; Model G: age, race, height, weight, BMI, triceps, subscapular, waist and arm circumference; Model H: age, race, height, weight, weight, weight, weight, weight, we igh circumference, arm Abbreviations: BMI, body mass index; NHANES, National Health and Nutrition Easultation Examination Survey; RMSE, root mean square error. Model A: age, race, height, (weight, liveleys, subscapular, waist, calf circumference race, height, weight and BMI; Model O: BMI.

 $\boldsymbol{a}_{\text{candidate}}$ variables not retained by the selection process are shown in parentheses. Candidate variables not retained by the selection process are shown in parentheses.