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Prediction of android and gynoid body adiposity via a three-dimensional stereovision body imaging system and dual-energy x-ray absorptiometry

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Abstract

Objective—Current methods for measuring regional body fat are expensive and inconvenient compared to the relative cost-effectiveness and ease-of-use of a stereovision body imaging (SBI) system. The primary goal of this research is to develop prediction models for android and gynoid fat by body measurements assessed via SBI and dual-energy x-ray absorptiometry (DXA). Subsequently, mathematical equations for prediction of total and regional (trunk, leg) body adiposity were established via parameters measured by SBI and DXA.

Methods—A total of 121 participants were randomly assigned into primary and cross-validation groups. Body measurements were obtained via traditional anthropometrics, SBI, and DXA. Multiple regression analysis was conducted to develop mathematical equations by demographics and SBI assessed body measurements as independent variables and body adiposity (fat mass and percent fat) as dependent variables. The validity of the prediction models was evaluated by a split sample method and Bland-Altman analysis.

Results—The R^2 of the prediction equations for fat mass and percent body fat were 93.2% and 76.4% for android, and 91.4% and 66.5% for gynoid, respectively. The limits of agreement for the fat mass and percent fat were -0.06 ± 0.87 kg and -0.11 ± 1.97 % for android and -0.04 ± 1.58 kg and -0.19 ± 4.27 % for gynoid. Prediction values for fat mass and percent fat were 94.6% and 88.9% for total body, 93.9% and 71.0% for trunk, and 92.4% and 64.1% for leg, respectively.

Conclusions—The three-dimensional (3D) SBI produces reliable parameters that can predict android and gynoid, as well as total and regional (trunk, leg) fat mass.

Keywords

Android fat; gynoid fat; prediction equations; stereovision body imaging; body composition; obesity

INTRODUCTION

Measurements of regional body adiposity, such as trunk, thigh, leg, and android fat have been linked closely with obesity-related risks. Thus, these regional areas may provide more information for assessment of health risks, as compared to overall obesity [1–4]. This is particularly true with the recent controversy of the efficiency of body mass index (BMI) for predicting obesity-related disease risks [5]. One of the previous reports involved with regional adiposity related-risks included android and gynoid fat determined via dual-energy x-ray absorptiometry (DXA) [6–8]. The android adiposity showed a positive correlation with visceral adiposity ($r=0.81$, $p<0.01$), as well as strong associations with metabolic risk factors including triglycerides, homeostatic model assessment of the insulin resistance (HOMA-IR), fasting glucose and insulin [6]. These relationships were even stronger when compared to visceral adiposity assessed by computed tomography (CT) [6]. In addition, gynoid fat assessed by DXA demonstrated decreased risks for stroke [7] and metabolic risk factors [8]. Thus, the ability to predict regional fat distribution, such as android and gynoid fat in an inexpensive and easy manner, would be advantageous for estimating risks associated with obesity-related diseases in the general population.

Instruments that assess regional body adiposity via advanced techniques include CT [9], DXA [10] and magnetic resonance imaging (MRI) [11]. In CT, the differences in the attenuation of X-rays through tissues permits imaging of internal body structures [9]. For DXA, a three-compartment model estimates body composition using varying attenuations of X-rays through bones, lean tissue, and fat [10, 12]. For the MRI, the basis for production of high quality, 3 dimensional (3D) anatomic images is an abundance of hydrogen nuclei [13]. Both CT and DXA involve the usage of radiation during assessment, and DXA is not always possible in morbidly obese subjects due to limits on weight and size [14, 15]. Moreover, CT, DXA and MRI are restricted for large scale epidemiological studies that measure a large number of subjects in a given time frame across various locations. All of these methods lack portability, are bulky, and expensive to operate. Thus, more precise, non-invasive, and low cost methods are needed to estimate regional body adiposity.

Previously, body measurements assessed by photonic stereovision body imaging (SBI) were effective in the development of prediction equations for abdominal adiposity determined by MRI [16]. The established equations were useful in predicting abdominal adiposity volumes, including total abdominal, subcutaneous, and visceral adiposity, which could replace the MRI and improve the efficiency of assessing abdominal adiposity in field settings. The current project utilized a 3D SBI system as an assessment method for body composition [17, 18], and compared it to android and gynoid fat as determined by DXA. The advantages of SBI as an evaluative method are: 1) it is a quantifiable, visual representation of body size and shape (Figure 1); 2) the degree of central obesity can be documented by central obesity depth and width [16]; 3) it utilizes a rapid and non-invasive (no radiation exposure) method to obtain various body measurements; and 4) it is cost-effective and portable.

This study was designed to test the hypothesis that total and regional body adiposity can be estimated effectively by the body measurements assessed by 3D SBI. This system will provide an accurate analysis of regional body fat, volume, and circumferences that is rapid

and much lower in cost than other techniques currently available. Therefore, the primary objective of this research was to develop prediction equations for android and gynoid body adiposity assessed via 3D photonic SBI and DXA. Additionally, mathematical models for total body, trunk and leg adiposity were established via parameters measured with SBI and DXA.

MATERIALS AND METHODS

Design of Study

A total of 121 adults, including 67 men and 54 women, were enrolled in this body composition study. Inclusion criteria for participation were healthy Caucasian or non-White Hispanic men and women, ages 19–65 years old, and BMI category of healthy weight (18.5–24.9 kg/m²), overweight (25–29.9 kg/m²), or obese (>30 kg/m²). Subjects with any known diseases and women who are or could be pregnant, or lactating were excluded. Informed consent documents were obtained from participants and the risks and benefits of the study were explained and informed consents were obtained. The University of Texas at Austin Institutional Review Board approved the study.

Subjects were instructed to restrict consumption of caffeine and alcohol, as well as heavy exercise at least 10 hours prior to the visit. Study participants completed demographic and health questionnaires and then were assessed for traditional anthropometrics, SBI, and DXA.

Assessment of Body Composition

Body composition assessment procedures and descriptions of the devices, including traditional anthropometrics and SBI were described previously [16]. Traditional anthropometrics evaluated weight and height, and BMI was calculated as weight in kg divided by height in m².

Body circumferences, central obesity measures, and total/regional body volumes and ratios (upper- and lower- body volume ratio factors) were assessed via 3D SBI. SBI utilizes a method of photogrammetry in order to acquire the body images of an individual. Four pairs of CMOS cameras (Videre Design, Menlo Park, CA) capture the image of the body, while four LCD projectors (NEC Corporation, Tokyo, Japan) illuminate the body surface [16]. Body circumferences assessed via SBI included chest, waist, hip, upper thigh, lower thigh and knee. Regional body volumes encompassed torso (lower neck to top of pelvis), abdomen-hip (smallest point of waist to crotch), and thigh (crotch to top of knee). Upper-body volume factors involved volume ratios of torso to total body, abdomen-hip to total body, and abdomen-hip to torso. Lower-body volume factors included volume ratios of thigh to total body, thigh to torso, and thigh to abdomen-hip. Measurements for both central obesity depth and width were taken at the umbilicus level. Central obesity width was defined as the widest length on the coronal plane; central obesity depth, as the length between the mid-point of central obesity width and the umbilicus [16]. Waist-to-hip ratio was computed as waist circumference (cm) divided by hip circumference (cm) and waist-to-thigh ratio was obtained as waist circumferences (cm) divided by upper thigh circumference (cm).

DXA was utilized to measure body composition, including android, gynoid, total body, trunk, and leg fat mass, fat-free mass and percent body fat via a Lunar Prodigy (GE Medical Systems, Madison, WI). Subjects laid flat on the scanner table where the X-ray sources were located. All were wearing light weight clothing and metals were removed. The scanning process required 7 to 20 minutes, depending on the size of the subject. The DXA device scans the whole body by interacting with the main computer, using two different energy levels of X-ray beams. These two varying levels of energy go through the body in diverse raster patterns so that the bone mineral density of the spine, hip, forearms and the soft tissues of the whole or specific area (trunk, leg) are measured.

This research focused on android and gynoid fat. For the DXA, the android region was defined as the area between the ribs and the pelvis, and was completely covered by the trunk region. The upper demarcation was 20% of the distance from the iliac crest and the neck; whereas, the lower demarcation was at the top of the pelvis. The gynoid region included the area of the hips and the upper thighs, and it overlapped the leg and trunk areas. For this region, the upper demarcation was below the top of the iliac crest at a distance of 1.5 times the android height. The total height of the gynoid region was two times the height of the android region [19]. Android and gynoid fat regions were computed via Prodigy enCORE software (version 11.0, GE Medical Systems) provided by the manufacturer. The regions of android and gynoid fat depots in men and women that were assessed by DXA are depicted in Figure 1.

Analysis of Statistics

Participants characteristics including demographics (age, sex), traditional anthropometrics (weight, height, BMI), SBI, and DXA measurements of overall, primary, and cross-validation groups were computed as a measure of descriptive statistics and expressed as mean $\pm$ standard error of mean (Table 1). Comparisons between primary and cross-validation groups were conducted by one-way analysis of variance (ANOVA). The normality of the distributions of quantitative variables was evaluated by histograms and the Kolmogorov-Smirnov test.

Stepwise multiple linear regression analysis utilized body fat mass (kg) and fat percentages (%) (android, gynoid, total body, trunk, leg) derived via DXA as dependent variables, and relevant body measurements assessed by demographics (age, sex) and SBI as independent variables. Independent parameters encompassed ratios of waist to hip, waist to thigh circumferences; circumferences of waist, hip, upper thigh, lower thigh and knee; volumes of total body, torso, abdomen-hip and thigh; volume ratios of torso to total body, abdomen-hip to total body, thigh to total body, abdomen-hip to torso, thigh to torso and thigh to abdomen-hip. Central obesity depth and width were calculated to construct prediction models for body adiposity. The impact of demographics, including age and sex, also were included as independent variables in order to examine the associations with android and gynoid body adiposity.

A dummy code was used to label sex as women=0 and men=1 and ethnicity as non-White Hispanic =0 and Caucasian=1. The method of sample splitting was used to confirm the validity of the developed predictive models, as it is the most common and accurate process

used for cross-validation techniques. This approach involved randomly splitting the participants into two subgroups (primary and cross validation groups) by using statistical software, and then establishing regression models by using the primary group. Consequently, these prediction equations were applied to the cross-validation group. If these models fit well to the cross-validation group, these equations can be generalized to other populations.

The total participants (n=121) were randomly assigned via the statistics software into primary (n=77, 65%) and cross-validation (n=44, 35%) groups. In addition, Bland-Altman limits of agreement analysis was implemented to confirm the validity of the developed equations and to visualize the mean differences and 95% limits of agreement for the bias between observed values measured by DXA and predicted values by the equation models [20]. Standardized β -coefficients (β) described the output of stepwise multiple regression analysis, which explains the change in terms of the standard deviation unit of the dependent variable that is associated with one standard deviation increase in the independent variable. Variables with a variance inflation factor greater than 10 were eliminated to reduce the impact of collinearity between the parameters.

All statistical analysis and data management was performed using Predictive Analytics Software Statistics 18.0 (IBM SPSS, Chicago, IL). A p -value of less than 0.05 was adopted as a statistically significant level.

RESULTS

Description of Statistics

Participants' characteristics and body composition for overall, primary, and cross-validation groups are described in Table 1. The study sample included men and women, whose age and BMI ranged from 18 to 65 years and 18 to 40 kg/m², respectively. None of the parameters were significantly different among participants in the primary and cross-validation groups ($p>0.05$).

Prediction Equations for Android and Gynoid Body Fat

The final equations for prediction of android and gynoid body adiposity are presented in Table 2. Changes of prediction value of R^2 and unstandardized/standardized B of the demographics and body parameters determined by SBI that were included in the final prediction models for body fat mass and percent body fat are shown in Table 3. The prediction equations for body fat mass (kg) resulted in higher prediction values (93.2% for android and 91.4% for gynoid), as opposed to the prediction of percent body fat (76.4% for android and 66.5% for gynoid). The android and gynoid fat mass and percent fat equations were composed of a combination of sex, upper thigh circumference, thigh to abdomen-hip volume ratio, waist to hip ratio, waist to thigh circumference ratio, volumes of torso and abdomen-hip, and/or central obesity depth.

Torso volume, sex and central obesity depth were identified for the prediction of android fat mass ($R^2=93.2\%$). For prediction of gynoid fat mass, upper thigh circumference, abdomen-hip volume and sex were selected ($R^2=91.4\%$). Among the independent variables, SBI-measured thigh to abdomen-hip volume ratio, waist to hip ratio and central obesity depth

were found to be the most effective parameters that explained android percent body fat, with a R^2 of 76.4%. Similarly, waist to thigh circumference ratio, upper thigh circumference and sex were identified in the stepwise multiple regression analysis for gynoid percent fat ($R^2=66.5\%$).

Prediction Equations for Total and Regional (Trunk, Leg) Body Fat

The prediction equations for body fat mass (kg) computed higher prediction values (R^2 from 92.4 to 94.6%), as opposed to the prediction of percent body fat (R^2 from 64.1 to 89.9%) (Table 2). Each equation contained from three to five parameters, including sex; circumferences of upper thigh and knee; circumference ratios of waist to hip and waist to thigh; volumes of torso and thigh; volume ratios of thigh to torso, thigh to abdomen-hip; and/or central obesity depth. Total body fat exhibited the highest prediction values of 94.6 and 88.9% for fat mass and percent body fat.

Central obesity depth was the most effective parameter for predicting total body fat mass. Also, sex, thigh and torso volumes were included in the model, which resulted in the highest R^2 value of 94.6%. Parameters that explained the highest proportions of total percent body fat were central obesity depth, sex and thigh volume. Central obesity depth and thigh volume showed a positive association with total percent body fat ($p<0.05$). The explained proportion of the total percent body fat was 88.9%, which was the highest compared to other percent body fat models.

For the trunk fat mass, central obesity depth, torso volume and sex were included in the final model ($R^2=93.9\%$). For the trunk percent fat, waist to hip circumference ratio and thigh to torso ratio determined by SBI were identified as crucial parameters that explained 71.0%. The direction of the standardized β -coefficients showed that having a greater waist to hip circumference ratio ($\beta=0.54$, $p<0.001$) and lower thigh to torso ratio ($\beta=-3.56$, $p=0.001$) contributed to an increase in trunk percent fat ($p<0.05$) (Table 3).

Circumferences of the upper thigh and knee, as well as sex, thigh to abdomen-hip volume ratio, and thigh volume were selected in the prediction model for leg fat mass (R^2 of 92.4%). Significant effects of waist to thigh circumference ratio and SBI measured thigh to abdomen-hip volume ratio were detected by regression analysis for leg percent fat, which explained 64.1% of its proportions ($p<0.05$).

Cross Validation for the Prediction Equations for Body Fat Mass and Percent Fat

The prediction equations that were developed for estimation of body adiposity by using the primary group were then applied to the cross-validation group in order to confirm the cross-validity of the developed mathematical models. All of the 95% intervals for the mean error (observed value – predicted value) encompassed zero, which assured that the body fat assessed via DXA and predicted body fat by the equation were not statistically different (Table 2).

Figure 2 depicts the mean value (solid line) and 95% limits of agreement (dotted lines) of android (Figure 2a,b) and gynoid (Figure 2c,d) fat mass and percent fat via Bland-Altman analysis to examine the absence of systematic bias between observed values assessed by

DXA and predicted values computed by prediction equations. Data were randomly dispersed without distinctive patterns within the 95% limits of agreement, which ensured the validity of the prediction equations. The limits of agreement for fat mass and percent fat were -0.06 ± 0.87 kg and -0.11 ± 1.97 % for android and -0.04 ± 1.58 kg and -0.19 ± 4.27 % for gynoid, respectively (Figure 2). A few outliers were observed in the Bland-Altman plots; however, these were not due to data error.

DISCUSSION

The high R^2 values for the equations of android (93.2%) and gynoid (91.4%) adiposity suggested that SBI is a reliable and effective system that can be used to estimate regional body fat mass. This research was the first to develop prediction equations for android and gynoid adiposity by incorporating body measurements derived via 3D SBI compared to DXA.

Previous studies showed that the upper body fat, such as trunk and android fat, are associated with increased obesity-related risk factors; whereas, lower body fat including thigh, leg and gynoid fat are linked with decreased risk factors [1–4, 7, 8, 21]. Particularly, android and gynoid fat determined by DXA showed inverse relationships with metabolic risk factors, in which android fat exhibited a positive association; whereas, gynoid fat deposition had decreased risks [8, 21]. In the current research, sex was included in the prediction equations for android and gynoid fat mass, as well as gynoid percent fat, as these reflected the differences in body size and shape between men and women. Moreover, central obesity depth acquired by SBI was entered in the mathematical models for android fat mass and percent fat, implying that this parameter can be used effectively as a surrogate measurement of central obesity. Finally, upper thigh circumference was selected as one of the variables for the prediction of gynoid adiposity fat mass and percent fat. Note that these types of body measurements (upper thigh circumference) cannot be obtained easily without physical contact. The ability to create these measurements electronically reflects the practicality of SBI.

Previous studies have indicated that accumulation of percent fat in the lower body has a protective effect on adiposity-related risk factors, in comparison to fat deposition in the upper body area [21–23]. For instance, large trunk fat measured via DXA was associated with increased insulin resistance in European ($r=0.40$, $p<0.05$) [1] and elderly women ($\beta=0.65$, $p<0.05$) [2]. Trunk fat also was related to greater fasting glucose and post-load glucose in elderly men ($\beta=0.44$, $p<0.05$, $\beta=0.41$, $p<0.05$) and women ($\beta=0.49$, $p<0.05$, $\beta=0.47$, $p<0.05$) [2]. In contrast, Zhang et al. (2013) indicated that leg percent fat was negatively linked with adiposity-related risk factors including triacylglycerol, and diastolic blood pressure among adults ($p<0.05$) [22]. Leg percent fat was associated with decreased risks for metabolic syndrome, as the odds ratios for lowest to the highest quintile was 0.22 [22]. Correspondingly, Hara et al. (2004) illustrated protective effect of leg percent fat on coronary atherosclerosis while trunk percent fat was associated with increased risks for coronary atherosclerosis [23]. Thus, determination of the body fat, especially total and regional body fat mass, in an easy and efficient manner via 3D SBI would improve assessment of clinical health risks.

Previous studies have utilized anthropometric body measurements to develop prediction equations for total and regional adiposity [24–29]. Yavari et al. (2011) used body weight to estimate total fat mass (fat mass = 0.59 weight – 16.5; $R^2=98\%$) and trunk fat (trunk fat = 0.32 weight – 11.1; $R^2=96\%$) derived by DXA in women with type 2 diabetes, metabolic syndrome, and healthy participants [24]. Ritchie and Davidson (2011) also used simple body measurements [weight, height, BMI, body circumferences (chest, waist, hip, upper and lower legs)] to predict regional body fat mass assessed by DXA. The R^2 for the models were 84.3 and 82.9% for chest; 85.1 and 80.4% for waist; 76.1 and 82.5% for hips; 72.6 and 73.4% for upper legs in men and women, respectively [26]. In addition, Scafoglieri et al. (2013) reported the prediction equations for trunk and leg regional adiposity. The R^2 were 92 and 94% for trunk fat mass and 91 and 86% for trunk percent fat; 94 and 85% for leg fat mass and 76 and 69% for leg percent fat in men and women, respectively [27]. Prediction equations by Scafoglieri et al. (2013) utilized numerous anthropometric measurements, by manual methods, such as weight, height, 14 body circumferences via measurement tape, 13 skinfold thicknesses, and 4 bone breadths to develop the prediction equation while regional body fat was assessed by DXA [27]. This degree of preciseness yields excellent results, but may not be practical for fast screening of populations.

The present research proposed mathematical equations for the prediction of total and regional (trunk, leg) adiposity (fat mass and percent fat) by integrating body measurements derived via an efficient and rapid method, a 3D photonic SBI. The R^2 of the prediction equations for total body, trunk and legs were 94.6, 93.9, and 92.4% for fat mass; and 88.9, 71.0 and 64.1% for percent body fat, respectively. These predictive values for total and regional (trunk, leg) fat mass, but not fat percentage, were relatively high compared to other equations calculated from previously reported models. This result implied that the relationship between percent body fat and SBI measured parameters were not as close as seen with body fat mass. These low prediction values indicate that the body parameters incorporated for the equations are not effective surrogate measurements for percent body fat. A greater number of more elaborate measurements as indicated by Scafoglieri et al. (2013) may be helpful [27].

Both regional fat mass and percent body fat (android, trunk) are associated closely with metabolic and cardiovascular risk factors with a negative impact on health. In contrast, greater gynoid and leg fat have positive effect on health-related risk factors. Almost all studies used regional fat mass [1–2, 4, 6–8, 21], rather than percent body fat [23], as a parameter for the regional body compartment confirming the practicality of this body measurement in terms of cardiovascular risk factors.

The parameters of regional body volumes and central obesity depth that were used in this study are unique because simple anthropometric assessment tools cannot easily discern these measurements. In particular, central obesity depth previously has been utilized as a promising indicator of abdominal obesity [16]. This variable was selected as an effective predictor for fat mass of total body (R^2 change 76.8%), and trunk (R^2 change 85.7%), as well as percent body fat of total body (R^2 change 53.8%). More specifically, increased values of central obesity depth were linked closely with greater accumulation of the total and regional adiposity (trunk fat mass).

Sex was the one of the most critical components that was incorporated in most of the equations. This finding confirms the disparities of the total and regional adiposity distribution between men and women. However, age was not included in any of the prediction models due to the existence of other stronger variables that were included in the models, such as body volumes and central obesity measurements.

In the current research, measurements, such as upper thigh circumference, that cannot be easily measured were incorporated in the prediction equation models. Additionally, the prediction equations derived from this research by SBI are more practical than other methods because the parameters assessed by the photonic device did not require any physical contact between the subject and researcher. Also, subject burden during assessment is substantially reduced because a large amount of information can be collected within a one second data acquisition period. Finally, the SBI system removes concerns regarding inter and intra-rater reliability, which is problematic in traditional anthropometric measurements [30].

The 3D surface imaging of the human body has received considerable attention due to its broad range of applications, such as body composition assessment in the clothing industry [31], animation in movies and computer games [32], 3D face recognition in biometrics [33], skin scanning in dermatology and cosmetics [34], and planning and evaluation of facial and breast plastic surgery [35]. In recent years, this technique has been integrated for obesity assessment as the technique is easy-to-use, safe, cost-effective, and accurate [18]. This laboratory previously used 3D laser body scanner to assess body composition, including waist and hip circumferences [36], and body volume [37]. The ability to measure body volume compared to hydrodensitometry was highly accurate with a correlation between these two methods of 0.99 ($p<0.01$) and an intraclass correlation coefficient of 0.99 ($p<0.01$) [37]. In addition, the efficacy of body measurements derived via the 3D photonic imager has been confirmed by predicting abdominal adiposity volume assessed by MRI, as the R^2 values were 89.9, 90.4, and 71.7% for total abdominal, abdominal subcutaneous and abdominal visceral adiposity, respectively [16].

A limitation of this study was the lower prediction values for total and regional (android, gynoid, trunk, leg) percent fat (R^2 ranging from 66.5 to 88.9%), as compared to total and regional fat mass (R^2 ranging from 91.4 to 94.6%). This implies that better body measurements are required to establish mathematical models for body fat percentage. Yet, the mathematical model for percent total body fat exhibited relatively high prediction value ($R^2=88.9\%$), as opposed to other percent fat equations. Due to the small sample size, men and women were combined and analyzed together to create the prediction equations. Prediction equations may have been more precise if the analysis was conducted separately. Moreover, ethnicity was not included as a factor for establishing prediction equation due to the small number of non-White Hispanics, as opposed to Caucasians.

CONCLUSION

In summary, SBI assessed body measurements were effective in developing prediction equations for android ($R^2=93.2$) and gynoid ($R^2=91.4$) body, as well as total ($R^2=94.6$),

trunk ($R^2=93.9$), leg fat mass ($R^2=92.4$) and total body fat percentage ($R^2=88.9$). This study confirmed the efficacy of SBI as a reliable instrument that provides information regarding body composition in an efficient and practical manner. The strong predictive values for assessment of android and gynoid, as well as total and regional (trunk, leg) body fat mass suggest that this state-of-the-art instrument could be utilized in field settings to inform consumers on their body status and disease risks. It is believed that the ability to predict regional fat distribution via SBI in an inexpensive and easy method will be advantageous for estimating risks associated with obesity-related diseases in the general population. Future studies are necessary to explore the relationship between measurements obtained via SBI and cardiometabolic risk factors.

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ABBREVIATIONS

ANOVA	analysis of variance
BMI	body mass index
CT	computed tomography
DXA	dual-energy x-ray absorptiometry
HOMA-IR	homeostatic model assessment of the insulin resistance
MRI	magnetic resonance imaging
SBI	stereovision body imaging
3D	three-dimensional

a) Men, BMI 30.8 kg/m²

(b) Women, BMI 30.2 kg/m²

Figure 1. Body image of men and women determined by a three-dimensional stereovision body imaging and matched figures of dual-energy x-ray absorptiometry, illustrating android and gynoid fat areas

(a) Android fat mass (kg)

(b) Android fat percentage (%)

(c) Gynoid fat mass (kg)

(d) Gynoid fat percentage (%)

Figure 2.

Bland-Altman analysis of agreement for prediction of android and gynoid fat mass and percent fat by stereovision body imaging and measured values by dual-energy x-ray absorptiometry. The solid line in the middle represents the mean values and two dotted lines stand for upper and lower limits of agreement (mean $\pm$ 1.96 standard deviation).

Table 1

Demographics and body composition of primary and cross-validation groups

Parameters	Overall Participants (n=121)	Group		<i>p</i> -value ^b
		Primary (n=77)	Cross-Validation (n=44)	
		Mean ± SEM ^a	Mean ± SEM ^a	
Demographics				
Age (years)	34.38 ± 0.98	33.75 ± 1.27	35.49 ± 1.51	0.39
Sex (%Men/%Women)	55.4/44.6	57.1/42.9	52.3/47.7	0.61
Ethnicity (%Caucasian/%Hispanic)	65.3/34.7	61.0/39.0	72.7/27.3	0.20
Traditional Anthropometrics				
Weight (kg)	81.63 ± 1.63	81.71 ± 2.04	81.50 ± 2.75	0.95
Height (cm)	170.34 ± 0.85	169.97 ± 1.00	170.99 ± 1.54	0.56
BMI (kg/m ²)	28.02 ± 0.49	28.24 ± 0.62	27.65 ± 0.77	0.57
Stereovision Body Imaging				
Circumference (cm)				
Waist	91.33 ± 1.27	91.26 ± 1.55	91.46 ± 2.22	0.94
Hip	109.30 ± 1.06	109.45 ± 1.46	109.04 ± 1.43	0.85
Upper thigh	63.81 ± 0.75	63.85 ± 1.03	63.74 ± 1.03	0.94
Lower thigh	42.53 ± 0.47	42.74 ± 0.63	42.16 ± 0.71	0.56
Knee	35.76 ± 0.35	35.75 ± 0.43	35.78 ± 0.59	0.97
Circumference ratio				
Waist-to-hip	0.85 ± 0.01	0.85 ± 0.01	0.85 ± 0.01	0.90
Waist-to-thigh	1.43 ± 0.02	1.43 ± 0.02	1.43 ± 0.04	0.92
Central obesity measure (cm)				
Central obesity depth	15.63 ± 0.34	15.48 ± 0.43	15.89 ± 0.58	0.56
Central obesity width	35.35 ± 0.46	35.30 ± 0.59	35.44 ± 0.74	0.88
Volume (L):				
Total body	77.14 ± 1.64	77.13 ± 2.04	77.16 ± 2.78	0.99
Torso	36.97 ± 1.01	36.95 ± 1.27	37.01 ± 1.69	0.98
Abdomen-hip	27.60 ± 0.84	27.46 ± 1.09	27.83 ± 1.33	0.83
Thigh	4.41 ± 0.12	4.39 ± 0.15	4.44 ± 0.21	0.83
Volume ratio:				
Torso to total body	0.47 ± 0.00	0.47 ± 0.00	0.47 ± 0.01	0.97
Abdomen-hip to total body	0.35 ± 0.00	0.35 ± 0.01	0.36 ± 0.01	0.44
Abdomen-hip to torso	0.74 ± 0.01	0.74 ± 0.01	0.75 ± 0.01	0.17
Thigh to total body	0.06 ± 0.00	0.06 ± 0.00	0.06 ± 0.00	0.54
Thigh to torso	0.13 ± 0.00	0.12 ± 0.00	0.13 ± 0.01	0.45
Thigh to abdomen-hip	0.17 ± 0.01	0.17 ± 0.01	0.17 ± 0.01	0.79
Dual-energy X-ray Absorptiometry				
Fat mass (kg):				

Parameters	Overall Participants (n=121)	Group		<i>p</i> -value ^b
		Primary (n=77)	Cross-Validation (n=44)	
		Mean ± SEM ^a	Mean ± SEM ^a	
Android	2.77 ± 0.15	2.79 ± 0.19	2.72 ± 0.23	0.80
Gynoid	5.06 ± 0.21	5.07 ± 0.28	5.04 ± 0.29	0.96
Total body	27.46 ± 1.23	27.61 ± 1.61	27.22 ± 1.86	0.88
Trunk	15.30 ± 0.70	15.33 ± 0.92	15.25 ± 1.08	0.96
Legs	9.28 ± 0.46	9.37 ± 0.60	9.12 ± 0.72	0.79
Percent body fat (%):				
Android	9.89 ± 0.19	10.00 ± 0.22	9.69 ± 0.37	0.44
Gynoid	20.11 ± 0.34	19.96 ± 0.40	20.36 ± 0.64	0.58
Total body	32.44 ± 1.09	32.28 ± 1.41	32.74 ± 1.70	0.84
Trunk	56.85 ± 0.64	56.89 ± 0.74	56.78 ± 1.20	0.94
Legs	35.36 ± 0.62	35.25 ± 0.72	35.54 ± 1.17	0.83

^aStandard error of mean

^bSignificant level determined by one-way analysis of variance (ANOVA)

Table 2

Final prediction equations for total and regional body fat mass and percentages via demographics, dual-energy x-ray absorptiometry and stereovision body imaging

Dependent Variable ^a	Predictive Models ^b	Primary Group		Validation Group
		R ² (%)	SEE ^c	ME(CI) ^d
Fat Mass (kg)				
Android	– 2.54 + 0.10 Torso Volume – 0.65 Sex + 0.13 Central Obesity Depth	93.2 [*]	0.44	– 0.17 (– 1.04, 0.70)
Gynoid	– 5.74 + 0.13 Upper Thigh Circumference + 0.12 Abdomen-Hip Volume – 1.35 Sex	91.4 [*]	0.74	– 0.12 (– 1.93, 1.69)
Total	– 18.85 + 1.25 Central Obesity Depth +2.07 Thigh Volume – 8.37 Sex + 0.62 Torso Volume	94.6 [*]	3.39	– 1.09 (– 13.13, 10.95)
Trunk	– 10.60 + 0.86 Central Obesity Depth + 0.41 Torso Volume – 4.10 Sex	93.9 [*]	2.03	– 0.66 (– 5.18, 3.86)
Leg	– 16.85 + 0.15 Upper Thigh Circumference +0.53 Knee Circumference –3.42 Sex – 26.13 Thigh to Abdomen-Hip Volume Ratio + 0.92 Thigh Volume	92.4 [*]	1.50	– 0.39 (– 3.52, 2.75)
Percent Fat (%)				
Android	5.72 – 18.13 Thigh to Abdomen-Hip Volume Ratio + 7.23 Waist to Hip Circumference Ratio + 0.08 Central Obesity Depth	76.4 [*]	0.96	– 0.31 (– 2.46, 1.85)
Gynoid	54.90 – 15.48 Waist to Thigh Circumference Ratio – 0.22 Upper Thigh Circumference + 1.68 Sex	66.5 [*]	2.08	0.53 (– 4.15, 5.21)
Total	– 1.89 + 2.01 Central Obesity Depth – 12.98 Sex +1.53 Thigh Volume	88.9 [*]	4.22	– 1.47 (– 9.12, 6.19)
Trunk	31.62 + 39.14 Waist to Hip Circumference Ratio – 63.48 Thigh to Torso Volume Ratio	71.0 [*]	3.55	0.20 (– 7.73, 8.13)
Leg	47.45 – 13.92 Waist to Thigh Circumference Ratio + 44.92 Thigh to Abdomen-Hip Volume Ratio	64.1 [*]	3.81	0.21 (– 8.12, 8.54)

^aDependent variables (body fat percentage and body mass) measured by dual-energy X-ray absorptiometry.

^bIndependent variables measured by stereovision body imaging. Body measurements include sex, age, upper thigh circumference, knee circumference, stereovision waist to hip circumference ratio, waist to thigh circumference ratio, total body volume, torso volume, abdomen-hip volume, thigh volume, torso volume to total body volume ratio, abdomen-hip volume to total body volume ratio, thigh volume to total body volume ratio, abdomen-hip ratio to torso volume ratio, thigh volume to torso volume ratio, thigh volume to abdomen-hip volume ratio, central obesity depth and central obesity width.

^cSEE, Standard error of the estimate

^dMean error = observed – predicted (confidence interval)

* Correlation is significant at 0.05 level (2-tailed)

Changes of R² and *B* values of the demographics and stereovision body imaging parameters included in the prediction equations for total and regional adiposity fat mass and percent fat

Table 3

Body Fat ^a	Parameters ^b	R ² Change (%)	Unstandardized <i>B</i>	Standardized <i>B</i>	<i>p</i> -value
Fat Mass (kg)					
Android	Torso Volume	85.5	0.10	0.66	<0.001
	Sex	6.0	-0.65	-0.20	<0.001
Gynoid	Central Obesity Depth	1.7	0.13	0.31	<0.001
	Upper Thigh Circumference	81.7	0.13	0.46	<0.001
	Abdomen-Hip Volume	5.2	0.12	0.47	<0.001
	Sex	4.5	-1.35	-0.27	<0.001
Total Body	Central Obesity Depth	76.8	1.25	0.33	<0.001
	Thigh Volume	12.3	2.07	0.19	<0.001
	Sex	2.4	-8.37	-0.29	<0.001
	Torso Volume	3.1	0.62	0.48	<0.001
Trunk	Central Obesity Depth	85.7	0.86	0.40	<0.001
	Torso Volume	2.7	0.41	0.56	<0.001
	Sex	5.6	-4.10	-0.25	<0.001
Leg	Upper Thigh Circumference	82.4	0.15	0.26	0.002
	Knee Circumference	3.3	0.53	0.38	<0.001
	Sex	3.6	-3.42	-0.33	<0.001
	Thigh to Abdomen Hip Volume Ratio	2.5	-26.13	-0.26	<0.001
Percent Fat (%)					
Android	Thigh Volume	0.6	0.92	0.22	0.02
	Thigh to Abdomen Hip Volume Ratio	69.6	-18.13	-0.49	<0.001
	Waist to Hip Circumference Ratio	5.2	7.23	0.33	<0.001
Gynoid	Central Obesity Depth	1.5	0.08	0.16	0.03
	Waist to Thigh Circumference Ratio	33.3	-15.48	-0.96	<0.001
	Upper Thigh Circumference	29.5	-0.22	-0.55	<0.001
	Sex	3.7	1.68	0.24	0.006

Body Fat ^a	Parameters ^b	R ² Change (%)	Unstandardized B	Standardized B	p-value
Total Body	Central Obesity Depth	53.8	2.01	0.61	<0.001
	Sex	33.4	- 12.98	- 0.52	<0.001
Trunk	Thigh Volume	1.6	1.53	0.16	0.002
	Waist to Hip Circumference Ratio	65.9	39.14	0.54	<0.001
	Thigh to Torso Volume Ratio	5.0	- 63.48	- 3.56	0.001
Leg	Waist to Thigh Circumference Ratio	57.9	- 13.92	- 0.48	<0.001
	Thigh to Abdomen Hip Volume Ratio	6.2	44.92	0.37	0.001

^aDependent variables (body fat mass and fat percentages) measured by dual-energy X-ray absorptiometry.

^bIndependent variables measured by stereovision body imaging. Body measurements include sex, age, upper thigh circumference, knee circumference, stereovision waist to hip circumference ratio, waist to thigh circumference ratio, total body volume, torso volume, abdomen-hip volume, thigh volume, abdomen-hip volume to total body volume ratio, thigh volume to total body volume to total body volume ratio, total body volume, torso volume, abdomen-hip volume, thigh volume to torso volume ratio, thigh volume to abdomen-hip volume ratio, central obesity depth and central obesity width.