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Three-dimensional optical body shape and features improve prediction of metabolic disease risk in a diverse sample of adults

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Abstract

Objective—We examined if body shape and composition obtained by 3DO scanning improved the prediction of MetS prevalence compared to BMI and demographics.

Methods—A diverse ambulatory adult population underwent whole-body 3DO, blood tests, manual anthropometrics, and blood pressure assessment in the Shape Up! Adults study. MetS prevalence was evaluated based on 2005 National Cholesterol Education Program criteria and prediction of MetS involved logistic regression to assess (1) BMI, (2) demographics-adjusted BMI, (3) eighty-five 3DO anthropometry and body composition measures, (4) BMI + 3DO + demographics models. Receiver operating characteristic area under the curve (AUC) values were generated for each predictive model.

Results—501 participants (280 female) were recruited with 87 meeting the criteria for MetS. Compared to the BMI model (AUC = 0.819), inclusion of age, sex, and race increased the AUC to 0.861, inclusion of 3DO measures further increased the AUC to 0.917. The overall integrated discrimination improvement between the 3DO + demographics and the BMI model was 0.290 (p<0.0001) with a net reclassification improvement of 0.214 (p<0.0001).

Conclusions—Body shape measures from an accessible 3DO scan, adjusted for demographics, predicted MetS better than demographics and/or BMI alone Risk classification in this population increased by twenty nine percent when using 3DO.

Keywords

3-dimensional optical imaging; digital anthropometry; body shape; metabolic syndrome; cardiometabolic prediction risk; area under the curve

INTRODUCTION

Noncommunicable diseases and related conditions such as metabolic syndrome (MetS) continue to grow in prevalence, with prevalence reaching one-third of the adult population in countries such as the United States and Spain (1, 2). Individuals diagnosed with metabolic

syndrome (MetS) have a five times greater risk of developing diabetes and three times greater risk of cardiovascular disease (CVD) (3, 4). As rates of MetS increase, staging of disease risk in children and adults can aid in identifying factors contributing to increasing disease risk (5). Monitoring the underlying risk factors associated with changes in metabolic status also remains a cornerstone of routine clinical practice in an effort to reduce lifetime healthcare expenditures (6).

MetS is a cluster of clinical findings that reflect overnutrition, sedentary lifestyle, and excess adiposity (7). Specifically, MetS is defined as possessing three or more directionally-unhealthy measures including waist circumference, plasma triglycerides, blood pressure, fasting blood glucose, and high-density lipoprotein cholesterol. These clinically accessible measures are linked with underlying risk factors that promote coronary heart disease, CVD, and all-cause mortality (7, 8). While each of these measures is independently associated with a variety of adverse health outcomes including CVD and cancers, each additional risk factor is also associated with a 24% increase in healthcare costs (4, 9). Due the fact that metabolic dysregulation occurs over time, the ability to monitor and treat symptoms related to MetS is necessary to reduce the overall healthcare burden (8).

Body mass index (BMI), a measure of body weight for size, serves as an indirect estimation of body fatness closely tied to each metabolic risk factor. As a predictor of MetS, increasing BMI is directly related to disease risk in normal weight and adults who are overweight (5). However, BMI cannot differentiate the weight of fat mass and fat-free mass, with both muscle and fat having an important role in disease risk (10, 11). These limitations in the predictive ability of BMI means those with higher muscle mass or normal weight obesity (normal BMI with low muscle and high fat mass) may be inappropriately evaluated for disease risk (12, 13). For example, 30% of people with obesity are metabolically healthy, while a recent analysis of National Health and Nutrition Examination Survey (NHANES) data showed that 8.6% of adults in the normal weight category have MetS (14, 15). BMI is also limited in that it is not representative of overall body fatness across age (in children and adults), sex, and ethnicity, meaning specific cut points for disease risk identification are limited (16, 17).

Body shape and body composition are increasingly being linked to obesity-related metabolic risk (18). Body shape change, often measured via anthropometric waist circumference or waist-to-hip ratio (WHR), reflects alterations in total and regional fat and muscle, with these shape factors being linked to vascular aging and risk of diabetes and mortality (19, 20). These markers of fat and tissue distribution, with further emphasis on central obesity, can now be captured with much greater frequency and noninvasively using 3-dimensional optical (3DO) imaging scanners in individuals of all ages, provided that they are capable of standing in the required pose for the duration of the test (21, 22). 3DO scanners are also capable of quickly capturing these anthropometrics along with additional body shape (volumes and circumferences) and composition (fat-free mass, fat mass, visceral fat mass) metrics that are also linked to MetS risk (10, 20, 23). Ng et al. (2019) showed the ability for 3DO body shape by principle component analysis to predict serum lipid and diabetes markers, while a recent meta-analysis highlighted the impact of markers of central fatness such as waist circumference being associated with higher all-cause mortality risk (24, 25).

Given the relative affordability and convenience of 3DO for body composition assessment, rapid expansion of this technology has occurred in clinical practice (23). With its ease of use and ability to track body composition trajectories with repeated measurements, these tools have the potential to inform patient education regarding disease risk and aid medical professionals in mitigating risk. With an increasing number of shape and composition features being individually linked to disease risk, it is of interest to explore if the combination of these features can improve the prediction of MetS risk over anthropometry or demographics alone. However, we are unaware of any studies looking at the ability for 3DO measures of body shape and body composition can improve the prediction of MetS. The current study aims to explore the ability for 3DO, without the need for manual measurements or the use of more expensive clinical measurement methods, to improve MetS identification in comparison to BMI in routine clinical practice. We hypothesize that the combination of measures obtained from a 3DO scan can improve the prediction of MetS over BMI or anthropometry.

METHODS

We performed a cross-sectional analysis to determine how body shape and body composition, as reported by 3D optical scanning, predicted MetS status in a healthy and diverse cohort of adults. Details of the entire protocol can be found in Ng et al. (25) and briefly described below. Participants received criterion measures for MetS as well as exploratory measures using a commercial 3DO system. Models with and without the 3DO measures were created to explore the relationship between the >80 circumferences, regional and whole-body volumes, and body composition variables and MetS. To assess the impact of body shape and composition variables on disease risk, models were compared using logistic regression and areas under the receiver-operating characteristic (ROC) curves.

Participants

Participants were recruited as part of the Shape Up! Adults cohort at University of Hawaii Cancer Center (UHCC), University of California, San Francisco (UCSF), and Pennington Biomedical Research Center (PBRC) between October 2016 and January 2020. Shape Up! Adults (NIH R01 DK109008, clinicaltrials.gov ID NCT03637855) is a cross-sectional sample of healthy adults with the goal to represent the breadth of body shape in the US population. The recruitment goals were for equal cells by age (18-40 y, 40-60 y, >60 y), ethnicity and body mass index (BMI in kg/m^2; <20, 20-24.9, 25-30, >30). Participants were excluded if they could not stand for two minutes without aid, or had significant body shape-altering procedures (e.g., liposuction, amputations, breast augmentation or reduction). Female participants were also excluded if pregnant or breastfeeding. The study protocols were approved by institutional review boards at all sites and participants provided written informed consent.

Anthropometric measurements—Anthropometry was measured using the NHANES protocol (26). Height and mass to the nearest 0.1 cm and 0.1 kg was measured using a stadiometer and digital scale (Seca, Chino, CA). Flexible measuring tapes were used to collect waist circumference. Waist circumference (WC) measurements were taken using

marks placed on the top of the iliac crest as reference while the participant stood up straight with their arms crossed. Measurements were recorded in triplicate to the nearest 0.1 cm and averaged. Though WC was measured and used in the MetS diagnosis, the aim was to explore the use of variables measured via 3DO, including 3DO WC, to improve the prediction of MetS. This allowed for the investigation of this simplified approach of 3DO and readily available demographic data, though we also explored the prediction of MetS using demographics and anthropometric WC (data not shown).

Blood measurements—Blood samples were collected from participants after an overnight fast. Biochemical analysis was performed at PBRC. Measurements included serum triglycerides, fasting glucose, and high-density lipoprotein (HDL) cholesterol. Systolic and diastolic blood pressure (BP) were measured by a certified technologist in a seated position after 5-minutes rest.

Three dimensional optical (3DO) scans—3DO scans were obtained using a commercial scanner comprised of a single depth camera incorporated into a sensor tower that stands approximately 6 feet in front of a rotating platform (S100 Body Scanner, Styku LLC, Los Angeles, CA, software version 4.1 using “Styku Advanced Phoenix Model for Body Composition” setting). Participants wore form-fitting shorts, a sports bra for females, and a swim cap and stood on the turntable with legs separated, arms away from the body at a 45-degree angle, hands closed into fists as recommended by the manufacturer. Each scan took 30-40 seconds to complete.. The reports include 65 whole-body and segmental surface areas, volumes, and circumferences along with 3 circumference ratios. Seventeen body composition estimates are also derived from these measures using proprietary algorithms built into the system software. Bennett et al. (2022) describes the accuracy and precision of fat and fat free mass (CCC > 0.95; CV < 1.94%), whole body volume (CCC = 0.99; CV = 1.45%), and circumference measurements (CCC > 0.97; CV < .63%) in a sample of adults (18-89 years) stratified by BMI and ethnicity (23). With the 3DO shown to be accurate compared to criterion measures for body composition and anthropometry, we aimed to utilize the 3DO variables exclusively as a simplified assessment technique to improve the prediction of MetS.

Metabolic Syndrome—Metabolic syndrome was defined using the 2005 National Cholesterol Education Program Adult Treatment Panel III (NCEP ATP III) guidelines as having ≥3 of the following: high waist circumference (as measured by manual anthropometry; ≥102 cm in men, ≥88 cm in women), elevated triglycerides (≥150 mg/dL), elevated blood pressure (≥130 mm Hg systolic or ≥85 mm Hg diastolic), elevated fasting glucose (≥100 mg/dL), and/or reduced HDL-C (< 40 mg/dL in men, <50 mg/dL in women) (8). For individuals with missing data points, presence or absence of metabolic syndrome was defined if at least 3 of the available variables met or were under the criteria for diagnosis, respectively. Individuals with 4 available measures with 2 above and 2 variables below the cut points were excluded from the dataset due to insufficient data to make an accurate diagnosis.

Statistical Methods—Logistic regression was performed to create the following models to predict MetS: BMI (model 1), BMI + demographics (age + sex + race; model 2), 3DO body shape variables (model 3), and model 2 + model 3 (BMI + demographics + 3DO; model 4). Selection of 3DO variables in model 3 and model 4 were performed using step forward logistic regression (proc LOGISTIC with stepwise option, SAS Institute, Cary, NC, USA). Variables were selected if they were significantly associated to MetS ($p < 0.10$) and kept in the final model if their significance was $p < 0.05$ to ensure the optimum fit while limiting risk of model overfitting. A ROC curve with its associated area under the curve (AUC) and concordance index measures were generated for each model. To determine the appropriate cut point, the highest Youden index (sensitivity + specificity – 1) was calculated (27). Integrated discrimination improvement (IDI) was used to visualize the separate improvements in sensitivity and specificity between model 1 and model 4 (28). Net reclassification index (NRI) was computed with 1000 rounds of bootstrapping for specific cut points in the prediction probability (28). The Model 4 MetS prediction equation was used to generate AUCs for each of the individual MetS blood parameter cutoffs. Statistical analysis was performed using SAS 9.4 (SAS Institute, Cary, NC, USA) and Scitkit Learn (Python Software 3.10, Beaverton, OR, USA).

RESULTS

A total of 619 adults were available for this study. Of this sample, 3DO scans were missing for 105 participants (due to the later inclusion of the 3DO scanner into the study protocol) and of the remaining participants, 12 did not have serum markers available to make a diagnosis. See the Consolidated Standards of Reporting Trials (CONSORT; Supplement Figure S1) checklist and Strengthening The Reporting in Observational studies in Epidemiology (STROBE; Supplement Figure S2) checklist for further details of exclusions. After these exclusions, 501 participants had 3DO scans and available parameters. Of those, 87 (17.4% of the total population) met the criteria for MetS. Individuals with MetS tended to be older, female, with a higher BMI, waist circumference (WC) and percent body fat (all $p<0.05$). Summary characteristics and subject counts by ethnicity are presented in Table 1.

Each model is presented in Table 2, which shows the progressive AUC improvement with each model. A total of 8 variables (4 3DO variables) were included in model 4. The contribution of each variable to the AUC is shown in table 3. Overall, WHR (AUC improvement of 0.022) showed the greatest improvement.

The ROC curves for each model are presented in Figure 1. We found a progressive improvement in the AUC values from Model 1 (AUC = 0.819, 95% confidence interval (CI): 0.775-0.862) to model 4 (AUC = 0.917, CI: 0.889-0.945). The combination of BMI and demographics variables with 3DO (model 4) made for the best model with high discriminatory power, as shown in Table 2.

The results of the IDI curve comparing the final BMI + demographics + 3DO model (Model 4) to the BMI-only model (Model 1) are presented in Figure 2. Adding the additional variables used in Model 4 resulted in an average predicted probability of MetS increase

of 71.8% and a 31.7% decrease in average predicted probability of nonevents. Overall, the model increased the IDI by 26.0% (95% CI: 23.5-34.5%, $p<0.0001$) and NRI by 19.4% (95% CI: 2.8-40.0%, $p<0.0001$).

The optimal cutoff used to derive a confusion matrix of results, presented in Table 4, showed that 78 (89.7%) of the 87 positive cases were correctly identified. Of the negative cases, 349 (84.3%) of the 414 cases were properly classified. Importantly, this cutoff correctly identified all 7 normal BMI MetS+ participants. Model 4 also improved prediction of MetS compared to a demographics + anthropometric WC (AUC = 0.888 CI: 0.804-0.906; data not shown). Further, the demographics + anthropometric WC model only successfully predicted 2 of the 7 normal BMI MetS+ participants and failed to capture 11 of the high BMI MetS− subjects, highlighting the significance of the 3DO system over a simplified WC assessment to identify disease risk.

Using the prediction equation generated by model 4, we examined the relationship to each individual blood parameter cutoff used in MetS diagnosis, presented in Figure 3. Generated AUCs for each blood parameter ranged from 0.702 for blood pressure to 0.820 for blood triglycerides, ranging from acceptable to excellent (29). In addition, we examined the relationship of model 4 to each individual blood parameter used in MetS diagnosis, presented in Supplement Table S1. We also included a correlation matrix for each 3DO measurement variable and MetS blood parameter in Supplement Figure S3.

In Figure 4 we matched MetS positive and negative subjects with similar characteristics to highlight how shape and composition more accurately reflect disease risk and diagnosis.

Discussion

The purpose of the present study was to evaluate potential improvements in MetS prediction by incorporating demographics, body shape, and body composition parameters, easily obtained using a clinically accessible 3DO technology. We found that our model resulted in a significant improvement in the prediction of MetS, further highlighting the importance of body shape and composition in disease prediction. Further, we confirmed our hypothesis that the combination of measures obtained from a 3DO scan provided a better diagnostic compared to simpler models or individual measurements.

A meta-analysis performed by Lee (2020) showed that obesity was associated with a 62% greater MetS risk (risk ratio = 1.62, 95% CI: 1.32-1.98; $p<.01$), regardless of cardiovascular fitness level (30). Body shape, as assessed by waist circumference (a surrogate for abdominal obesity) and trunk to hip volume ratio (a surrogate for regional adiposity), has been shown to be an important metric for understanding the distribution of adipose tissue related to MetS disease risk (20, 24, 31). The results of our study show that both body composition and body shape parameters can provide valuable information regarding disease risk. WHR, an indirect marker of both abdominal and regional obesity, better predicted MetS risk compared to WC, which is consistent with findings of other studies looking at body shape on MetS risk (32-35). While WC is considered to be a strong predictor of MetS risk, WHR may better reflect adipose tissue storage in the gluteal subcutaneous region, which

may be protective of MetS risk (34). Our study showed that WC had an inverse association to MetS risk. Given the larger impact of the WHR on prediction risk, we believe the negative association observed may be a correction to address high BMI individuals who do not have MetS and therefore further highlights the benefits of body shape over BMI or WC assessment(35).

Body composition has a clear association with MetS risk (10, 14). The 3DO model found 2 body composition variables to be predictive of MetS risk. Calf circumference, an indirect measure of muscle mass that is less affected by fat deposition, has been associated with MetS risk using NHANES datasets (33). We believe that the average calf volume reflects the leg musculature and therefore serves as a protective factor for MetS risk. While bone mass is linked to MetS, the causal direction between these factors remains unclear (36). Thus, while low bone mass may be an independent predictor of MetS risk, a low proportion of body weight as bone mass may also reflect increased adiposity, a clear predictor of MetS risk (4). This finding was supported by the strong positive correlation of bone mass percent to lean mass percent and strong negative correlation to body fat percent (Supplement Figure S3).

Previous studies have explored the use of body composition by bioimpedance for the prediction of MetS, however this method is unable to derive body shape measurements that reflect adipose tissue distribution and predict disease risk (32, 37). Researchers have explored the utility of body shape using dual-energy X-ray absorptiometry, however this technology is not accessible or cost-effective to be used for routine diagnostic purposes (20). 3DO measures have added benefits for clinical practice by reducing measurement bias associated with manual anthropometry and providing rapid access to body composition and shape data. Given that these measures are low cost, easily accessible, and associated with disease risk, these findings support the use of 3DO measures as a novel and feasible approach for routine clinical risk assessment.

Body shape measures of waist circumference have long been linked to visceral adiposity; waist circumference has been validated using 3DO scanners previously (21, 22, 25). In relation to blood, Jaeschke et al. (2015) found 3DO measures of waist circumference were significantly associated with MetS blood parameters (38). Ng et al. (2019) showed the relationship of principle components of 3DO scans and their individual relationships to blood metabolites (25). While these studies examined the relationship of body shape to individual blood parameters, our study was the first to examine disease risk by 3DO. The results showed that the final body shape and composition model as derived from 3DO (Model 4) had a significant (all $p<.05$) relationship to MetS risk as well as each MetS blood parameter, showing that 3DO is a useful metric to reflect adipose distribution and its relationship to blood markers and overall disease risk.

Because parameters of MetS can occur independently, it is important to develop metrics that are useful to evaluate the risk of disease in high weight as well as normal weight individuals. Our study found that all 7 individuals (4.7% of the normal weight population, slightly below the 8.6% observed in the NHANES sample) with a normal BMI were properly identified as MetS+ using the derived model. Similarly, 201 of the 222 (90.5%) subjects defined by BMI as possessing excess weight were correctly classified as MetS− using the final

3DO model. Due to the fact that metabolic dysregulation develops over time, the ability to monitor progress is essential for guiding education and awareness as a strategy towards disease prevention (39). As seen in the sample subject images, use of both body shape and composition can improve MetS modeling when compared between individuals. Further, these images provide clinicians with easily accessible body shape images that can be used to educate patients on their current body composition, while tracking this information over time can serve as a potent indicator of change in disease risk for both the patient and clinician. Use of this information and the visuals provided by the 3DO system will allow medical professionals to monitor change over time, an essential aspect of monitoring disease risk (39).

A strength of this study is that it utilized a diverse sample of adults of varying age, ethnicity, and BMI. The range of BMIs included is significant as our sample included a strong sample of underweight, normal weight, and people with overweight/obesity. We also show the importance of age and gender adjustment and their importance in MetS diagnosis (40). Due to the relatively small sample of participants with MetS (n=87), we were unable to separate training and test sets to examine the accuracy of our prediction model. That said, our sample (n=501) was well above the amount required to detect differences between AUCs with a 95% probability (n=58) (41). Given the cross-sectional nature of the study, we were unable to examine the changes in body shape and their association with change in MetS risk. Nor is our model able to tease out the impact of factors such as vitamin D and exercise on MetS risk (42, 43). The review by Lee (2020) shows the importance of cardiovascular fitness in the prevention of MetS (30). However, because these individuals met the NCEP ATP III criteria for MetS, we believe the application of these findings remain, regardless of physical activity level.

It should be noted that while 3DO systems are increasingly being utilized in clinical and field settings, their adoption in clinical practice is not universal and access to 3DO technology may be limited in certain settings (23). Though the WC + anthropometric model increased the AUC compared to model 1, the proper identification of 16 individuals of the 3DO model 4 compared to a WC assessment further highlights the importance of other body shape variables as significant predictors of MetS disease risk. Given the increased reliability from the automated 3DO system, we believe the advantages noted earlier warrant the use of these systems, when available. That said, we also included the BMI + demographics model for clinicians to use when 3DO scanning is unavailable.

Finally, the cutoffs for MetS continue to be debated based on a variety of factors including body size, race/ethnicity, and cutoffs selected. For example, male patients can develop multiple metabolic risk factors when waist circumference is only marginally elevated (94-102 cm) (8). Given the criteria used by the NCEP ATP III focuses on MetS instead of focusing on obesity or insulin resistance being the primary cause of CVD and the common use of these criteria, we believe this to be a strength of our study in our target population. That said, without including population-specific cut points such as those included in the International Diabetes Foundation criteria, the generalizability of these results to non-American populations is limited (44). Further work should explore the predictive ability of these models in different populations to identify where the proposed model may be

improved or identify limitations in the model based on the issues related to MetS risk discussed earlier. This work could also be expanded to youth populations in future works, as the rapid change in body size, shape, and composition may pose valuable information regarding changes to disease risk over time. Future studies should also look at the ability for 3DO to track body composition and shape changes longitudinally and their associations to MetS risk (45). Prospective studies regarding MetS prediction over time, along with a greater understanding of how the information provided to patients informs clinical decision-making using this technology, will further improve the application of this technology as a tool for disease prevention and treatment. Monitoring the role of diet and exercise in the progression of MetS disease risk may also improve the application of 3DO technology in clinical practice.

Conclusion

Our results confirm the findings of previous studies examining the link between body shape and composition with MetS disease risk. By building a prediction model with better predictive power, we show the usefulness of a 3DO scanner for routine clinical practice in the assessment of MetS disease risk that is accessible, non-invasive, and cost-effective.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Abbreviations:

MetS	metabolic syndrome
3DO	3-dimensional optical
BMI	body mass index
WC	waist circumference
ROC	receiver operating characteristic
AUC	area under the curve
NRI	net reclassification index
IDI	integrated discrimination improvement

References

1. Ford ES. Prevalence of the Metabolic Syndrome Defined by the International Diabetes Federation Among Adults in the U.S. Diabetes Care. 2005;28(11):2745–9. doi: 10.2337/diacare.28.11.2745. [PubMed: 16249550]
2. Saklayen MG. The Global Epidemic of the Metabolic Syndrome. Curr Hypertens Rep. 2018;20(2). doi: 10.1007/s11906-018-0812-z.
3. Malik S, Wong ND, Franklin SS, Kamath TV, L'Italien GJ, Pio JR, et al. Impact of the Metabolic Syndrome on Mortality From Coronary Heart Disease, Cardiovascular Disease, and All Causes in United States Adults. Circulation. 2004;110(10):1245–50. doi: 10.1161/01.cir.0000140677.20606.0e. [PubMed: 15326067]
4. O'Neill S, O'Driscoll L. Metabolic syndrome: a closer look at the growing epidemic and its associated pathologies. Obes Rev. 2015;16(1):1–12. doi: 10.1111/obr.12229.
5. Sarma S, Sockalingam S, Dash S. Obesity as a multisystem disease: Trends in obesity rates and obesity-related complications. Diabetes, Obesity and Metabolism. 2021;23(S1):3–16. doi: 10.1111/dom.14290.
6. Zhuo X, Zhang P, Barker L, Albright A, Thompson TJ, Gregg E. The Lifetime Cost of Diabetes and Its Implications for Diabetes Prevention. Diabetes Care. 2014;37(9):2557–64. doi: 10.2337/dc13-2484. [PubMed: 25147254]
7. Cornier M-A, Dabelea D, Hernandez TL, Lindstrom RC, Steig AJ, Stob NR, et al. The Metabolic Syndrome. Endocr Rev. 2008;29(7):777–822. doi: 10.1210/er.2008-0024. [PubMed: 18971485]
8. Grundy SM, Cleeman JI, Daniels SR, Donato KA, Eckel RH, Franklin BA, et al. Diagnosis and Management of the Metabolic Syndrome. Circulation. 2005;112(17):2735–52. doi: 10.1161/circulationaha.105.169404. [PubMed: 16157765]
9. Boudreau D, Malone D, Raebel M, Fishman P, Nichols G, Feldstein A, et al. Health care utilization and costs by metabolic syndrome risk factors. Metab Syndr Relat Disord. 2009;7(4):305–14. [PubMed: 19558267]
10. Srikanthan P, Karlamangla AS. Relative Muscle Mass Is Inversely Associated with Insulin Resistance and Prediabetes. Findings from The Third National Health and Nutrition Examination Survey. The Journal of Clinical Endocrinology & Metabolism. 2011;96(9):2898–903. doi: 10.1210/jc.2011-0435. [PubMed: 21778224]
11. Katzmarzyk PT, Janssen I, Ross R, Church TS, Blair SN. The Importance of Waist Circumference in the Definition of Metabolic Syndrome: Prospective analyses of mortality in men. Diabetes Care. 2006;29(2):404–9. doi: 10.2337/diacare.29.02.06.dc05-1636. [PubMed: 16443895]
12. Wijayatunga NN, Dhurandhar EJ. Normal weight obesity and unaddressed cardiometabolic health risk—a narrative review. Int J Obes. 2021. doi: 10.1038/s41366-021-00858-7.
13. St-Onge MP, Janssen I, Heymsfield SB. Metabolic Syndrome in Normal-Weight Americans: New definition of the metabolically obese, normal-weight individual. Diabetes Care. 2004;27(9):2222–8. doi: 10.2337/diacare.27.9.2222. [PubMed: 15333488]
14. Engin A The Definition and Prevalence of Obesity and Metabolic Syndrome. Springer International Publishing; 2017. p. 1–17.
15. Shi TH, Wang B, Natarajan S. The Influence of Metabolic Syndrome in Predicting Mortality Risk Among US Adults: Importance of Metabolic Syndrome Even in Adults With Normal Weight. Prev Chronic Dis. 2020;17:E36. [PubMed: 32441641]
16. Duncan J, Duncan EK, Schofield G. Accuracy of body mass index (BMI) thresholds for predicting excess body fat in girls from five ethnicities. Asia Pac J Clin Nutr. 2009;18(3):404–11. [PubMed: 19786389]
17. Gallagher D, Visser M, Sepulveda D, Pierson RN, Harris T, Heymsfield SB. How Useful Is Body Mass Index for Comparison of Body Fatness across Age, Sex, and Ethnic Groups? Am J Epidemiol. 1996;143(3):228–39. doi: 10.1093/oxfordjournals.aje.a008733. [PubMed: 8561156]
18. Pi-Sunyer X Changes in body composition and metabolic disease risk. Eur J Clin Nutr. 2019;73(2):231–5. [PubMed: 30275524]

19. Van Sloten TT, Boutouyrie P, Lisan Q, Tafflet M, Thomas F, Guibout C, et al. Body Silhouette Trajectories Across the Lifespan and Vascular Aging. Hypertension. 2018;72(5):1095–102. doi: 10.1161/hypertensionaha.118.11442. [PubMed: 30354814]
20. Wilson JP, Kanaya AM, Fan B, Shepherd JA. Ratio of Trunk to Leg Volume as a New Body Shape Metric for Diabetes and Mortality. PLoS One. 2013;8(7):e68716. doi: 10.1371/journal.pone.0068716. [PubMed: 23874736]
21. Ng BK, Hinton BJ, Fan B, Kanaya AM, Shepherd JA. Clinical anthropometrics and body composition from 3D whole-body surface scans. Eur J Clin Nutr. 2016;70(11):1265–70. doi: 10.1038/ejcn.2016.109. [PubMed: 27329614]
22. Wong MC, Ng BK, Kennedy SF, Hwaung P, Liu EY, Kelly NN, et al. Children and Adolescents' Anthropometrics Body Composition from 3-D Optical Surface Scans. Obesity. 2019;27(11):1738–49. doi: 10.1002/oby.22637. [PubMed: 31689009]
23. Bennett JP, Liu YE, Quon BK, Kelly NN, Wong MC, Kennedy SF, et al. Assessment of clinical measures of total and regional body composition from a commercial 3-dimensional optical body scanner. Clin Nutr. 2022;41(1):211–8. Epub December 6, 2021. doi: 10.1016/j.clnu.2021.11.031. [PubMed: 34915272]
24. Jayedi A, Soltani S, Zargar MS, Khan TA, Shab-Bidar S. Central fatness and risk of all cause mortality: systematic review and dose-response meta-analysis of 72 prospective cohort studies. BMJ. 2020:m3324. doi: 10.1136/bmj.m3324. [PubMed: 32967840]
25. Ng BK, Sommer MJ, Wong MC, Pagano I, Nie Y, Fan B, et al. Detailed 3-dimensional body shape features predict body composition, blood metabolites, and functional strength: the Shape Up! studies. The American Journal of Clinical Nutrition. 2019;110(6):1316–26. [PubMed: 31553429]
26. Prevention CfDCa. National Health and Nutrition Examination Survey (NHANES) Anthropometry Procedures Manual. Available from: https://wwwn.cdc.gov/nchs/data/nhanes/2017-2018/manuals/2017_Anthropometry_Procedures_Manual.pdf.
27. Yin J, Tian L. Optimal linear combinations of multiple diagnostic biomarkers based on Youden index. Stat Med. 2014;33(8):1426–40. [PubMed: 24311111]
28. Pickering JW, Endre ZH. New Metrics for Assessing Diagnostic Potential of Candidate Biomarkers. Clin J Am Soc Nephrol. 2012;7(8):1355–64. doi: 10.2215/cjn.09590911. [PubMed: 22679181]
29. Hosmer DW Jr, Lemeshow S, Sturdivant RX. Applied logistic regression: John Wiley & Sons; 2013.
30. Lee J Influences of cardiovascular fitness and body fatness on the risk of metabolic syndrome: A systematic review and meta-analysis. Am J Health Promot. 2020;34(7):796–805. [PubMed: 32431155]
31. Fu X, Song A, Zhou Y, Ma X, Jiao J, Yang M, et al. Association of regional body fat with metabolic risks in Chinese women. Public Health Nutrition. 2014;17(10):2316–24. doi: 10.1017/s1368980013002668. [PubMed: 24148901]
32. Sagun G, Oguz A, Karagoz E, Filizer AT, Tamer G, Mesci B. Application of alternative anthropometric measurements to predict metabolic syndrome. Clinics. 2014;69:347–53. [PubMed: 24838901]
33. Wu C-J, Kao T-W, Chang Y-W, Peng T-C, Wu L-W, Yang H-F, et al. Does the Additional Component of Calf Circumference Refine Metabolic Syndrome in Correlating With Cardiovascular Risk? The Journal of Clinical Endocrinology & Metabolism. 2018;103(3):1151–60. doi: 10.1210/jc.2017-02320. [PubMed: 29346655]
34. Lee HJ, Hwang SY, Hong HC, Ryu JY, Seo JA, Kim SG, et al. Waist-to-hip ratio is better at predicting subclinical atherosclerosis than body mass index and waist circumference in postmenopausal women. Maturitas. 2015;80(3):323–8. [PubMed: 25631349]
35. Zhou Y, Hou Y, Xiang J, Dai H, Li M, Wang T, et al. Associations of body shapes with insulin resistance and cardiometabolic risk in middle-aged and elderly Chinese. Nutr Metab (Lond). 2021;18(1). doi: 10.1186/s12986-021-00629-1.
36. Hwang DK, Choi HJ. The relationship between low bone mass and metabolic syndrome in Korean women. Osteoporos Int. 2010;21(3):425–31. doi: 10.1007/s00198-009-0990-2. [PubMed: 19565174]

37. Lee Y-C, Lee Y-H, Chuang P-N, Kuo C-S, Lu C-W, Yang K-C. The utility of visceral fat level measured by bioelectrical impedance analysis in predicting metabolic syndrome. Obes Res Clin Pract. 2020;14(6):519–23. [PubMed: 33071188]

38. Jaeschke L, Steinbrecher A, Pischon T. Measurement of Waist and Hip Circumference with a Body Surface Scanner: Feasibility, Validity, Reliability, and Correlations with Markers of the Metabolic Syndrome. PLoS One. 2015;10(3):e0119430. doi: 10.1371/journal.pone.0119430. [PubMed: 25749283]

39. Müller MJ, Lagerpusch M, Enderle J, Schautz B, Heller M, Bosy-Westphal A. Beyond the body mass index: tracking body composition in the pathogenesis of obesity and the metabolic syndrome. Obes Rev. 2012;13:6–13. doi: 10.1111/j.1467-789x.2012.01033.x. [PubMed: 23107255]

40. Slagter SN, Van Waateringe RP, Van Beek AP, Van Der Klauw MM, Wolffenbuttel BHR, Van Vliet-Ostaptchouk JV. Sex, BMI and age differences in metabolic syndrome: the Dutch Lifelines Cohort Study. Endocrine Connections. 2017;6(4):278–88. doi: 10.1530/ec-17-0011. [PubMed: 28420718]

41. Hanley JA, McNeil BJ. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology. 1982;143(1):29–36. [PubMed: 7063747]

42. Moy F-M, Bulgiba A High prevalence of vitamin D insufficiency and its association with obesity and metabolic syndrome among Malay adults in Kuala Lumpur, Malaysia. BMC Public Health. 2011;11(1):735. doi: 10.1186/1471-2458-11-735. [PubMed: 21943301]

43. Rennie K, McCarthy N, Yazdgerdi S, Marmot M, Brunner E. Association of the metabolic syndrome with both vigorous and moderate physical activity. Int J Epidemiol. 2003;32(4):600–6. doi: 10.1093/ije/dyg179. [PubMed: 12913036]

44. Huang PL. A comprehensive definition for metabolic syndrome. Dis Model Mech. 2009;2(5-6):231–7. doi: 10.1242/dmm.001180. [PubMed: 19407331]

45. Oh YH, Choi S, Lee G, Son JS, Kim KH, Park SM. Changes in Body Composition Are Associated with Metabolic Changes and the Risk of Metabolic Syndrome. Journal of Clinical Medicine. 2021;10(4):745. doi: 10.3390/jcm10040745. [PubMed: 33668451]

Study Importance

- What is already known about this subject?

Metabolic abnormalities can occur in normal weight individuals, while some individuals who are overweight do not meet the criteria for metabolic syndrome, highlighting the limitations of using body mass index (BMI) for disease risk identification

Body shape features as measured through three-dimensional optical (3DO) body scans correlate to serum lipid markers linked to metabolic syndrome (MetS).

- What are the new findings in your manuscript?

Body shape and composition from 3DO scans improve the modeling of metabolic syndrome over BMI and demographics

The prediction model successfully identifies normal weight subjects with metabolic syndrome and improves identification of subjects who are overweight without metabolic syndrome

- How might your results change the direction of research or the focus of clinical practice?

Accessible optical body shape and composition scans can improve clinical detection of metabolic syndrome and aid in clinical guidance of disease risk or management

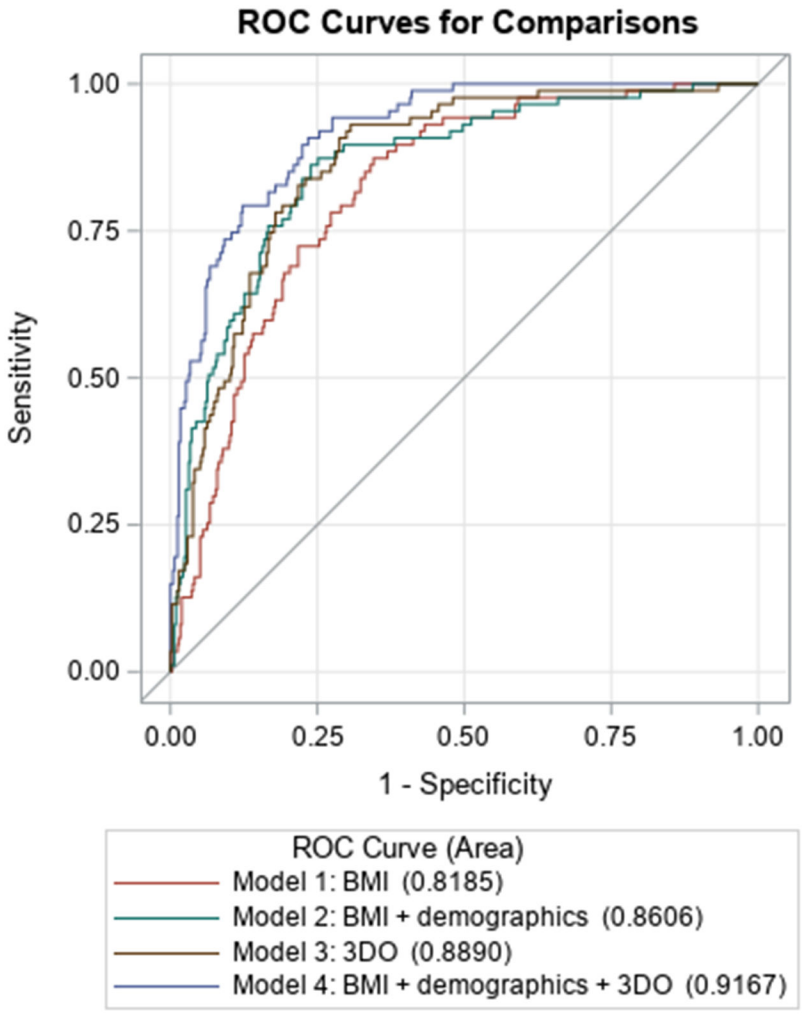

Figure 1: Stepwise Receiver-Operating Characteristic Curves for MetS Prediction
Abbreviations: 3DO: 3-dimensional optical scan variables

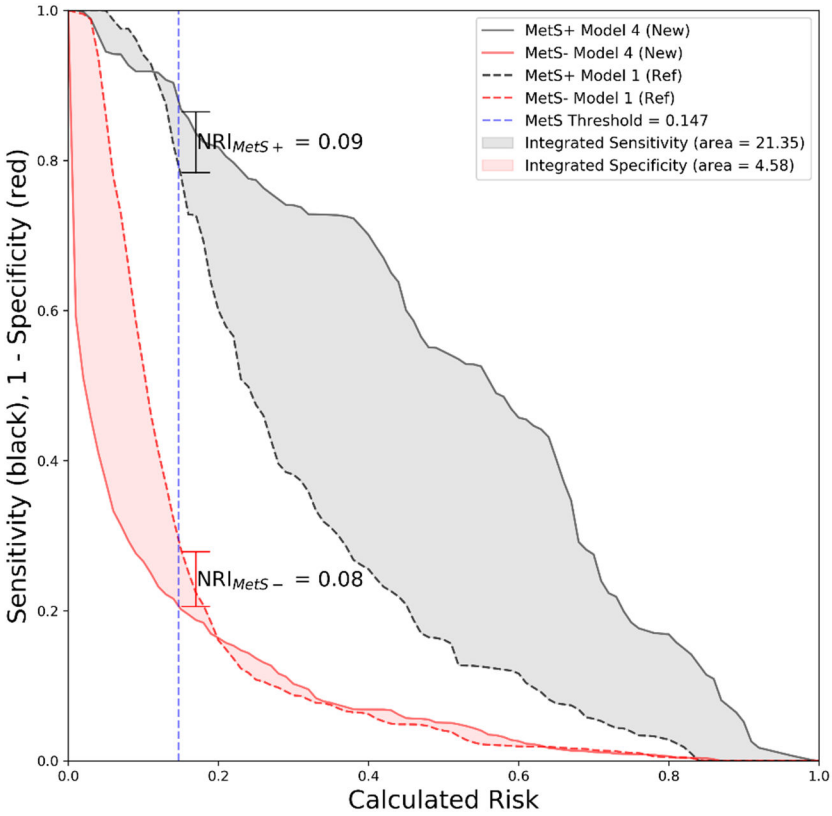

Figure 2: Integrated Discrimination Improvement and Net Reclassification Index for MetS Prediction When Comparing Model 4 to Model 1

The integrated sensitivity (IS), black shaded region, indicates the change in sensitivity model 4 compared to model 1 across all risk thresholds. The integrated 1-sepcificity (IP), red shaded region, indicates the change in specificity with the addition of the 3DO model. Using a threshold of 0.147, model 4 was able to identify 9% more MetS+ individuals than model 1. The IDI is the sum of the IS and IP and the positive IDI indicates that predictive models benefit from the addition of 3DO. NRI are presented for prediction of MetS (black) and non-events (red).

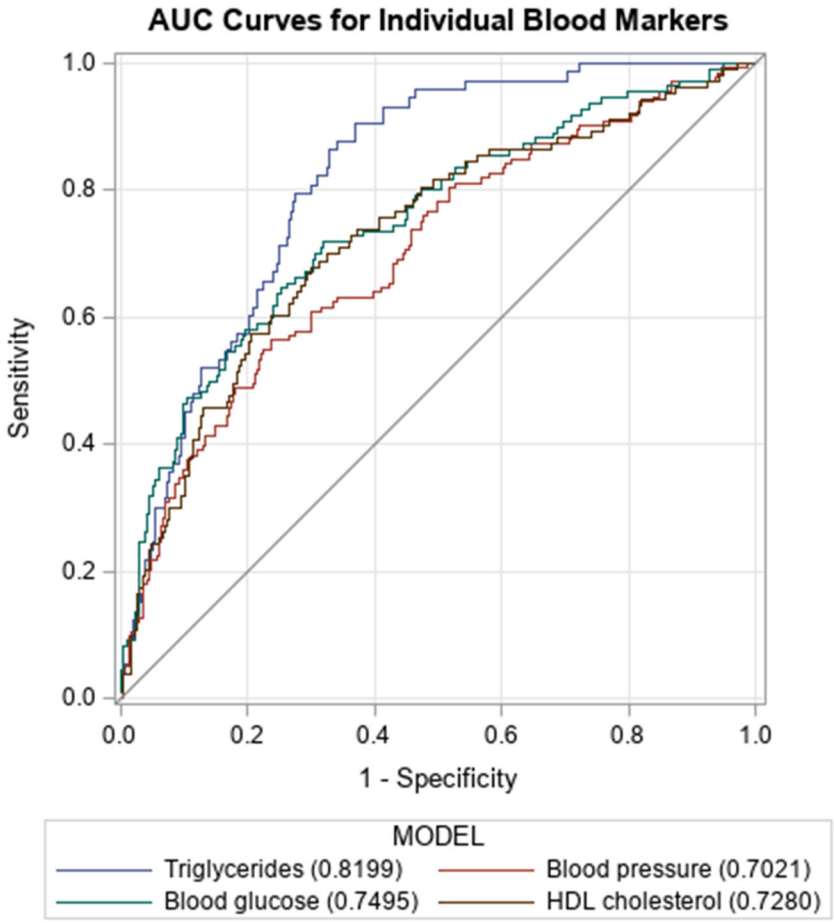

Figure 3: Stepwise Receiver-Operating Characteristic Curves for Individual Blood Markers

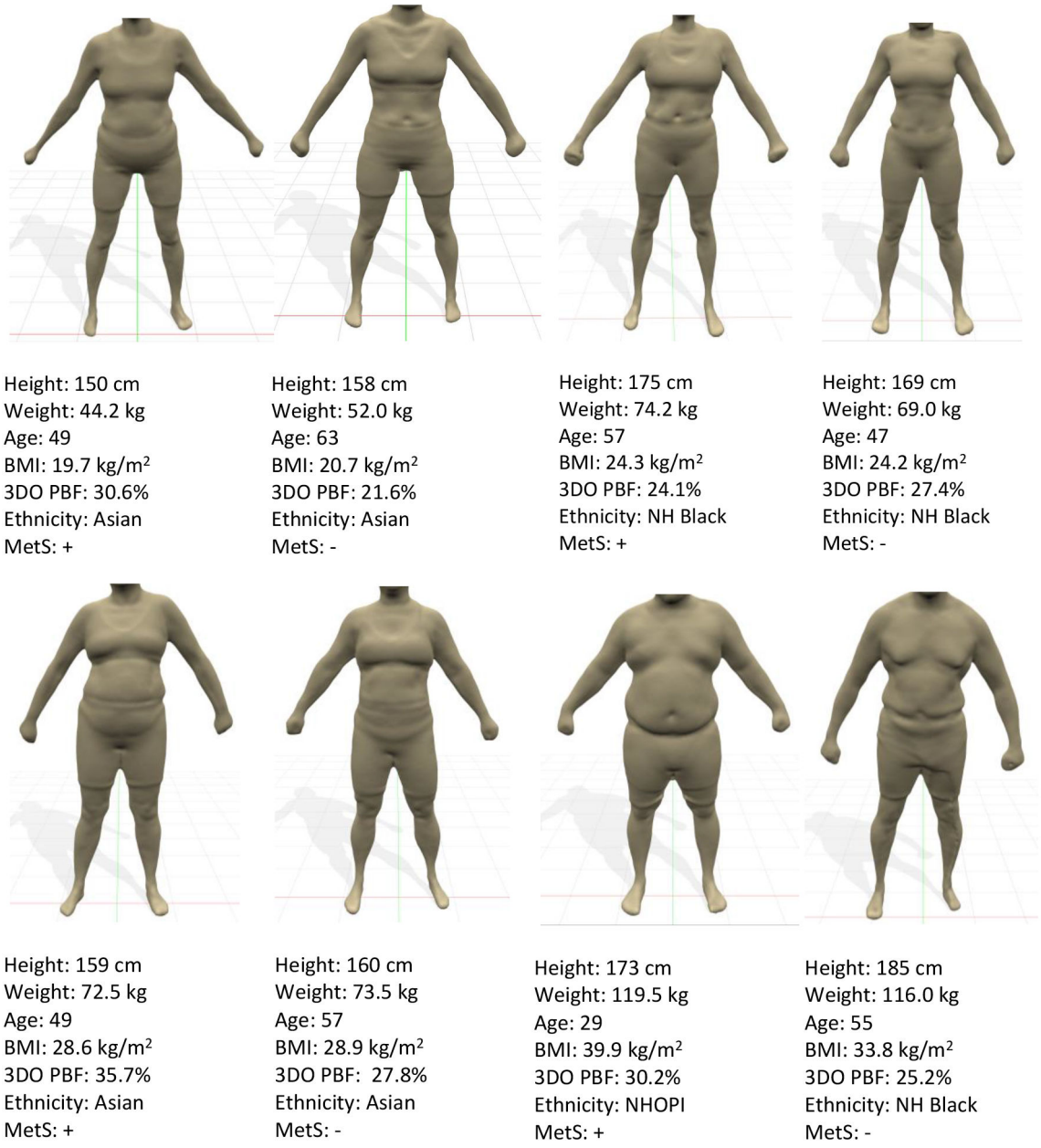

Figure 4: Sample images of Metabolic Syndrome positive vs. negative subjects

Example 1: Similar BMI (normal), higher PBF, WC, WHR in MetS+

Example 2: Same BMI (normal), higher PBF in MetS− but greater WC and WHR in MetS+

Example 3: Same BMI (with overweight), different PBF with greater WC and WHR in MetS+

Example 4: Same WC, greater WHR in MetS+

Table 1:

Subject Characteristics (n = 501 [280 female])

Variable	*Male (n=221) Mean (SD)*		*Female (n=280) Mean (SD)*		**Total (n=501)**		
					Mean (SD)	***Min***	***Max***
Age (years)	45.0 (16.6)		46.7 (16.2)		46.2 (16.5)	18.0	89.0
Height (cm)	175.3 (8.0)		162.7 (6.4)		167.7 (10.0)	144.1	202.1
Weight (kg)	86.0 (21.0)		73.5 (21.6)		77.8 (22.2)	35.4	173.5
BMI (kg/m^2)	27.9 (6.2)		27.8 (8.0)		27.5 (7.0)	14.2	52.6
3DO PBF (%)	20.8 (6.5)		31.0 (7.9)		26.2 (8.9)	2.0	48.0
Ethnicity	***Count***	***MetS+***	***Count***	***MetS+***	**Count**	**%**	**MetS+**
Asian	*46*	*6*	*65*	*16*	111	22.2	22
NH Black	*63*	*8*	*68*	*5*	131	26.1	13
Hispanic	*30*	*2*	*39*	*5*	69	13.8	7
NHOPI	*17*	*6*	*27*	*10*	44	8.8	16
NH White	*65*	*11*	*81*	*18*	146	29.1	29

Abbreviations: SD: standard deviation, BMI: body mass index, WC: waist circumference, 3DO: 3-dimensional optical scan, PBF: percent body fat, NH: non-Hispanic

[†] Metabolic syndrome positive using NCEP ATP III criteria

[1] NHOPI: native Hawaiian or Pacific Islander

Note: Percentage values are rounded

Table 2:

Prediction equations derived using logistic regression to predict metabolic syndrome

Model	Name	Test Variables	AUC	Equation†
1	BMI	BMI	0.819	−5.768 + 0.143*BMI
2	BMI + demographics	BMI, age, race, sex,	0.861	−9.643 + 0.177*BMI + 0.059 * Age – 0.059 * NH Black + 1.159 * NHOPI
3	3DO	3DO	0.889	−12.583+0.073*3DO Body fat percent +0.009*3DO Chest volume – 0.046*3DO Left arm area + 0.025*3DO Left arm volume + 14.516*3DO WHR
4	BMI + demographics + 3DO	BMI, age, race, sex, 3DO	0.917	−17.328 + 0.192*BMI + 0.033*age + 1.569*sex – 1.131*NH Black + 0.986 * NHOPI – 1.061 * 3DO Bone mass percent – 0.015 * 3DO Left calf volume – 0.157 * 3DO WC + 19.887 * 3DO WHR

Where sex (male = 0, female = 1); NH Black (all other = 0, NH Black = 1); NHOPI (all other = 0, NHOPI = 1)

† Probability of MetS calculated using = $\frac{1}{1 + exp^{-(equation)}}$

Abbreviations: 3DO: 3-dimensional optical, WC: waist circumference, WHR: Waist-to-hip ratio

Table 3:

Variables Included in BMI + demographics + 3DO Metabolic Syndrome Prediction Model (Model 4) compared to BMI models (Models 1 & 2)

Variable	AUC	AUC Improvement
BMI (Model 1)	0.819	
BMI +demographics (Model 2)		0.042
3DO Waist-to-hip ratio		0.022
3DO Bone mass percent		0.006
3DO Waist circumference		0.006
3DO Calf volume (left)		0.004
BMI + demographics + 3DO (Model 4)	0.917	

Abbreviations: BMI: Body mass index, 3DO: 3-dimensional optical

Table 4:

Confusion matrix of prediction model using optimal cutoff by minimizing difference between sensitivity and specificity

	MetS +	**MetS −**	
Predicted +	78	65	
Predicted −	9	349	
	87	**414**	**501**

MetS+ is diagnosed as metabolic syndrome positive by NCEP ATP III criteria (criterion measure)