

Development of a metabolic syndrome prediction model using smartphone-derived digital anthropometry

Caleb F. Brandner¹, Grant M. Tinsley², Abby T. Compton³, Sydney H. Swafford³, Molly F. Johnson³, Maria G. Kaylor³, Hunter Haynes³, Jon Stavres⁴, Austin J. Graybeal⁵

¹Department of Health and Human Physiology, University of Iowa, Iowa City, IA, USA

²Department of Kinesiology and Sports Management, Texas Tech University, Lubbock, TX, USA

³School of Kinesiology and Nutrition, University of Southern Mississippi, Hattiesburg, MS, USA

⁴Department of Kinesiology, Nutrition, and Health, College of Education, Health, and Society, Miami University, Oxford, OH 45056, USA

⁵Department of Kinesiology, Harris College of Nursing and Health Sciences, Texas Christian University, Fort Worth, TX 76129, USA

Corresponding Author: Austin J. Graybeal, PhD, CSCS, Assistant Professor, Department of Kinesiology, Harris College of Nursing and Health Sciences, Texas Christian University, TX 76129, USA. Phone: 817-257-5624. Email address: austin.graybeal@tcu.edu. ORCID: 0000-0003-4520-9230



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ABSTRACT

Integrating metabolic syndrome (MetS) screening procedures into routine care remains challenging. Traditional anthropometric and body composition assessments, while useful, have drawbacks that limit their application. However, automated anthropometrics produced from smartphone scanning applications may offer a solution. This study aimed to determine whether smartphone-derived anthropometrics could effectively predict both MetS and its severity. A total of 281 participants underwent a MetS screening assessment to determine fasting blood pressure, lipids, glucose, and waist circumference, and completed a smartphone scanning assessment (MeThreeSixty®) to collect digital anthropometrics. Actual MetS classification and MetS severity (MetS_{index}), a continuous estimate of MetS progression, were determined using MetS screening data. Then, LASSO regression was used to develop a new MetS_{index} prediction equation in a subset of participants (n=226), which was subsequently tested in the remaining participants (n=55), and MetS classification was predicted from the retained variables using logistic regression. The following equation was produced:

Smartphone-predicted MetS_{index}: $-0.8880 + 0.1493(\text{medication use}=1; 0=\text{no medication use}) + 0.0089(\text{weight}) + 0.0079(\text{bust circumf.}) + 0.0140(\text{thigh circumf.}) - 0.6247(\text{appendage-to-trunk circumf. index}),$

where *medication use* includes medications for hypertension, dyslipidemia, or hyperglycemia. The newly-developed MetS_{index} prediction model demonstrated equivalence with actual MetS_{index} and revealed acceptable agreement (R^2 : 0.72; RMSE: 0.42; SEE: 0.22) when evaluated in the testing sample (n=55), although proportional bias was observed ($p < 0.001$). Smartphone-predicted MetS classification demonstrated acceptable diagnostic performance with an accuracy of 92.7% and an AUC of 0.89. Smartphone scanning applications can accurately assess MetS prevalence and severity, presenting new possibilities for health screening beyond clinical environments.

Keywords: mobile application, 3D scanning, digital imaging, cardiometabolic health, smartphone

LIST OF ABBREVIATIONS

β : unstandardized beta coefficients

3D: 3-dimensional

AI: artificial intelligence

ATI: appendage-to-trunk circumference index

ATP III: National Cholesterol Education Program Adult Treatment Panel III

AUC: area under the curve

BMI: body mass index

CCC: concordance correlation coefficient

DBP: diastolic blood pressure

FBG: fasting blood glucose

HDL-C: high-density lipoprotein cholesterol

LASSO: least absolute shrinkage and selection operator

LOA: 95% limits of agreement

LR+: positive and likelihood ratio

LR-: negative likelihood ratio

MetS: metabolic syndrome

MetS_{index}: metabolic syndrome severity index

R²: coefficient of determination

RMSE: root mean squared error

ROC: receiver operating characteristic

SBP: systolic blood pressure

SEE: standard error of the estimate

TRG: triglycerides

US: United States

VIF: variance inflation factor

WC: waist circumference

INTRODUCTION

Metabolic syndrome (MetS), a condition characterized by the presence of several adiposity-related cardiometabolic abnormalities, is a prominent precursor of many chronic diseases¹. In fact, MetS now mirrors obesity in its prevalence and recognition as a public health priority, with recent estimates suggesting that >40% of US adults have MetS². With the continuous rise in obesity, an aging US population more susceptible to cardiometabolic diseases³, and the increased rate of MetS amongst young adults⁴, it is unsurprising that integrating MetS screening techniques into routine care remains challenging for overwhelmed healthcare systems. Nevertheless, routine health screenings are critical for identifying those at elevated risk.

Screening for MetS typically involves evaluating individual risk factors such as abdominal obesity, hypertension, hyperglycemia, and dyslipidemia. However, acquiring these diagnostic biomarkers is often challenged by cost, availability, technician dependence, and access, particularly for those in rural and low socioeconomic communities. Consequently, anthropometric measures are frequently used as primary indicators of cardiometabolic complications, given the relationship between MetS development and increasing adiposity. While BMI has historically been used to assess cardiometabolic health status due to its convenience, its oversimplified nature has led to a lack of clinical consensus. More recently, combining BMI with proxies of central adiposity, such as absolute and/or relative waist circumference (WC) has been the preferred approach, as it may better represent fat distribution patterns indicative of cardiometabolic dysfunction⁵. However, these proxies often depend on access to trained personnel, measurement location, and intra/interrater reliability. As a result, many desire more detailed body composition assessments, which have well-demonstrated associations with chronic disease⁶. Unfortunately, the most widely-accepted methods are expensive and typically unavailable outside of research environments, and many consumer-level devices are inaccessible and often require patients to incur additional costs. Although most healthcare systems have begun addressing accessibility concerns through the rapid adoption of digital health services, most anthropometric methods cannot provide remote assessments without a technician present, and self-assessments are often inaccurate⁷. Given the limited clinical acceptance and feasibility of these approaches, it is essential to identify accessible, non-invasive,

time- and cost-efficient anthropometric tools capable of evaluating MetS both remotely and at point-of-care.

A potential solution may lie in recent adaptations of 3-dimensional (3D) body scanning. Specifically, 3D scanning uses light emission and detection techniques to create a 3D avatar capable of automating hundreds of anthropometric measurements. While prior studies highlight the potential of this method as a MetS screening tool ^{8,9}, it remains limited by the same drawbacks as many previously described strategies. However, since most smartphones are equipped with the high-quality imaging and machine learning capabilities necessary for these assessments, 3D scanning procedures have now been optimized for smartphone applications. Although integration of this technique into smartphone applications represents a promising advancement in remote and automated cardiometabolic health screenings, the ability of smartphone-derived anthropometrics to effectively evaluate MetS remains unclear. Therefore, this study aimed to determine whether anthropometrics obtained from a smartphone application could be used to predict both MetS and its severity.

METHODS

Participants

A total of 281 participants aged 18-65 were prospectively recruited through a combination of convenience and snowball sampling methods (i.e., in-person and online word-of-mouth) and completed this cross-sectional evaluation. Participants were excluded if they were <18y or >65y; pregnant; or breastfeeding/lactating. The age range for study eligibility was established based on the American Aging Association's guidelines for clinically meaningful age groupings in the context of disease ¹⁰. Moreover, this age group is at the highest risk for developing MetS, particularly among individuals in the younger subcategories ⁴. Because the MetS severity (MetS_{index}) equations used in this study are unavailable for Asian individuals ¹¹, Asian participants were also not included in this analysis. This study was conducted according to the guidelines laid down in the Declaration of Helsinki and all procedures involving human subjects were approved by the University of Southern Mississippi Institutional Review Board (IRB#22-1012/23-0446). Written informed consent was obtained from all subjects.

Procedures

Participants arrived at the laboratory for testing after an ≥ 8 -h overnight fast from food, beverage, and supplements/medications, and after abstention from exercise for ≥ 24 -h. Participants were instructed to wear tight form-fitting athletic clothing, and to remove any external metal or accessories prior to testing. After sitting for a minimum of 5-min, systolic (SBP) and diastolic (DBP) blood pressure were collected using an automated digital blood pressure monitor. Afterward, participants underwent several anthropometric evaluations including measurements of height, weight, WC at the superior iliac crest using traditional tape measure, and automated anthropometric assessments using a freely downloadable 3D smartphone application (MeThreeSixty[®], Size Stream, Cary, NC) that provides users with both the images and anthropometric data free-of-charge (additional metrics provided via a \$4.99 USD/month subscription at time of this study). Finally, capillary blood was collected to assess fasting blood glucose (FBG), high-density lipoprotein cholesterol (HDL-C), and triglycerides (TRG).

Anthropometric Smartphone Application

Body composition, circumferences, surface areas, and volumes were measured using a smartphone scanning application, and the procedures used to collect these measurements have been described in detail elsewhere^{12–16}. Notably, the measurements produced by this smartphone application have well-demonstrated precision^{12,13,16,17} and have shown to agree with criterion methods^{12–15,17}. Importantly, the mobile application used in this study has demonstrated acceptable agreement and test-retest reproducibility across multiple smartphone models¹³, including various Apple[®] devices equipped with body scanning capabilities¹⁴. For these assessments, participants were required to wear only tight-form fitting athletic clothing and to tie their hair up so that it was not present below the shoulder line. After entering the participant's descriptive information into the application, the smartphone (iPhone 14 Pro Max, Apple[®], Cupertino, CA) was placed into a stationary tripod at a standardized height, and the smartphone's orientation was confirmed by the application. Participants were then instructed to stand on top of a foot guide at a standardized distance from the smartphone. Once positioned, the application prompted participants to situate themselves into two poses: 1) the A pose, which required

participants to face the smartphone, widen their feet, and laterally raise their arms; and 2) the *side* pose, which required participants to turn to the side, bring their feet together, and place their hands to their sides. The smartphone's front facing camera captured a single image during each pose. All scans were conducted in a designated area featuring a neutral-colored backdrop (gray) and no external light sources (e.g., window light) nor light at the participants back. Importantly, according to the manufacturer, raw image files are neither stored on the device nor uploaded to the cloud to protect user privacy.

Blood Biomarkers and Metabolic Syndrome Assessments

The procedures for the collection of blood biomarkers and the determination of MetS and MetS_{index} have been published elsewhere^{18–22}. In summary, ~40 µL of capillary blood were collected via fingerstick, placed into a single-use testing cassette, and inserted into a validated capillary blood analyzer²³ (Cholestech LDX, Abbot, Abbott Park, IL) for the analysis of HDL-C (%CV: 3.3–4.9), TRG (%CV: 1.6–3.6), and FBG (%CV: 4.5–6.2). Importantly, this capillary blood analyzer does not report HDL-C for HDL-C <15 mg/dL (n=3) nor TRG measurements >650 mg/dL (n=3), and does not report TRG for TRG >650 mg/dL nor TRG <45 mg/dL (n=39). As such, HDL-C and TRG below these thresholds were recorded as 15 mg/dL and 45 mg/dL, respectively, and TRG >650 mg/dL were recorded as 650 mg/dL. Because all participants with TRG >650 mg/dL were classified as having MetS, irrespective of their HDL classification, HDL-C values for these participants were recorded as the median HDL-C of sex, race/ethnicity, and MetS matched participants. Quality assurance tests were performed in compliance with the manufacturer's standards.

MetS classification was determined using the ATP III criterion¹, which includes possessing any three of the following five risk factors: 1) FBG ≥100 mg/dL; 2) SBP ≥130 mmHg or DBP ≥85 mmHg; 3) TRG ≥150 mg/dL; 4) WC ≥88 cm for females and ≥102 cm for males; and 5) HDL-C <50 mg/dL for females and <40 mg/dL for males. Participants that were currently being prescribed medications for the treatment of hypertension, hyperglycemia, and/or dyslipidemia (n=17) were classified as meeting the criteria for the treated risk factor. The only other medications reported by participants with the potential to meaningfully influence cardiometabolic outcomes were muscle relaxants (n=3) and over-the-counter anti-inflammatory

drugs (n=12). However, as part of the overnight fasting protocol, participants were instructed to abstain from taking these medications until after their study visit. Because these medications were used on an as-needed basis for personal or prescribed reasons, and are not considered in the formal diagnostic criteria for MetS, they were not included in model development. Nonetheless, their prevalence is reported here to provide transparency and contextual clarity.

The primary outcome variable in the current study was $\text{MetS}_{\text{index}}$, defined as an expansion of the simple dichotomous classification system (i.e., MetS positive or negative) into a continuous value whose magnitude represents the severity and progression of MetS. $\text{MetS}_{\text{index}}$ scores were calculated from the aforementioned risk factors for each participant using the sex and race specific equations put forth by Gurka et al.¹¹. Interpreted as a z-score, positive and negative $\text{MetS}_{\text{index}}$ values represent greater and lesser MetS severity and progression, respectively, and these values have shown to be associated with additional markers of cardiometabolic dysfunction¹¹.

Model Development

A new $\text{MetS}_{\text{index}}$ prediction equation was developed using least absolute shrinkage and selection operator (LASSO) regression procedures¹⁵ after employing the demographic and smartphone-derived anthropometric predictor variables listed hereafter. Demographic predictor variables included: age, height, weight, sex, race (White/Black), ethnicity (Hispanic/non-Hispanic), medication use (prescribed or not prescribed medication to treat hypertension, hyperglycemia, and/or dyslipidemia), and smoking status. Anthropometric predictor variables produced by the smartphone application included: circumferences (cm) of the head, collar, neck, halter, shoulder, chest, bust (designated as *HingedBust* in the application), upper arms, biceps, forearms, wrists, thighs, knees, calves, ankles, and vertical trunk; lengths (in cm) of the arms, outside legs, and central trunk; surface areas (cm^2) and volumes (cm^3) of the whole-body, arms, legs, and torso; and appendage-to-trunk circumference index (ATI), defined as the sum of left and right upper arm, thigh, and calf circumferences divided by the stomach circumference²⁴. Circumferences and lengths collected from the right and left sides were averaged to produce a single estimate, whereas right and left surface areas and volumes were summed. To evaluate whether smartphone-derived anthropometric measurements offered additional predictive value

beyond demographic variables alone, we first developed a baseline model using only demographic predictors via LASSO regression. This was followed by the construction of a comprehensive model incorporating both demographic and smartphone anthropometric variables.

Statistical analyses

Using a medium effect size (f^2 : 0.25) and five predictor variables, power analyses for multiple linear regression revealed that 57 participants would yield 80% power at an $\alpha = 0.05$. To create and assess a newly-developed $\text{MetS}_{\text{index}}$ prediction equation, a training dataset comprised of 80% of the sample ($n=226$) and a testing dataset containing the remaining 20% ($n=55$) were produced using random sampling techniques in R²⁵. LASSO regression was then used to fit models in the training dataset using the *glmnet* package in R²⁶. Importantly, LASSO regression works by identifying the predictor variables that decrease prediction error while simultaneously shrinking the coefficients of extraneous variables towards zero so that they are effectively omitted from the model²⁷; which ultimately produces the most parsimonious model that minimizes multicollinearity and model overfitting. To determine the LASSO shrinkage technique, the best λ value was calculated using 10-fold cross-validation with the one SE rule¹⁵.

After the $\text{MetS}_{\text{index}}$ prediction model was developed in the training sample, the model was used to predict $\text{MetS}_{\text{index}}$ in the testing sample. The performance of the smartphone-predicted $\text{MetS}_{\text{index}}$ was evaluated against the actual $\text{MetS}_{\text{index}}$ in the testing sample using paired t-tests, equivalence tests, coefficients of determination (R^2), Deming regression, Bland-Altman analyses, root mean squared error (RMSE), standard error of the estimate (SEE), and concordance correlation coefficients (CCC). Because $\text{MetS}_{\text{index}}$ is interpreted as a z-score, the equivalence regions were defined as ± 0.34 to represent approximately one-third of a standard deviation, which have been used to assess z-score values in prior studies²⁸. The agreement between smartphone-predicted $\text{MetS}_{\text{index}}$ and the line-of-identity using Deming regression was determined if the 95% confidence intervals for the intercept and slope contained the values 0 and 1, respectively. The 95% limits of agreement (LOA) and proportional biases were determined using Bland-Altman and linear regression techniques.

Additionally, the ability of the retained smartphone variables to correctly predict MetS classification was evaluated using binomial logistic regression with a cutoff point of 0.5 (MetS negative: <0.5 ; MetS positive: ≥ 0.5). The true positive and true negative proportions of smartphone-predicted MetS were compared to the proportions determined by the actual diagnostic procedures using the receiver operating characteristic (ROC) area under the curve (AUC), chi-square tests with corrections for continuity, R^2_{McFadden} , and sensitivity, specificity, accuracy, and positive (LR+) and negative (LR-) likelihood ratios. Acceptable accuracy of the smartphone-predicted MetS classification was defined as having a both an AUC ≥ 0.70 and having a summed sensitivity and specificity of ≥ 1.50 ^{29–31}. Variance inflation factors (VIF) were used to assess the multicollinearity of the final LASSO and logistic regression models (all VIFs ≤ 6.24). Statistical significance was accepted at $p < 0.05$.

RESULTS

Metabolic Syndrome Severity

Descriptive characteristics of the participants in the combined, training, and testing samples are presented in **Table 1**. The initial model, which included only demographic predictors (intercept: -0.2925), retained age ($\beta = 0.0028$), medication use ($\beta = 0.2692$), height ($\beta = -0.0113$), and weight ($\beta = 0.0234$). However, this model performed worse overall ($R^2 = 0.63$; LOA = 0.82; AUC = 0.84; joint sensitivity and specificity = 1.48) compared to the full model that incorporated both demographic and smartphone-derived anthropometric variables (reported below). Notably, when LASSO regression was applied to the complete model, age and height were excluded, while the coefficients for medication use and weight were substantially reduced, indicating that the additional anthropometric features provided stronger predictive value.

The coefficients of the retained variables using LASSO regression in the complete model are presented in **Table 2**. Retained variables included medication use, weight, bust circumference, thigh circumference, and ATI, which produced the following equation:

Smartphone-predicted MetS_{index}: -0.8880 + 0.1493(medication use=1; 0=no medication use) + 0.0089(weight) + 0.0079(bust circumf.) + 0.0140(thigh circumf.) - 0.6247(ATI).

The equation presents unstandardized coefficients for the predictors retained in the final model. All other predictor variables, as detailed in the preceding sections, had their coefficients shrunk to 0, effectively excluding them from the model. **Figure 1a-d** illustrates the agreement between the newly-developed smartphone $\text{MetS}_{\text{index}}$ prediction equation and the actual $\text{MetS}_{\text{index}}$ in the testing sample. Paired t-tests revealed significant differences between smartphone-predicted and actual $\text{MetS}_{\text{index}}$ ($p=0.006$; Fig.1a), though smartphone-predicted $\text{MetS}_{\text{index}}$ demonstrated equivalence with actual $\text{MetS}_{\text{index}}$ (Fig.1d). **Supplemental Table 1** presents the prevalence and risk factors of MetS across $\text{MetS}_{\text{index}}$ groups, as defined by these equivalence bounds, to further support the results of our equivalence testing procedures. R^2 , CCC, RMSE, and SEE values (Fig. 1c) revealed good agreement between methods, and LOA were moderate. Proportional biases ($p<0.001$; Fig.1a) and differences in the slope (but not intercept) from the line-of-identity were observed (Fig.1b).

Metabolic Syndrome Classification

The ROC plots and associated contingency tables of **Figure 2** demonstrate the ability of the retained smartphone variables to accurately diagnose MetS compared to the traditional diagnostic standards. The true prevalence of MetS was 18.2% whereas the apparent prevalence of smartphone-predicted MetS was 14.5%. Chi-square tests for the overall model were significant ($p<0.001$), and smartphone-predicted MetS had a diagnostic accuracy of 92.7%, with sensitivity (70%), specificity (97.8%; joint sensitivity+specificity: 1.68), and LR+ (31.5) and LR- (0.31) indicating acceptable diagnostic performance. Moreover, the model AUC (0.89) and R^2_{McFadden} (0.43) revealed excellent model performance.

DISCUSSION

After developing a $\text{MetS}_{\text{index}}$ prediction model using LASSO regression and cross-validating this model in an independent subset of participants, our evaluations revealed that smartphone-acquired anthropometrics can provide accurate estimates of MetS severity and progression. While the ability to predict a continuous $\text{MetS}_{\text{index}}$ score from a smartphone application may improve diagnostic flexibility and better inform clinicians of MetS progression, the absence of diagnostic cutoffs may complicate clinical decision making and limit the implementation of this technique at scale. Therefore, we also assessed whether smartphone-

derived anthropometrics could accurately predict MetS classification, and our model demonstrated good-to-excellent ability to identify MetS in accordance with traditional diagnostic standards. These findings affirm that both MetS and its severity can be accurately determined using a smartphone application.

The ability of 3D body scanners to deliver accurate estimates of conventional anthropometrics is well-established³². However, ongoing advancements in artificial intelligence (AI) and digital imaging now offer new opportunities to leverage the predictive power of these automated anthropometrics to produce more clinically significant outcomes. For example, 3D scanners have accurately predicted measurements such as appendicular lean mass¹⁵ and MetS⁹ based on the established relationship between key anthropometrics and both muscularity³³ and chronic disease³⁴. In fact, prior studies have demonstrated that body volumes obtained from 3D scanners predict MetS more accurately than traditional anthropometric assessments⁵, which is likely attributed to the advanced landmarking procedures that can eliminate human error while simultaneously automating more elaborate measurements. However, given the existing limitations of 3D scanning, manufacturers have begun to couple 3D scanners with smartphone equivalents, which have demonstrated a similar ability to predict MetS⁵.

Our findings align with previous studies that employed both 3D^{5,9} and smartphone⁵ scanning techniques for predicting MetS classification. However, to our knowledge, only one study has assessed whether a smartphone application can predict the prevalence and severity of MetS⁵. Although the predictive power of our smartphone scanning model for detecting binary MetS status was nearly identical to other methods^{5,9}, our model exhibited markedly greater accuracy in predicting MetS_{index}⁵. While the improved performance of our model could be due to the technological differences between applications, it could also result from variations in the strength of the predictor variables. For example, other applications use body volume estimates to predict MetS, which have shown comparable performance to traditional circumferences collected from similar regions⁸. In fact, previous studies have shown that the prediction of MetS⁹ and MetS risk factors³⁵ improves most when using automated circumferences. Since body circumferences appear to be stronger predictors of binary MetS status, and MetS_{index} is simply an extension of this status, the systematic selection and omission of body circumferences and volumes, respectively, likely accounts for the performance differences between applications.

Importantly, since WC is a risk factor for MetS, and is included in $\text{MetS}_{\text{index}}$, we chose to exclude closely related raw circumferences as predictor variables. This allowed us to avoid potential biases, and addressed the challenges of predicting $\text{MetS}_{\text{index}}$ from abdominal circumferences in Black adults²¹. Despite excluding these variables, we still observed acceptable model performance using only circumferences of the bust, thighs, and ATI. Recent investigations using AI to predict diabetes and hypertension from biometric data have shown that thigh circumference enhances model specificity more than BMI; likely because it can better discern young adults with greater muscularity from those with higher body fat³⁶. While it is reasonable to assume that bust circumference was included as a marker of upper body adiposity in the absence of raw abdominal measurements, bust circumference may also uniquely contribute to MetS. Exploratory analyses of the present dataset revealed that bust, but not WC (r : -0.09, 0.00; $p > 0.050$), was significantly associated with SBP (r : 0.30, $p = 0.029$) and HDL-C (r : -0.27, $p = 0.047$) after adjusting for both age and BMI. Interestingly, HDL-C is inversely associated with estradiol³⁷, which contributes to fat accumulation in breast tissue³⁸. Greater fat accumulation could stimulate aromatase activity, and elevated conversion of androgens-to-estrogens may increase bust size³⁹ whilst exerting vasoconstrictive responses that increase SBP⁴⁰. Despite the historical reliance on abdominal measurements to assess cardiometabolic abnormalities, our findings suggest that individual components of MetS could be more effectively captured using alternative anthropometrics, and mobile scanning presents an emerging opportunity to automate anthropometrics that have traditionally been difficult to obtain.

There are a few limitations that warrant discussion. While our sample was diverse, we were unable to evaluate Asian adults, as $\text{MetS}_{\text{index}}$ is currently unavailable for this group. The average age of our sample was also relatively young. However, the prevalence of MetS in our sample matches the national prevalence for this age range and reflects the age group experiencing the most rapid increase in MetS⁴. Although age was included as a continuous predictor in the initial LASSO regression model, it was not retained in the final model, suggesting that it did not contribute additional predictive value beyond the selected variables. Similarly, sex was included as a predictor but was excluded during model selection. While future models evaluating the performance of smartphone-derived anthropometrics for predicting $\text{MetS}_{\text{index}}$ within sex-specific subgroups may be warranted, the sample sizes in our study were

insufficient to support adequately powered stratified analyses and may have introduced bias into subgroup-specific models. Future studies seeking to improve these models should consider employing age- and sex stratified models. The use of prescription medication to treat specific MetS risk factors may have lowered MetS_{index} for these participants. However, we accounted for this during LASSO, and medication use was retained as a variable in the final model. Because DBP is not included in MetS_{index}, unique hypertensive MetS phenotypes may have been overlooked²¹. The prediction model in our study exhibited significant proportional biases and differences from the line-of-identity, which, in the context of chronic disease diagnosis, may lead to underestimation of risk among high-risk individuals. However, such biases, particularly underestimation, are commonly reported in studies validating novel anthropometric and body composition methods. Despite this, our model demonstrated excellent classification accuracy for MetS, supporting its potential utility in risk stratification. Still, users and practitioners should employ caution when using this technique. Because the mobile application used in our study has well-established test-retest reliability^{12,13,16,17}, we did not collect duplicate measures of the smartphone-derived anthropometric variables, and therefore cannot report test-retest reproducibility for these features (thigh, ATI, and bust circumference) within the context of this study. However, previous studies have demonstrated the reproducibility of the thigh and chest circumferences produced by this mobile application, as well as the circumferences used to calculate ATI^{14,17}. Although, to our knowledge, no studies have specifically evaluated the test-retest reproducibility of bust measurements using this mobile application, unpublished pilot data from our laboratory in an independent sample of female participants demonstrated acceptable agreement between smartphone-derived and tape-measured bust measurements ($R^2 = 0.82$; mean difference = 3.07 cm). Additionally, other studies have reported acceptable agreement between smartphone-derived and MRI-based breast volume estimates⁴¹. Together, these findings support the reliability and/or validity of the anthropometric variables retained in our prediction model. Finally, our findings are specific to the application used in our study.

In conclusion, smartphone scanning applications can accurately assess MetS prevalence and severity, supporting its use in remote settings. While longitudinal studies are needed to determine its effectiveness in monitoring changes, our findings highlight the predictive power of automated anthropometrics and presents new possibilities for health screening beyond clinical environments.

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CONFLICT OF INTEREST

The funding agency (National Institute of General Medical Sciences) had no role in the study design, collection, analysis or interpretation of the data, writing the manuscript, or the decision to submit the paper for publication. GMT has received support for his research laboratory, in the form of research grants or equipment loan or donation, from manufacturers of body composition assessment devices, including Size Stream LLC; Naked Labs Inc.; Prism Labs Inc.; RJL Systems; MuscleSound; and Biospace, Inc. None of these entities played a role in the present manuscript. There are no other competing interests to declare.

AUTHORSHIP

AJG designed the work and supervised the study. AJG and JS provided essential resources; AJG, CFB, GMT, and JS helped conceptualize the study; AJG primarily performed the statistical analyses and GMT assisted with the analyses. CFB, ATC, SHS, MFJ, MGK, and HH collected the data; CFB drafted the initial manuscript; all authors reviewed the manuscript for intellectual content, approved the manuscript, and have agreed to be accountable for the work.

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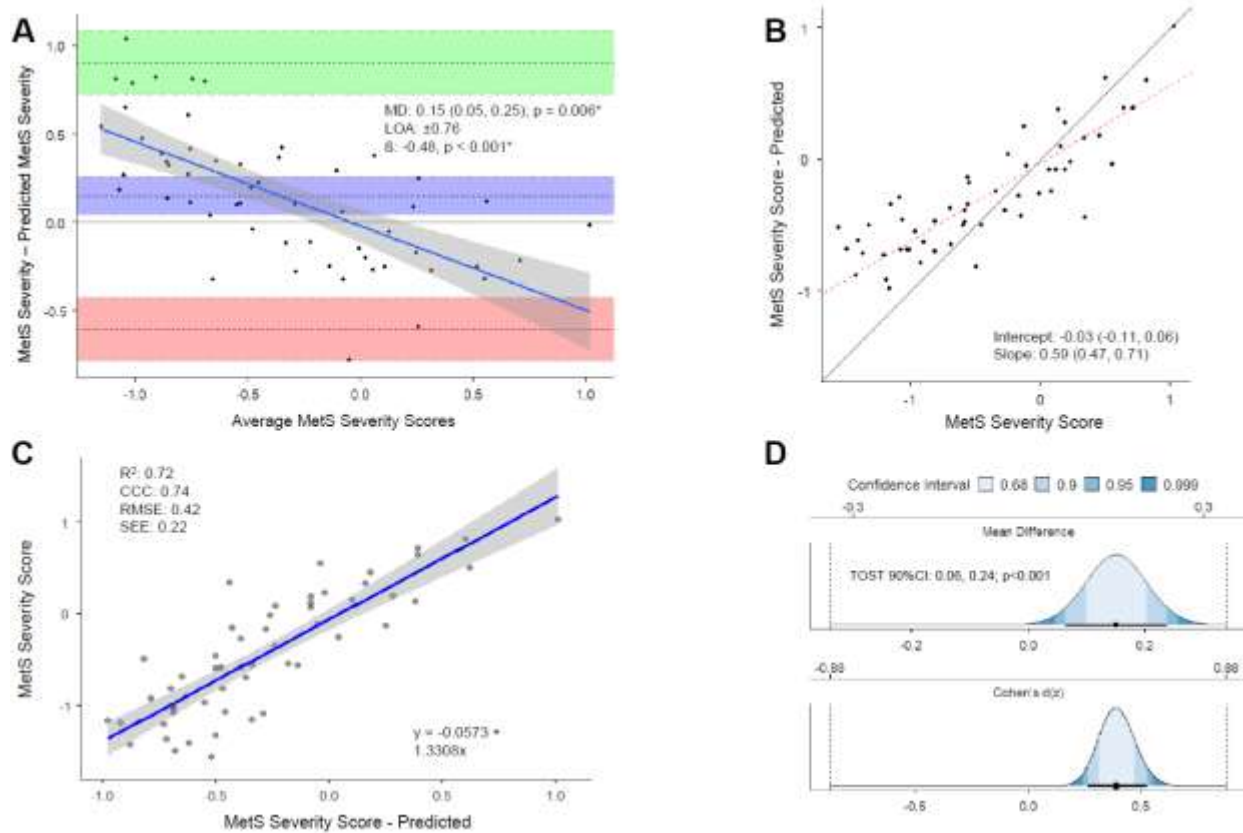
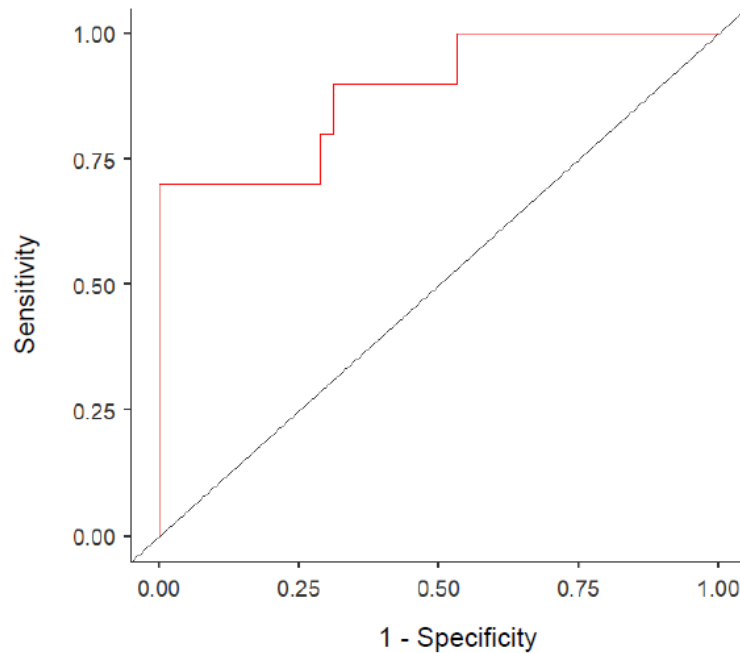


Figure 1a-d. Bland-Altman (a), Deming regression (b), simple regression (c), and equivalence plots demonstrating the agreement between smartphone-predicted $\text{MetS}_{\text{index}}$ and the actual $\text{MetS}_{\text{index}}$ in the testing sample ($n = 55$). For the Bland-Altman plots (a), the upper and lower dashed lines represent the 95% LOA, the middle-dashed line represents the MD between the smartphone-predicted $\text{MetS}_{\text{index}}$ and the actual $\text{MetS}_{\text{index}}$, and the solid blue line and its corresponding shaded area represents the regression line and its 95%CI, respectively. For the Deming regression plots (b), the solid black line represents the line of identity and the red dashed line represents the regression line. For the simple regression plot (c), the solid blue line and its corresponding shaded area represents the regression line and its 95%CI, respectively. For the equivalence plots, the average MD (top) and effect size MD (bottom) are presented, where the blue shaded regions represent the TOST CIs displayed in the CI legend, the black circles and intersecting horizontal lines represent the MD and the TOST 90%CIs, respectively, and the vertical dashed lines indicate the equivalence regions.

β : proportional bias coefficient; CCC: concordance correlation coefficient; CI: confidence interval; LOA: 95% limits of agreement; MD: mean difference calculated as the smartphone-predicted $\text{MetS}_{\text{index}}$ minus the actual $\text{MetS}_{\text{index}}$; $\text{MetS}_{\text{index}}$: metabolic syndrome (MetS) severity score; R^2 : coefficient of determination; RMSE: root mean square error; SEE: standard error of the estimate; TOST: values from the TOSTER package in R.

* statistically significant at $p < 0.050$.

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R^2_{McFadden}	χ^2	AUC	Accuracy	LR+/LR-
0.43	22.2*	0.89	92.7%	31.5/0.31

Smartphone-Predicted MetS	Observed MetS		Total	Specificity
	MetS (n)	No MetS (n)		
MetS (n)	7	1	8	97.8%
No MetS (n)	3	44	47	
Total	10	45	55	
Sensitivity	70%			
Joint Sensitivity + Specificity				1.68

Figure 2. An ROC curve and corresponding AUC demonstrating the ability of the predictor variables retained during LASSO regression to predict conventional MetS classification relative to actual MetS status in the testing sample (n=55). Positive and negative MetS cases are presented for both smartphone-predicted and actual MetS, as well as the sensitivity, specificity, and accuracy of smartphone-predicted MetS status. R^2_{McFadden} , chi-square, and LR+ and LR- are also tabulated.

χ^2 : chi-square; AUC: area under the curve; LASSO: least absolute shrinkage and selection operator; LR+: positive likelihood ratio; LR-: negative likelihood ratio; MetS: metabolic syndrome; R^2_{McFadden} : McFadden pseudo coefficient of determination; ROC: receiver-operating characteristic.

* statistically significant at $p < 0.050$.

Table 1. Descriptive Characteristics of the Combined, Training, and Testing Samples

	Combined Sample	Training Sample	Testing Sample
N	281	226	55
Sex (F/M)	173/108	136/90	37/18
Race (W/B)	170/111	133/93	37/18
Ethnicity (H/NH)	17/264	9/217	8/47
Metabolic Syndrome	49	39	10
Medication use	18	12	6
Smoke	16	14	2
Age (y)	24.5 ± 8.7	24.6 ± 8.8	24.3 ± 8.3
Height (cm)	169.6 ± 9.8	169.8 ± 10.1	168.7 ± 8.1
Weight (kg)	77.1 ± 20.2	76.9 ± 20.6	77.8 ± 18.8
BMI (kg/m ²)	26.7 ± 5.9	26.5 ± 5.9	27.3 ± 6.1
Body fat (%) ^a	27.3 ± 8.2	26.9 ± 8.1	28.9 ± 8.7
Fat Mass (kg) ^a	21.7 ± 11.4	21.3 ± 11.4	23.3 ± 11.6
Fat-free mass (kg) ^a	55.4 ± 12.8	55.6 ± 13.3	54.5 ± 11.0
Metabolic Syndrome Severity Score	-0.36 ± 0.70	-0.33 ± 0.71	-0.43 ± 0.68
Smartphone Metabolic Syndrome Severity Score ^b	-	-	-0.28 ± 0.43
Waist Circumference (cm) ^a	88.5 ± 14.4	88.1 ± 14.3	90.2 ± 14.6
Systolic blood pressure (mmHg)	117.2 ± 13.4	117.6 ± 13.4	115.7 ± 13.5

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Diastolic blood pressure (mmHg)	78.9 ± 10.4	78.5 ± 10.3	80.9 ± 10.7
HDL-C (mg/dL)	48.4 ± 13.9	48.0 ± 14.3	50.4 ± 12.1
Triglycerides (mg/dL)	111.2 ± 100.7	116.3 ± 108.6	90.0 ± 54.2
Fasting blood glucose (mg/dL)	89.7 ± 8.1	89.8 ± 7.8	89.4 ± 9.1
Head (cm)	59.2 ± 3.5	59.1 ± 3.6	59.6 ± 2.9
Collar (cm)	37.3 ± 4.5	37.3 ± 4.6	37.3 ± 4.0
Neck (cm)	43.1 ± 4.1	43.1 ± 4.3	42.9 ± 3.5
Halter (cm)	85.2 ± 8.1	84.9 ± 8.1	86.4 ± 8.2
Shoulder (cm)	110.8 ± 12.3	110.7 ± 12.5	111.4 ± 11.5
Chest (cm)	101.6 ± 14.6	101.2 ± 14.7	103.1 ± 14.5
Bust (cm)	104.1 ± 13.7	103.6 ± 13.7	105.8 ± 13.8
Upper arms (cm)	33.8 ± 5.1	33.6 ± 5.0	34.5 ± 5.4
Biceps (cm)	31.6 ± 5.1	31.5 ± 5.0	32.2 ± 5.5
Forearms (cm)	26.7 ± 3.4	26.7 ± 3.4	26.8 ± 3.3
Wrists (cm)	16.4 ± 1.7	16.4 ± 1.7	16.5 ± 1.6
Stomach (cm)	92.1 ± 13.7	91.6 ± 13.6	93.8 ± 14.0
Waist (cm)	91.3 ± 13.5	90.8 ± 13.6	93.6 ± 13.7
Hips (cm)	104.9 ± 11.8	104.4 ± 11.7	107.0 ± 12.3
Thighs (cm)	59.9 ± 7.7	59.5 ± 7.4	61.4 ± 8.7
Knees (cm)	38.3 ± 3.9	38.1 ± 3.8	39.0 ± 4.4
Calves (cm)	38.0 ± 3.9	37.9 ± 3.9	38.6 ± 4.0
Ankle (cm)	24.5 ± 2.0	24.5 ± 2.1	24.7 ± 1.8

Arm length (cm)	58.6 ± 4.2	58.6 ± 4.4	58.3 ± 3.2
Outside leg length (cm)	103.3 ± 6.4	103.4 ± 6.7	103.0 ± 4.5
CTL (cm)	154.5 ± 13.2	154.4 ± 13.6	155.0 ± 11.7
VTC (cm)	162.4 ± 14.9	162.2 ± 15.3	163.3 ± 13.3
Surface area (cm ²)	18,201 ± 2,716	18,156 ± 2,764	18,385 ± 2,524
Arm surface area (cm ²)	3,280 ± 564	3,280 ± 575	3,278 ± 521
Leg surface area (cm ²)	8,804 ± 1,211	8,778 ± 1,227	8,914 ± 1,149
Torso surface area (cm ²)	6,120 ± 1,056	6,102 ± 1,078	6,191 ± 968
Body volume (cm ³)	75,494 ± 21,854	74,981 ± 21,969	77,605 ± 21,444
Arm volume (cm ³)	8,134 ± 2,632	8,109 ± 2,623	8,236 ± 2,693
Leg volume (cm ³)	19,629 ± 5,036	19,430 ± 4,880	20,449 ± 5,606
Torso volume (cm ³)	47,661 ± 14,933	47,373 ± 15,190	48,841 ± 13,892
ATI	2.88 ± 0.19	2.87 ± 0.19	2.88 ± 0.15

Data are presented as N or mean ± standard deviation.

All body circumferences from the right and left sides were averaged to produce a single estimate. Appendicular surface areas and volumes were calculated as the sum of the right and left sides. For ATI, all variables were collected using smartphone-derived measurements. Medication use was defined as being prescribed medication to treat hypertension, hyperglycemia, and/or dyslipidemia. Smoking was defined as currently smoking or vaping.

F: female; M: male; White; B: Black; H: Hispanic; NH: non-Hispanic; BMI: body mass index; CTL: center trunk length; VTC: vertical trunk circumference; ATI: appendage-to-trunk circumference index

^a estimates produced using smartphone application; ^b estimates produced using the newly developed smartphone prediction model.

Table 2. LASSO regression model coefficients predicting metabolic syndrome severity from smartphone-derived anthropometrics

Predictor Variables	Metabolic Syndrome Severity Prediction Coefficients
Intercept	-0.8880
Medication use	0.1493
Weight (kg)	0.0089
Bust (cm)	0.0079
Thighs (cm)	0.0140
ATI	-0.6247

All data are presented as the unstandardized coefficients for each variable within the corresponding body composition prediction model. The coefficients of all other predictor variables were shrunk to “0” and are therefore not included in the final model equations nor the table.

“Medication use” was defined as: 1 = prescribed medication to treat hypertension, hyperglycemia, and/or dyslipidemia; or 0 = no prescribed these medications. For ATI, all variables were collected using smartphone-derived measurements, and was defined as the sum of left and right upper arm, thigh, and calf circumferences divided by the stomach circumference

ATI: appendage-to-trunk circumference index.