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Research article

Comparative assessment of anthropometric and bioimpedence methods for determining adiposity

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ABSTRACT

Background: Obesity is a risk factor for different chronic conditions. Over the years, obesity has become a pandemic and it is therefore important that effective diagnostic tools are developed. Obesity is a measure of adiposity and it has become increasingly evident that anthropometric measures such as body mass index (BMI) used to estimate adiposity are inadequate. This study therefore examined the ability of different anthropometric measurements to diagnose obesity within a cross-section of Ghanaian women.

Methods: We obtained anthropometric measurements and used that to generate derived measures of adiposity such as body adiposity index (BAI) and conicity index. Furthermore we also measured adiposity using a bio-impedance analyser. Associations between these measurements and percentage body fat (%BF) were drawn in order to determine the suitability of the various measures to predict obesity. The prevalence of obesity was determined using both %BF and BMI.

Results: BMI, Waist and hip circumference and visceral fat (VF) were positively correlated with % BF whereas skeletal muscle mass was negatively correlated. Prevalence of obesity was 16% and 31.6% using BMI and %BF respectively. Receiver operating characteristic (ROC) analysis showed that these differences in prevalence was due to BMI based misclassification of persons who have obesity as overweight. Similar, shortfalls were observed for the other anthropometric measurements using ROC.

Conclusions: No single measure investigated could adequately predict obesity as an accumulation of fat using current established cut-off points within our study population. Large scale epidemiological studies are therefore needed to define appropriate population based cut-off points if anthropometric measurements are to be employed in diagnosing obesity within a particular population.

1. Introduction

Chronic diseases such as diabetes, hypertension, and metabolic syndrome are rapidly taking over as the major causes of morbidity and mortality in sub-Saharan Africa [1, 2]. The chronic disease burden is attributed to lifestyle changes such as westernized diet, sedentary lifestyle and urbanization [2]. In sub-Saharan Africa, the prevalence of infectious diseases such as malaria, HIV, tuberculosis and neglected tropical diseases remains sturdy thereby inflicting a heavy blow on health systems [3, 4]. With the rapidly increasing prevalence of chronic diseases, the health systems will be affected by the rise in infectious diseases co-existing with chronic diseases [5]. Many health systems in the region are under-funded and under-resourced, hence, the chronic disease burden, if not checked, could potentially crash them [6, 7].

Obesity is a widely reported risk factor for many chronic diseases such as diabetes, cardiovascular diseases, premature mortality and some cancers. In recent years there has been an alarming increase in the incidence of obesity worldwide [8]. Due to the high health risk associated with obesity, it is important that methods that accurately determine obesity are developed and used. Body mass index (BMI), the ratio of body weight in kilograms to the height in meters squared, has been used to measure obesity for a long while, especially in the clinical settings

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Table 1. Anthropometric characteristics of study participants.

	Number of participants	Age	Height (m)	Weight (kg)	Hip Circumference (m)	Waist Circumference (m)	Skeletal Muscle (%)	Visceral Fat Level	Resting metabolic rate
Total	467	46.782 ± 13.307	1.582 ± 0.062	62.550 ± 14.679	100.842 ± 10.708	0.880 ± 0.134	27.437 ± 3.877	6.458 ± 2.848	1312.056 ± 146.297
Underweight	51	50.020 ± 16.592	1.578 ± 0.077	45.386 ± 8.351	89.882 ± 7.868	0.772 ± 0.098	33.235 ± 3.450	2.647 ± 1.016	1150.784 ± 87.753
Normal	150	45.707 ± 14.159	1.583 ± 0.063	54.496 ± 7.421	95.460 ± 8.117	0.822 ± 0.094	29.560 ± 2.454	4.793 ± 1.439	1242.053 ± 104.067
Overweight	118	46.636 ± 12.504	1.590 ± 0.058	63.141 ± 7.234	101.483 ± 7.873	0.881 ± 0.126	26.805 ± 1.780	6.788 ± 1.862	1322.873 ± 97.445
Obese	148	46.872 ± 11.630	1.576 ± 0.059	76.156 ± 14.380	109.561 ± 8.844	0.973 ± 0.128	23.791 ± 2.235	9.196 ± 2.237	1429.953 ± 136.315

Note: Means and standard deviations are presented.

Table 2. Anthropometry derived adiposity indices of study participants.

	Number of participants	Body Mass Index (kg/m^2)	Waist-to-Hip Ratio	Body adiposity index	Abdominal volume index	Visceral adiposity index*	Conicity index
Total	467	24.730 ± 4.897	0.880 ± 0.069	32.776 ± 6.121	16.055 ± 4.627	0.027 ± 0.022	1.303 ± 0.118
Underweight	51	18.139 ± 2.556	0.865 ± 0.076	27.430 ± 4.172	12.310 ± 3.061	0.026 ± 0.013	1.323 ± 0.160
Normal	150	21.667 ± 2.075	0.861 ± 0.066	29.998 ± 3.837	13.878 ± 3.181	0.029 ± 0.028	1.289 ± 0.117
Overweight	118	24.985 ± 2.554	0.881 ± 0.063	32.664 ± 4.409	16.163 ± 3.349	0.027 ± 0.025	1.297 ± 0.107
Obese	148	29.903 ± 3.549	0.904 ± 0.067	37.522 ± 6.480	19.466 ± 4.907	0.025 ± 0.014	1.317 ± 0.109

Note: Means and standard deviations are presented.

however, BMI measurement does not differentiate between lean and fat mass thus leading to misclassification in some instances [9]. Hence methods that measure direct body fat composition may represent the best standards for determining obesity.

Recent advances in technology have resulted in the development of various tools for measuring adiposity directly, among others. For example, methods like X-ray absorptiometry (DEXA), magnetic resonance imaging (MRI), and bioelectrical impedance analysis (BIA) are available to assess the relative body composition and adiposity. Of these, the BIA methods are relatively cheaper, simple, and well adapted for resource-limited settings [10]. The types of BIA instruments have been increasing over time. These instruments can report over 20 parameters on the full body composition, including body segment analysis (left arm, right arm, trunk, left leg and right leg), body fat percentage and mass, fat-free mass, visceral fat, muscle mass, total body water, and body water percentage, among others. However, in many health centres across Ghana, lack of the availability of these devices has resulted in the continual use of BMI to predict obesity.

According to a systematic review by Ofori-Asenso et al the prevalence of obesity is 17.1%. Alarmingly, the prevalence of overweight was 25.4% [8]. The primary method for assessing obesity in Ghana is by the BMI method using the WHO established guidelines. It has been reported that compared to white Caucasians, the South Asian Population have higher amounts of percentage body fat and visceral fat despite having similar BMI values leading to a high prevalence of metabolic diseases in low risk Asians [11, 12, 13]. To the best of our knowledge no studies have looked at the relationship between % BF fat and BMI levels among Ghanaians in general. As a starting point we sought to determine the appropriateness of different anthropometric derived measurements to predict adiposity accurately. Accurate information on fat and other body composition measures will benefit dieticians and other professionals who assist individuals in weight modification programmes.

2. Materials and methods

2.1. Study design and population

We conducted a retrospective analysis comparing the prevalence of obesity among a cross-section of women in Ho, Ghana. These were all apparently healthy women. The data was collected as part of a community-based Healthy Eating Advocacy Drive (HEAD) outreach conducted between May and December 2016 using a questionnaire (Supplementary file 1). The HEAD outreach is a community engagement activity that is undertaken in collaboration with community groups. In these activities the women were brought together to be educated on their health as well as also to be screened hypertension, diabetes and other conditions for which they will otherwise not just walk into a health facility to undertake. Persons consented to their data being used were included. Data on anthropometric and BIA characteristics included Age, Height (m), Weight (kg), Hip Circumference (HC, cm), Waist Circumference (WC, cm), Skeletal Muscle (SM, %), Body fat (BF, %), Visceral Fat (VF) and the Resting metabolism rate (RMR). Body Mass Index (BMI) (kg/m^2), Waist-to-Hip Ratio (WHR), Body adiposity index (BAI), Abdominal volume index (AVI), Visceral adiposity index (VAI) and Conicity index (CI) were derived from the measurements as alternative methods for determining general and central adiposity. The study was approved by the Research Ethics Committee (REC) of the University of Health and Allied Sciences. Informed Consent was obtained from all participants. A standardized questionnaire was used to collect demographic data.

2.2. Anthropometric and BIA measurements

The height was taken using a stadiometer, with the participants having no footwear on. The Omron body composition monitor (Omron Healthcare Co., Ltd., Kyoto, Japan) was used to measure weight to the nearest 0.1 kg without footwear. There was no adjustment for clothing. Age and gender were inputted into the analyser prior to measurements. The VF, SM, BF and RMR were obtained from the Omron body composition monitor following the manufacturer's instructions. WC and HC were measured using a non-stretchable measuring tape to the nearest 0.1 cm. The WC measurements were taken at the level of the umbilicus with arms folded across the chest, whereas the HC measurements were taken at the maximum circumference over the buttocks.

In addition to the BIA measures of adiposity, anthropometric measures of adiposity were calculated using the following standard formulae:

(1) Abdominal Volume Index (AVI) - [14].

$$\mathrm{AVI} = \frac{\left[2(\mathrm{WC\ (cm)})^2 + 0.7(\mathrm{WC\ (cm)} - \mathrm{HC\ (cm)})^2\right]}{1000}$$

(2) Body Adiposity Index (BAI) - [15].

$$\mathrm{BAI} = \frac{\mathrm{HC\ (cm)}}{[\mathrm{Height\ (m)}]^{1.5}} - 18$$

(3) Body Mass Index (BMI)

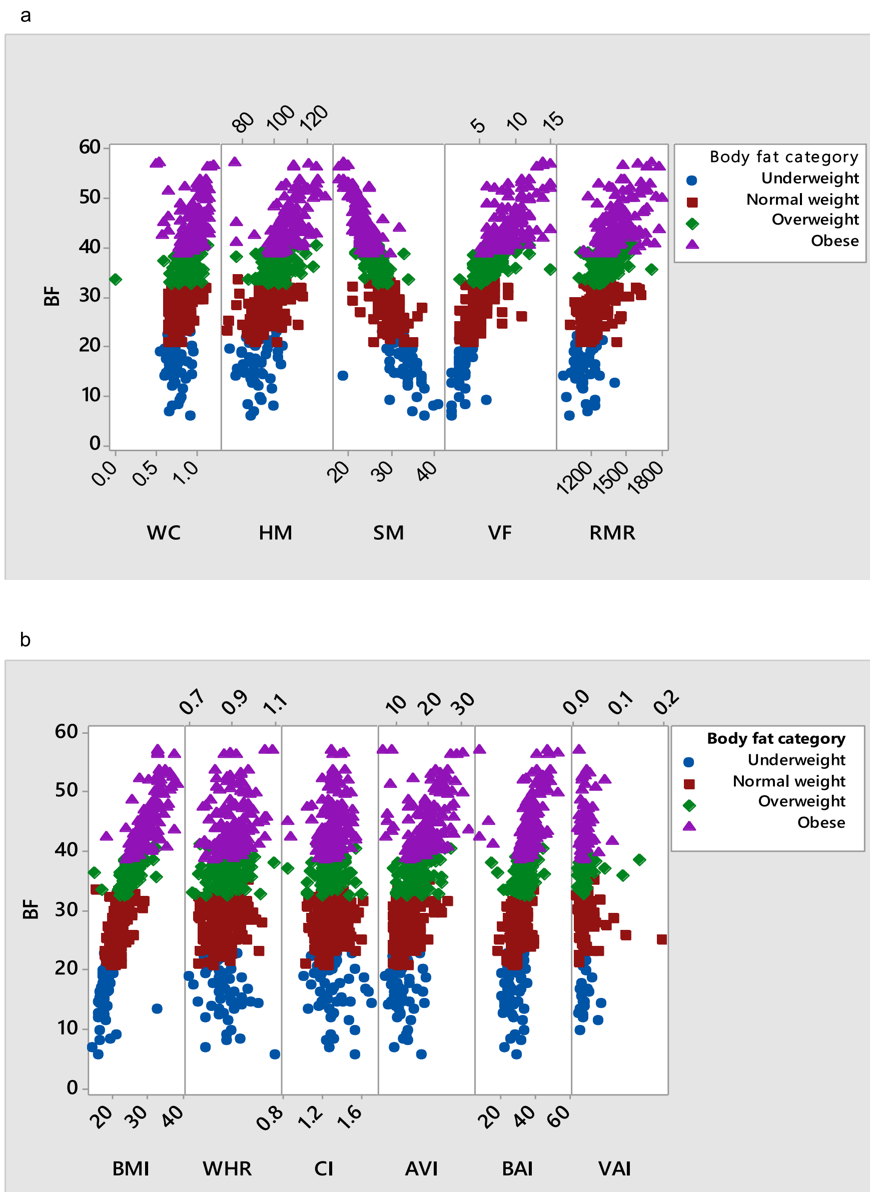


Figure 1. Correlations between % BF and other indices of obesity classified by BMI status. (A) The correlations between % BF classifications and waist circumference (WC), Hip measure (HM), Skeletal Muscle(SM), Visceral fat(VF), Resting metabolic rate (RMR). (B) The correlation between %BF classifications and Body mass index (BMI), Waist to hip ratio (WHR), Conicity Index (CI), Abdominal volume index (AVI), and Body adiposity index (BAI) and Visceral adiposity index (VAI).

$$\mathrm{BMI} = \frac{\mathrm{Weight\ (Kg)}}{\mathrm{Height\ (m)}^2}$$

(4) Conicity Index (CI) - [16].

$$\mathrm{CI} = \frac{\mathrm{WC\ (m)}}{\left[0.109 \times \sqrt{\mathrm{Weight\ (Kg/Height\ (m)}}\right]}$$

(5) Visceral Adiposity Index (VAI) [14]: for females

$$\mathrm{VAI} = \frac{\mathrm{WC\ (m)}}{36.58 + (1.89 \times \mathrm{BMI})} \times \frac{\mathrm{TG}}{0.81} \times \frac{1.52}{\mathrm{HDL-C}}$$

Triglycerides (TG) and high-density lipoprotein cholesterol (HDL-C) were measured using the enzymatic colorimetric method and respective reagents on the Selectra ProS chemistry analyser (ELItech, France) according to the manufacturer's instructions.

Cut off points for classifying persons as being normal weight, underweight, overweight or having obesity.

BMI - [17]

Underweight	<18.5
Normal	$18.5 \leq BMI < 24.9$
Overweight	$25 \leq BMI < 29.9$
Obese	≥ 30

Percentage Body Fat (%)

Age	Low	Normal	High	Very High
18–39	<21.0	21.0–32.9	33.0–38.9	≥39.0
40–59	23.0–33.9	<23.0	34.0–39.9	≥40.0
60–80	<24.0	24.0–35.9	36.0–41.9	≥42.0

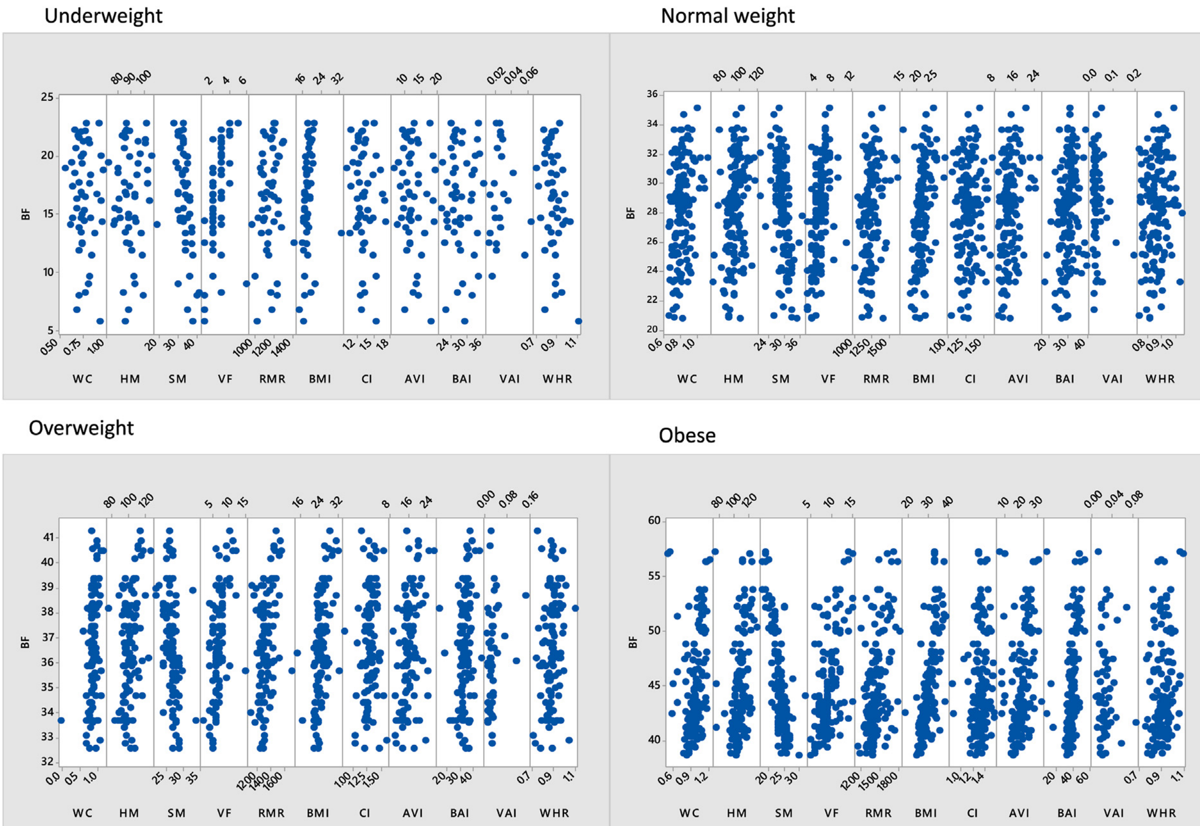


Figure 2. Correlations within different %BF categories and adiposity indices. The individual scatter plots (Underweight, Normal, Overweight and Obesity) between %BF classes and the remaining candidate obesity measures.

These values were provided by the manufacturer based on research work by McCarthy *et al* and Gallagher *et al* [18, 19]. Values are for females only.

Note: Low %BF represents underweight; normal %BF represents the normal body weight; High %BF represents overweight; and very high %BF represent obesity.

2.3. Statistical analysis

The data was analysed using Minitab version 17 and XLSTAT. Descriptive statistics are presented as (mean ± standard deviation). The strength of linear correlation between % BF and the other alternative methods were carried out using the Pearson product-moment correlation. The Matrix-plot of %BF and other alternative methods was also performed. It was very crucial to assess the variation in the alternative methods to %BF for the groups of the BF status. Analysis of variance concept (ANOVA) was used to test differences between these measures for the four groups of the %BF status. The parametric approach to ANOVA was used for the variables that satisfied both the normality and equal variance assumption, and the variables which did not satisfy these assumptions we applied the non-parametric method (Kruskal-Wallis). The Fisher's method for multiple comparisons was employed for the parametric data and the Steel-Dwass-Critchlow-Fligner procedure of multiple comparisons was employed for the non-parametric data. All statistical tests were carried out with a statistical significance level of 5%.

The Receiver operative characteristics (ROC) is appropriate when assessing the predictive ability of continuous predictors [20]. The ROC was used to assess the ability of the different anthropometric and BIA methods to predict adiposity accurately. The ROC curve was plotted with sensitivity on false positives. Where sensitivity is the probability of a measure classifying someone as having obesity when the person actually is obese. A false positive was the probability that a person was classified obese when the person is not.

3. Results

We analysed data on 467 women participants with a mean age of 46.8 ± 13.3. The prevalence of underweight, normal weight, overweight and obesity using BMI was 9%, 48%, 27% and 16% respectively. Using %BF the prevalence of underweight, normal weight, overweight and obesity was 10.9%, 32.1%, 25.3%, and 31.7%, respectively. Of the data analyzed, 52%, 18%, 15% and 12% were married, single, divorced and widowed respectively with the remainder cohabiting. Twenty percent of the respondents were primary school leavers, 41% were Middle/Junior High School leavers, 10% had secondary school certificate and 12% were tertiary leavers, while the remaining had no formal educational background. Anthropometric indices of the study participants are presented in Table 1.

Since HM, WHR, CI, WC, and VAI had equal variances, parametric analysis of variance with Fisher's LSD test for the multiple comparisons was used for the statistical analysis whereas BMI, AVI. BAI, VF, RMR, age, and SM had unequal variance so Welch ANOVA with Games-Howell post hoc analysis.

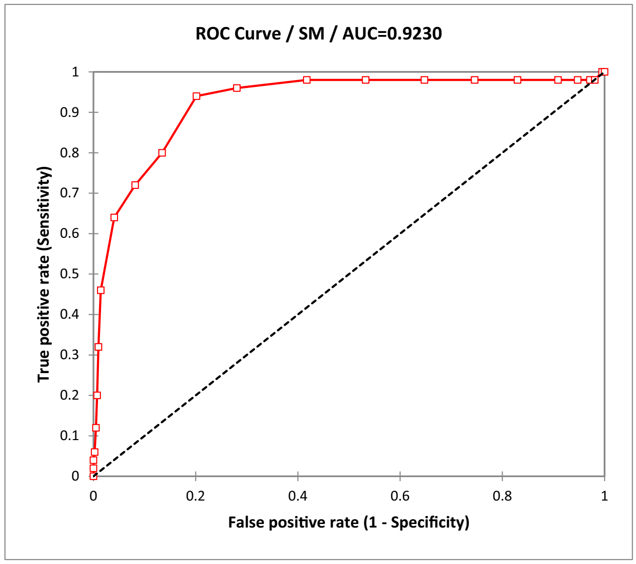
These results show that there was a difference in the population mean waist circumference, weight and hip measure, skeletal muscle mass, visceral fat and resting metabolic rates (*p-value* < *0.0001*) for the %BF classes (Table 1).

The relationships between the secondary measures of adiposity and %BF are presented in Table 2.

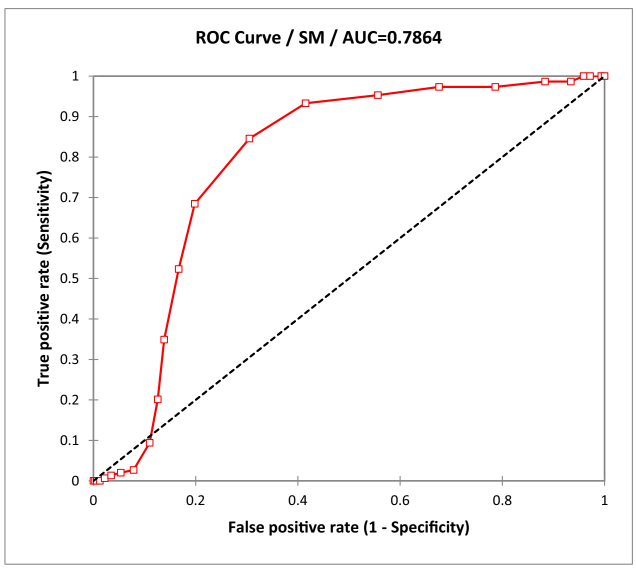
The results show that body mass index, abdominal volume index, body adiposity index, waist to hip ratio, and skeletal muscle mass are significantly different for the various weight classifications using body fat. Generally, the values for these adiposity measures increased with

Table 3. Receiver operator analysis.

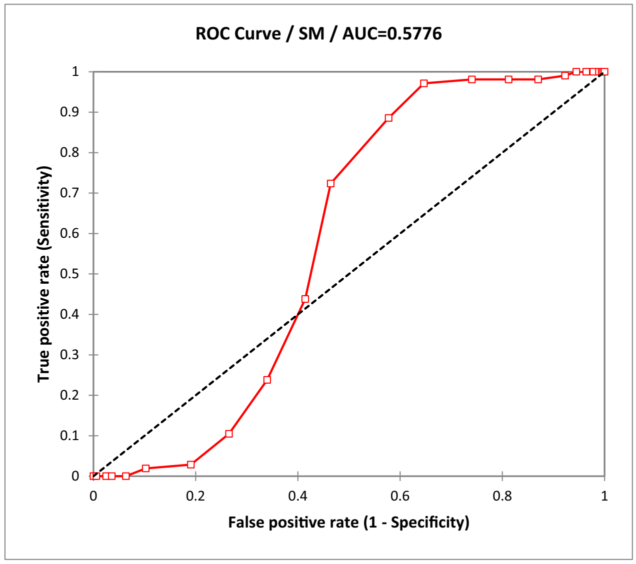
Test variable	Sensitivity	Specificity	PPV	NPV	Accuracy	AUC	P-value
Underweight							
BMI	0.9000	0.9305	0.6081	0.9873	0.9272	0.9524	<0.0001
AVI	0.8400	0.6739	0.2360	0.9723	0.6916	0.7874	<0.0001
BAI	0.6800	0.8441	0.3434	0.9565	0.8266	0.8064	<0.0001
WC	0.8400	0.6403	0.2188	0.9709	0.6617	0.7867	<0.0001
HM	0.7200	0.7794	0.2813	0.9587	0.7730	0.8242	<0.0001
WHR	0.5600	0.6331	0.1547	0.9231	0.6253	0.5861	0.0371
VF	0.9400	0.8177	0.3821	0.9913	0.8308	0.9442	<0.0001
RMR	0.7600	0.8225	0.3393	0.9662	0.8158	0.8655	<0.0001
SM	0.9400	0.7986	0.3588	0.9911	0.8137	0.9230	<0.0001
Normal weight							
BMI	0.8472	0.7802	0.6321	0.9197	0.8009	0.7915	<0.0001
AVI	0.7292	0.6409	0.4751	0.8415	0.6681	0.7139	<0.0001
BAI	0.7222	0.7028	0.5200	0.8502	0.7088	0.7358	<0.0001
WC	0.6597	0.6997	0.4948	0.8218	0.6874	0.7118	<0.0001
HM	0.7153	0.6718	0.4928	0.8411	0.6852	0.7250	<0.0001
WHR	0.4306	0.7740	0.4593	0.7530	0.6681	0.6284	<0.0001
VF	0.7569	0.7709	0.5956	0.8768	0.7666	0.7753	<0.0001
RMR	0.7014	0.7337	0.5401	0.8464	0.7238	0.7325	<0.0001
SM	0.8456	0.6950	0.5650	0.9057	0.7430	0.7864	<0.0001
Overweight							
BMI	0.9905	0.3923	0.3210	0.9930	0.5268	0.5774	0.0021
AVI	0.8190	0.4337	0.2955	0.8920	0.5203	0.5640	0.0210
BAI	0.8952	0.3066	0.2725	0.9098	0.4390	0.5233	0.3983
WC	0.8095	0.4254	0.2901	0.8851	0.5118	0.5634	0.0128
HM	0.9429	0.2873	0.2773	0.9455	0.4347	0.5421	0.0724
WHR	0.7048	0.4171	0.2596	0.8297	0.4818	0.5346	0.2436
VF	0.8000	0.4475	0.2958	0.8852	0.5268	0.6025	<0.0001
RMR	0.9048	0.3204	0.2786	0.9206	0.4518	0.5558	0.0409
SM	0.9714	0.3536	0.3036	0.9771	0.4925	0.5776	0.0150
Obese							
BMI	0.9116	0.8563	0.7444	0.9547	0.8737	0.9431	<0.0001
AVI	0.7347	0.7688	0.5934	0.8632	0.7580	0.8038	<0.0001
BAI	0.8299	0.7969	0.6524	0.9107	0.8073	0.8753	<0.0001
WC	0.7347	0.7625	0.5870	0.8622	0.7537	0.8050	<0.0001
HM	0.8231	0.7938	0.6471	0.9071	0.8030	0.8614	<0.0001
WHR	0.5986	0.6250	0.4231	0.7722	0.6167	0.6336	<0.0001
VF	0.8912	0.7688	0.6390	0.9389	0.8073	0.8998	<0.0001
RMR	0.8027	0.7781	0.6243	0.8957	0.7859	0.8423	<0.0001
SM	0.9388	0.8188	0.7041	0.9668	0.8565	0.9254	<0.0001



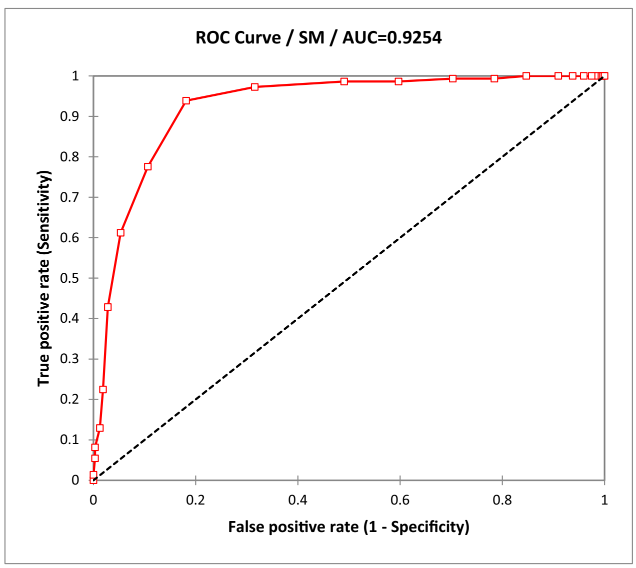
ROC Curves of variables for predicting underweight



ROC Curves of variables for predicting normal weight



ROC Curves of variables for predicting overweight



ROC Curves of variables for predicting obese weight

increasing % BF except for VAI where the normal group had the highest value and CI where the underweight group had higher values than the normal and overweight group however, the population means were not significantly different between the groups (Table 2).

Anthropometric measurements such as body mass index, visceral fat, RMR, hip measure, Body Adiposity Index, Abdominal Volume Index, and waist circumference, showed strong positive correlations (R = 0.874, 0.867, 0.804, 0.764, 0.708, 0.667, 0.622 respectively) with %BF, whilst skeletal muscle had a strong negative linear correlation with %BF (R = -0.685). The waist-to-hip ratio showed weak relationships with BF% (R = 0.283 and -0.184 respectively) whereas the visceral adiposity index and conicity index, showed no relationships (R = -0.002 and 0.059 respectively) with %BF (Figure 1). The category of normal weight had similar correlations as non-classified BMI correlations in Figure 1 whilst the overweight and obese categories showed weak correlations with %BF (Figure 2).

A receiver operating characteristic analysis was performed to determine the suitability of predicting obesity by the different indices of adiposity using %BF as the gold standard. The Area under the curve (AUC) values show that measures such as BMI and visceral fat were excellent predictors of low %BF (underweight) and very high %BF (obesity). However, they were moderate predictors of normal %BF and poor predictors of high %BF (overweight). All the other adiposity measures performed moderately well for classifying all the adiposity classes except for overweight (Table 3).

4. Discussion

Several large longitudinal studies have shown that obesity is associated with increased risk of chronic diseases such as cardiovascular disease, cancers, and diabetes, amongst others whilst weight reduction reduces the risk of these diseases [21]. In recent years we have witnessed an alarmingly increased prevalence of non-communicable diseases (NCD) [22]. This increased NCD burden is associated with an increase in the prevalence of obesity [21]. Thus, reducing the obesity epidemic may in part be an effective tool to solving this increased prevalence of NCDs.

The gold standard in diagnosing obesity is to estimate the percentage body fat; however, in many resource-limited settings instruments for direct measurement of body fat are not readily available. Hence, the increased dependence on anthropometric measurements such as the BMI in predicting obesity. Recent studies suggest that in certain populations, the use of BMI and other anthropometric indices using the current established cut-off points may be misleading [13]. For instance, studies within Mexican and Caucasian population have reported that the prevalence of obesity in their study populations differ depending on whether the classification was done with BMI or %BF [23, 24]. Such misclassifications do not only affect the prevalence estimation of obesity but also affect how obesity-induced risk for other chronic conditions is estimated. Furthermore, BMI is often confounded in studies on mortality by diseases which cause weight loss and increased mortality, a phenomenon called reverse causation which is further confounded by smoking [25]. In our study however, none of the participants reported as a smoker. In a recent study in patients with chronic kidney disease, it was observed that while high body mass index was protective, a high %BF was associated with increased all-cause mortality [9] thus suggesting the need for more direct measures of obesity to be incorporated into clinical practice measurements. These results call for population-based studies that look at the effectiveness of the different adiposity measures in predicting obesity and the risk of obesity-associated diseases.

In this study, we assessed how other anthropometric measures of obesity compared with %BF composition and found significant differences in the group means for weight, VF, WC, HC, SM, BMI, WHR and RMR for the %BF classes (Tables 1 and 2). These trends are similar to what has been reported previously [21, 26]. Of particular interest is the fact that for measures like WHR and CI, the underweight individuals showed higher levels than normal weight individuals, whereas, for VAI, the normal group had the highest mean value even though they did not achieve statistical significance. No reason can be given for this observation at the moment and further studies are required to determine what could account for this.

To determine the sensitivity and specificity of these measures of obesity to predict obesity, we carried out receiver operator analysis using the %BF as the gold standard. From the AUC values, we see that BMI is an excellent predictor of underweight, normal weight, and obesity, however, it was a bad predictor of overweight. This is particularly due to its low specificity even though it has a high sensitivity (Table 3). This observation is problematic since overweight represent pre-obese state and therefore having an accurate measurement is important in preventing the obesity epidemic. In a related study looking at the performance of BMI to diagnose obesity, a similar observation was seen for the overweight group; however, here, the BMI cut-off point of overweight had lower specificity instead. Additionally, that study reported that BMI was not a good diagnostic tool for obesity using the current established cut-offs. This, however, is in contrast with the current study which showed that BMI was sensitive in diagnosing obesity within our cohort [27].

The prevalence of obesity increased (doubled) when %BF was used as against BMI indicating that, some of the obesity cases will be missed when BMI is used. This suggests that the current WHO classification for BMI may not be an accurate predicator of obesity in all populations. Our findings are unique to our population and hence extrapolation to other populations that share similar characteristics will be largely predictions. Thus, there is the need to conduct large multicentre epidemiological studies among different groups of people to ascertain the real association between these parameters.

Declarations

Author contribution statement

K. Duedu: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

D. Mensah, S. Lokpo and I. Afeke: Performed the experiments.

D. Adedia and A. Boakye: Analyzed and interpreted the data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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