

1 **Prediction of whole-body fat percentage and visceral**
2 **adipose tissue mass from five anthropometric**
3 **variables**

4 **Short title: Anthropometric predictors of adiposity**

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17 **Abstract**

18 **Background:** The conventional measurement of obesity utilises the body mass index (BMI)
19 criterion. Although there are benefits to this method, there is concern that not all individuals at risk
20 of obesity-associated medical conditions are being identified. Whole-body fat percentage (%FM),
21 and specifically visceral adipose tissue (VAT) mass, are correlated with and potentially implicated
22 in disease trajectories, but are not fully accounted for through BMI evaluation. The aims of this
23 study were (a) to compare five anthropometric predictors of %FM and VAT mass, and (b) to
24 explore new cut-points for the best of these predictors to improve the characterisation of obesity.

25 **Methods:** BMI, waist circumference (WC), waist-to-hip ratio (WHR), waist-to-height ratio (WHtR)
26 and waist/height^{0.5} (WHT.5R) were measured and calculated for 81 adults (40 women, 41 men;
27 mean (SD) age: 38.4 (17.5) years; 94% Caucasian). Total body dual energy X-ray absorptiometry
28 with Corescan (GE Lunar iDXA, Encore version 15.0) was also performed to quantify %FM and
29 VAT mass. Linear regression analysis, stratified by sex, was applied to predict both %FM and
30 VAT mass for each anthropometric variable. Within each sex, we used information theoretic
31 methods (Akaike Information Criterion; AIC) to compare models. For the best anthropometric
32 predictor, we derived tentative cut-points for classifying individuals as obese (>25% FM for men
33 or >35% FM for women, or > highest tertile for VAT mass). **Results:** The best predictor of both
34 %FM and VAT mass in men and women was WHtR. Derived cut-points for predicting whole body
35 obesity were 0.53 in men and 0.54 in women. The cut-point for predicting visceral obesity was
36 0.59 in both sexes. **Conclusions:** In the absence of more objective measures of central obesity
37 and adiposity, WHtR is a suitable proxy measure in both women and men. The proposed DXA-
38 %FM and VAT mass cut-offs require validation in larger studies, but offer potential for
39 improvement of obesity characterisation and the identification of individuals who would most
40 benefit from therapeutic intervention.

41 **Key words:** Fat mass; Visceral Fat; Measurement; DXA

42 Introduction

43 In clinical practice, public health and the wider health and fitness industry, obesity is
44 conventionally defined using the body mass index (BMI) criterion, with a value of ≥ 30 kg/m²
45 categorising both men and women as obese [1]. Although there are many benefits to using BMI,
46 particularly for population-based screening, evidence indicates the existence of obesity sub-
47 groups such as metabolically healthy but obese, or metabolically unhealthy but normal weight [2,
48 3]. Therefore, use of BMI only, is potentially falling short of identifying those at an increased risk
49 of associated conditions, in particular cardio-metabolic diseases. Strong associations have been
50 identified between whole body and regional fat mass with risk of certain diseases [4], and as such
51 research indicates that visceral adiposity is an independent predictor of all-cause mortality in men
52 and women [5, 6]. More recently, greater emphasis has been placed upon the relationships
53 between visceral adiposity within the abdominal region (visceral adipose tissue; VAT) and
54 components of metabolic syndrome [7], insulin resistance [8, 9], cardiovascular disease [10, 11]
55 and even non-spine fractures [12], indicating that VAT is an important target for investigation.

56
57 VAT can be quantified with confidence using imaging modalities such as abdominal computed
58 tomography (CT). However, due to high radiation exposure and cost implications, CT is not ideal
59 for large-scale screening or routine practice. However, recent advancements in densitometry
60 imaging have led to a new Corescan software that enables the quantification of VAT through total
61 body dual-energy x-ray absorptiometry (DXA) scans, with significantly lower radiation and
62 expense than CT [13-15]. Although confounded by levels of subcutaneous fat [10], proxy
63 measures of fat mass, such as BMI, waist circumference (WC) and waist-to-hip ratio (WHR) are
64 more frequently used [16]. In particular, there is an emerging appreciation of waist-to-height ratio
65 (WHtR) as a risk indicator for poor cardio-metabolic health [17-23]. Ashwell [24, 25] first devised
66 the WHtR, proposing that cut-point values of 0.5 and 0.6 can identify individuals who are at

67 increased health risk and substantial health risk, respectively. It is important to evidence the
68 validity of proxy measures of overall and visceral obesity using gold standard criteria, which would
69 support their use in practice. Roriz et al. [26] performed CT scans in 191 adults and this is the
70 only study to date that has provided evidence supporting the notion that WHtR is a good predictor
71 of visceral obesity (defined as $>130\text{cm}^2$). These authors proposed WHtR cut-points in 20-59 year
72 olds of 0.54 in men and 0.59 in women, and 0.55 (men) and 0.58 (women) in participants ≥ 60
73 years. Recently, a new index was proposed – waist/height^{0.5} – that was a stronger predictor of
74 cardiometabolic risk than other anthropometric variables, including WHtR, BMI, WC, a body
75 shape index, and WHR [27].

76
77 There is also growing interest in the clinical utility of multiple anthropometric measures for
78 identifying individuals at risk of cardiometabolic diseases, but this could be time-consuming, and
79 not always feasible or realistic in practice. Research indicates that compared to separate
80 measures, BMI and WC combined can more accurately predict abdominal fat mass [10]. Similarly,
81 BMI and WHtR combined, can identify elevated cardiovascular disease risk better than BMI alone
82 [28]. There have been several studies that have used DXA-derived VAT, although these have
83 mainly reported on the ability of DXA-VAT to predict cardiometabolic risk and not its utility for
84 obesity identification [29, 30].

85
86 The current study measured VAT mass and overall fat mass as a percentage of body mass (%FM)
87 using DXA imaging in UK men and women. The main aims were (a) to compare 5 separate
88 anthropometric variables in the prediction of %FM and DXA-VAT mass and (b) to identify tentative
89 new obesity cut-off points for the anthropometric variable in the model found to be the best from
90 the five candidates.

91

92 **Materials and Methods**

93 **Participants and Ethics Approval**

94 As part of a University-wide health screening programme, data from eighty-one adults were
95 analysed which included a heterogeneous sample of 41 men (mean (SD) age: 40.5 (20) years;
96 BMI: 26.3 (4.1) kg/m²) and 40 women (age: 36.3 (14.5) years; BMI: 24.8 (4.4) kg/m²). The ethnicity
97 distribution was 94% Caucasian (n=76), 5% Indian/Pakistani (male n=2; female n=2), and 1%
98 African-Caribbean (male n=1). The study was reviewed and approved by the Leeds Beckett
99 University Research Ethics Committee, and in accordance with the Declaration of Helsinki. All
100 participants provided signed informed consent to participate in the study, and all data was
101 collected between 08:00 am and 12:00 noon during a single visit to the laboratory.

102

103 **Anthropometric measurements**

104 Participants were measured wearing light loose clothing or a hospital gown, and no jewellery or
105 footwear. Body mass was measured using calibrated, digital flat platform scales (Seca Alpha,
106 SECA, Birmingham, UK) to the nearest 0.1 kg. Standing height was measured to the nearest 0.1
107 cm using a free-standing stadiometer (SECA, Birmingham, UK) and body mass index (BMI) was
108 subsequently calculated using the standard Quetelet formula (mass divided by squared height)
109 (kg/m²) with categories in accordance with the WHO [1] guidelines, more specifically obesity
110 defined by a BMI ≥ 30 kg/m². Waist circumference (WC) was measured at the midway point
111 between the iliac crest and the lowest rib [31] to the nearest 0.1 cm. Hip circumference (HC) was
112 measured at the widest part of the buttocks [31] to the nearest 0.1 cm in order to calculate waist-
113 to-hip ratio (WHR) by the simple division of WC/HC. Subsequently, waist to height ratio (WhtR),
114 a more contemporary measure, was calculated by WC/Height [32]. We also calculated an index
115 proposed recently as a superior predictor of cardiometabolic risk – WC/Height^{0.5} (WHT.5R; [27]).

116

117 **DXA-derived measurements**

118 Each participant received one total body fan-beam dual energy X-ray absorptiometry (GE Lunar
119 iDXA, GE Healthcare, Madison, WI) scan, from which body composition, namely percentage fat
120 mass (%FM), was determined. VAT was quantified using the validated CoreScan software
121 (EnCore version 15.0). Participants were placed in the supine position on the scanning table and
122 the body aligned with the central horizontal axis. Arms were positioned parallel to, but not touching
123 the body, with a 1 cm space in between the thigh and the hand. Forearms were pronated with
124 hands flat on the bed. Legs were fully extended and feet were secured with a canvas and Velcro
125 support to avoid foot movement during the scan acquisition. Scans were conducted using
126 standard (153 mm/sec) or thick (80 mm/sec) mode depending on body stature. One skilled DXA
127 technologist led all scans and analyses, which were checked by an International Society for
128 Clinical Densitometry (ISCD) clinically certified densitometrist. The regions of interest (ROI) for
129 the total body cut-offs were manually adjusted according to the manufacturer's instructions. The
130 ROI over the android region for the assessment of VAT was automated by the software. Precision
131 error for our Unit has previously been published for both fat mass [33] and VAT mass [15]. The
132 machine's calibration was checked and passed on a daily basis using the GE Lunar calibration
133 hydroxyapatite and epoxy resin phantom. There was no significant drift in calibration for the study
134 period.

135

136 **Data analysis**

137 Linear regression analyses were used to compare five candidate models in the prediction of whole
138 body fat percentage and VAT mass. The five anthropometric predictors compared were BMI, WC,
139 WHR, WHtR, and WHT.5R. Diagnostic plots revealed badly behaved residuals for the VAT

140 models; therefore, VAT was log-transformed prior to the primary analysis. All analyses were
141 stratified by sex. We used an information-theoretic approach (Akaike's Information Criterion; AIC)
142 to compare the five candidate models, separately for both whole body fat percentage and VAT
143 [34]. The model with the lowest AIC identifies the best of the candidate models, and provides a
144 reference for model comparison. The remaining models are then compared to the best model and
145 evaluated using the difference in AIC ($AIC\Delta$) according to the following scale [35]: Essentially
146 equivalent model ($AIC\Delta <2$), plausible alternative ($AIC\Delta 2-7$), weak support ($AIC\Delta 7-14$), and
147 unsupported ($AIC\Delta >14$). The AIC identifies the best model of a set of candidates, but its
148 meaningfulness depends on there being a good predictive model in the set. Therefore, we also
149 present adjusted R^2 and the standard error of the estimate for all models.

150
151 Following the identification of the best model, we used the prediction equation to derive tentative
152 cut-points for identifying obesity based on %FM and VAT mass. For the %FM equation, standard
153 thresholds of 25% and 35% were used as the definition of obesity in men and women respectively.
154 However, due to no known cut-points for VAT mass derived by DXA in males or females, we
155 generated distributional tertiles whereby the highest third was proposed as the obese group. For
156 both %FM and VAT mass, we derived the cut-point for the best anthropometric predictor that
157 resulted in a probability of ≥ 0.75 (odds of 3:1 in favour) of an individual being obese, as defined
158 above, given the prediction error from the regression equation (standard error of the estimate;
159 SEE). To account for the downward bias of the SEE associated with small sample sizes (<50) for
160 men and women groups, we adjusted the SEE upwards required in the derivation of the cut-
161 points. A probability of ≥ 0.75 was selected as this is the threshold denoting "likely to be" in the
162 magnitude-based inferences framework [36]. Briefly, the probability that an individual's true %FM
163 or VAT mass value is greater than some threshold value – given the predicted value from a
164 regression equation - is obtained from the one-tailed area under the t-distribution for the
165 appropriate degrees of freedom at the following t value:

166

167 $t = (\text{Predicted value minus threshold value for obesity})/\text{standard error of the estimate.}$

168

169 In small validity studies ($n < 50$), due to sampling variability in the prediction equation, the standard
170 error of the estimate should ideally be adjusted upwards by a factor given by:

171 $\sqrt{(1 + 1/n + 1/(n - 3))}$. Knowing the t-value associated with a probability of 0.75, the threshold

172 value for obesity, and the standard error of the estimate allows us to derive the required predicted

173 value. We can then derive the cut-point for the anthropometric predictor by rearranging the

174 obtained regression equation. A worked example is provided in the Results. All analyses were

175 conducted using SPSS Statistics software (v.23, Armonk, NY: IBM Corp).

176

177 **Results**

178 Descriptive data for the five anthropometric predictors and the two dependent variables (%FM

179 and VAT mass) are shown in Table 1.

180

181 **Table 1: Sample characteristics**

Obesity measure	Men (n=41)	Women (n=40)
BMI (kg/m ²)	26.2 (4.1)	24.8 (4.4)
BMI ≥ 30 kg/m ²	17% (n=7)	10% (n=4)
WC (cm)	88.8 (12.3)	78.7 (13.0)
WHR	0.91 (0.07)	0.80 (0.07)
WHtR	0.50 (0.07)	0.48 (0.08)
WHT.5R	0.67 (0.09)	0.61 (0.10)
Total body fat mass (%)	25.5 (8.4)	34.0 (7.8)
FM >25%	54% (n=22)	-
FM >35%	-	48% (n=19)
VAT mass (g)	604 \times/\div 2.9	204 \times/\div 4.9

182 Data presented as Mean (SD)
 183 BMI - Body mass index; WC – waist circumference; WHR – waist-to-hip ratio; WHtR – waist-to-height ratio;
 184 WHT.5R – WC/height^{0.5}; fat mass (FM); visceral adipose tissue (VAT).
 185 For VAT mass, which was log-transformed prior to analysis, the geometric mean is shown, with the
 186 dispersion given as a \times/\pm factor standard deviation (SD) [36].
 187

188 Only around 1 in 6 men and 1 in 10 women were obese according to the BMI criterion versus
 189 around half of each sample according to the whole-body fat percentage thresholds. The
 190 comparison of candidate models for the prediction of %FM (Table 2) and VAT mass (Table 3)
 191 revealed that the WHtR was the best predictor in both men and women.

192

193 **Table 2: Prediction of whole body fat percentage from anthropometric measures**

	AIC Difference (Inference)	Adjusted R ²	Standard Error of Estimate*
Males (n=41)			
BMI	8 (weak support)	0.71	4.5
WC	5 (plausible)	0.73	4.4
WHR	50 (unsupported)	0.19	7.5
WHtR	0 (best)	0.76	4.1
WHT.5R	<1 (equivalent)	0.76	4.1
Females (n=40)			
BMI	8 (weak support)	0.51	5.5
WC	6 (plausible)	0.53	5.3
WHR	27 (unsupported)	0.21	6.9
WHtR	0 (best)	0.60	5.0
WHT.5R	2 (plausible)	0.57	5.1

194 AIC - Akaike's Information Criterion; BMI - Body mass index; WC – waist circumference; WHR – waist-to-
 195 hip ratio; WHtR – waist-to-height ratio; WHT.5R – WC/height^{0.5}
 196 *The 95% confidence interval for the standard error of the estimate is \times/\pm a factor of 1.25 at these degrees
 197 of freedom.
 198

199

200 **Table 3: Prediction of VAT mass (Log) from anthropometric measures**

	AIC Difference (Inference)	Adjusted R ²	Standard Error of the Estimate \times/\div factor (95% CI)
Males (n=41)			
BMI	13 (weak support)	0.60	2.0 (1.8 to 2.4)
WC	4 (plausible)	0.68	1.8 (1.6 to 2.1)
WHR	41 (unsupported)	0.21	2.6 (2.2 to 3.3)
WHtR	0 (best)	0.71	1.8 (1.6 to 2.1)
WHT.5R	<1 (equivalent)	0.71	1.8 (1.6 to 2.1)
Females (n=32*)			
BMI	6 (plausible)	0.58	2.8 (2.3 to 4.1)
WC	3 (plausible)	0.61	2.7 (2.2 to 3.7)
WHR	25 (unsupported)	0.22	4.1 (3.0 to 6.7)
WHtR	0 (best)	0.65	2.6 (2.2 to 3.7)
WHT.5R	<1 (equivalent)	0.64	2.6 (2.2 to 3.7)

201 AIC - Akaike's Information Criterion; BMI - Body mass index; WC – waist circumference; WHR – waist-to-
 202 hip ratio; WHtR – waist-to-height ratio; WHT.5R - WC/height^{0.5}

203 *8 females excluded due to undetectable levels of VAT mass leading to badly behaved residuals

204

205 The individual cut-point for WHtR associated with a probability of being obese (>25% fat in men
 206 and >35% fat in women) of ≥ 0.75 was 0.53 in men and 0.54 in women. Below, as an illustration
 207 of the method, we present the derivation of the male cut-point. The value from the t-distribution
 208 associated with a probability of 0.75 at 39 degrees of freedom (n-2) is 0.681. The standard error
 209 of the estimate from the prediction equation was 4.1% fat (adjusted to 4.2%). From the Methods:

210

211 $t = (\text{Predicted value minus threshold value for obesity}) / \text{standard error of the estimate.}$

212 Therefore, the required predicted value is given by:

213 Predicted = $25 + 4.2 \times 0.681 = 27.9.$

214 The derived prediction equation was: $\%FM = 99.7 \times WHtR - 24.7$. Therefore, the required WHtR
215 cut-point is given by: $(27.9+24.7)/99.7 = 0.53$.

216

217 The individual cut-point for WHtR associated with a probability ≥ 0.75 of being in the highest third
218 for VAT mass (>1108 g for men and > 477 g for women) was 0.59 in both men and women.

219

220 **Discussion**

221 Our main finding is that from five anthropometric variables (BMI, WC and WHR, WHtR, and
222 WHT.5R) the WHtR is the best predictor of DXA-derived whole body fat percentage and VAT
223 mass, in both men and women. The new WHT.5R index was an essentially equivalent predictor
224 of VAT mass in both sexes. For whole body fat percentage, WHT.5R was an equivalent predictor
225 in males and a plausible alternative in females. Waist circumference (unadjusted for height) was
226 a plausible alternative model for both sexes for both outcomes. Models with BMI as the predictor
227 had weak support for the prediction of whole body fat percentage in both sexes and for VAT mass
228 in males. However, BMI was a plausible alternative for the prediction of VAT mass in females.
229 The use of WHR was unsupported in all models. Even for the best model, the R^2 and standard
230 errors of the estimate reveal that simple anthropometric indices are uncertain predictors of DXA-
231 measured body composition outcomes, with prediction errors similar to, if slightly larger, than
232 those of skinfold methods [37, 38].

233

234 It is encouraging that WHtR was identified as the best predictor of both whole-body fat percentage
235 and VAT mass in both men and women, whereas to account for both factors, a clinician would
236 typically need to measure both BMI and WC, which require differential categorisation by age, sex
237 and ethnicity that is not required for WHtR [39]. In contrast, in NHANES survey participants, Heo
238 et al. [40] investigated optimal scaling for both weight and WC to height in the prediction of DXA-

239 measured total %FM, and reported that WC alone, without adjustment for height, is the optimal
240 index for both sexes. However, in the current study we found that WHtR was the best model,
241 although WC was still a plausible alternative. Indeed, WC alone, unadjusted for height, might be
242 more appealing in the clinical setting as it requires just a single measurement. These findings
243 highlight that these simple measurements may be used as surrogates, reducing the need for DXA
244 scans in the clinical setting.

245

246 In the current study, the AIC differences (Tables 2 and 3) revealed that models with WHR as the
247 predictor were by far the worst of all candidate models, and were unsupported. The rationale
248 supporting the use of WHR is that it accounts for central and peripheral fat distribution [31], but
249 changes in WC and hip circumference are relative to each other so favourable weight loss will not
250 necessarily lead to reductions in WHR. This observation would therefore support that WHR is not
251 ideal for identification of obesity or monitoring changes in weight status, hence it is not included
252 in UK National Institute for Health and Care Excellence guidance [41]. Our study indicates that
253 monitoring WC in absolute terms or in relation to the practically unchanged anthropometric
254 measure of height is a better surrogate measure for levels of adiposity with the propensity to
255 cause cardiometabolic diseases.

256

257 Despite the generally well-accepted understanding that BMI has its limitations, it is still valuable
258 for population-level screening with Ortega and colleagues [42] recently reporting that that BMI
259 was a better predictor of mortality than fat mass, when determined by hydrostatic weighing or
260 skinfold thickness, in 60,000 adults. Also, WC - a plausible alternative to WHtR in the current
261 study - is generally accepted as a proxy for central adiposity, especially as there are well-
262 established risk categories and it is recommended in the UK National Institute for Health and Care
263 Excellence 2014 guidelines for obesity assessment [41]. Despite this recommendation and the
264 growing evidence-base in support of waist measurements, emphasis from NICE remains on

265 weight and BMI with focus on WC only in those with a BMI under 35 kg/m². In the current study,
266 around 1 in 7 participants were classified as obese using the conventional BMI criterion versus 1
267 in 2 participants using whole-body fat percentage criteria. This observation suggests that sole use
268 of BMI may be misleading. The finding is underscored by the fact that models with BMI as the
269 predictor of whole-body fat percentage had weak support in both sexes.

270

271 A second major outcome of our study was identification of obesity cut-off points for WHtR based
272 on percentage fat mass and VAT mass. The derived cut-points for whole-body fat percentage
273 were almost identical in men (0.53) and women (0.54). Moreover, our study is the first to derive a
274 tentative cut-point for WHtR in the prediction of high DXA-derived VAT mass (defined as the
275 highest third in our sample distribution, in the absence of an established threshold). Remarkably,
276 in a cross-sectional study of 191 adults, Roriz et al. [26] reported WHtR cut-points ranging from
277 0.54 to 0.59 for predicting high visceral adiposity (VAT area of ≥ 130 cm² determined by CT) in
278 men and women aged 20-59 years and ≥ 60 years, respectively. Elsewhere, it has been reported
279 that WHtR is a proxy for visceral adiposity and the existing cut-points of >0.5 and >0.6 are related
280 to high and very high health risk (obesity and metabolic syndrome) respectively [43]. Our study
281 differs as we propose cut-off points for visceral adiposity defined arbitrarily as the upper third of
282 the distribution. Indeed, our proposed 0.59 cut-point aligns closely to Ashwell's 0.6, which is often
283 referred to as the threshold above which patients should be advised to "take action" based on the
284 knowledge of visceral fat-associated links with negative health outcomes [5-7, 10, 11]. Our
285 findings also support Ashwell and Gibson [23] in their proposal that WHtR should be fully
286 considered as a replacement for the BMI and WC combined matrix, which could support obesity
287 characterisation when DXA is not available or not desirable.

288

289 Although it is accepted that use of DXA is not feasible in all clinical settings, for those who do
290 have access we also highlight the advantages of using DXA to obtain important and precise

291 information on fat mass and VAT [15, 33], which as an adjunct to WHtR, might further improve
292 identification of patients at risk of associated negative health outcomes. A prospective study on a
293 larger scale would enable evaluation of this hypothesis. In this way, an individual participant
294 exceeding a valid and robust WHtR cut-point could perhaps be used as a simple clinical indicator
295 for further exploration with more sophisticated methods. This form of risk stratification would
296 require more research identifying the WHtR cut-points that best ‘rule in’ and ‘rule out’ negative
297 health outcomes.

298

299 It is well-documented that the number of adults who are defined as obese differs depending on
300 the measurement method used [44]. Relying, therefore, on just one standard measure of obesity
301 may lack the required accuracy for the identification of individuals with adiposity at risk of adverse
302 health outcomes. In an effort to promote the simple public health message of “keep your waist
303 less than half of your height”, it was recently reported that 10% of the UK population would be
304 misclassified if only BMI is used, and over one quarter of people with a healthy BMI (18.5-24.9
305 kg/m²) are misclassified when WHtR >0.5 is implemented [39]. Our results indicate that using BMI
306 alone classified a much lower number of participants as obese, in comparison to obesity cut-
307 points for measures of WHtR and %FM; this observation cannot be confirmed for visceral obesity
308 due to the arbitrary nature of our VAT mass classification. Even in a small sample, this is
309 somewhat alarming and does provide further evidence that alternative measures are fundamental
310 to the more accurate identification of obesity, therefore ensuring that individuals are referred to
311 the most suitable therapeutic approach to reduce risk of obesity-related conditions.

312

313 Strengths of our study include the use of precise DXA measures of body composition outcomes,
314 the use of information-theoretic methods for robust model comparison, and the application of a
315 novel method to derive cut-points for predicting obesity status. However, it is important to
316 acknowledge explicitly some key limitations. First, the sample sizes of men and women are small

317 for a validity study. We have presented cut-points based on standard errors of the estimate
318 adjusted for sample size (inflated prediction error resulting from sampling variability) but,
319 nonetheless, our findings need to be replicated in a large definitive measurement study. Second,
320 our sample is 94% Caucasian, and our findings cannot be generalised to other ethnic groups.

321

322 **Research and Practical implications**

323 Our findings indicate that WHR should not be relied on in clinical practice for obesity identification.
324 Interestingly, however, in middle-to-older aged adults WHR has been shown to have a greater
325 predictive ability to identify health outcomes than %FM and BMI [45]. Our study has devised
326 tentative new cut-off points that need to be validated in a larger sample and could potentially be
327 utilised in further research and in clinical practice. One key strength of our identified cut-points is
328 that, despite using different equations for men and women, the generated threshold values are
329 virtually identical. If replicated, this provides a consistent and simple message to clinicians that
330 can be transferrable to the general public. The cut-points are more specific but still align broadly
331 to the WHtR guidance that adults and children should keep WC to less than half their height i.e.
332 <0.5 [39, 46]. A further advantage of using WHtR is cost effectiveness given that this measure
333 only requires the use of a tape measure and stadiometer, both of which are inexpensive and
334 portable. We advise that future prospective research should implement and test these new cut-
335 points to explore associations with negative health outcomes such as cardiometabolic disease,
336 especially with stratification by obesity phenotypes of metabolically healthy but obese, or
337 metabolically unhealthy but normal weight, in an effort to increase capture of at-risk individuals.

338

339 In conclusion, our data indicate that in this study WHtR is the best predictor of the five models
340 compared for obesity characterisation in adults, and in combination with DXA-derived fat mass
341 and/or VAT mass, the proposed cut-off points might improve obesity identification in both men

342 and women. Our results cannot yet be generalised to other population groups but provide new
343 information which is intended to provide direction for validation and/or exploration in future
344 studies.

345

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349

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476

477 Supporting Information

478

479 S1 Table. Sample characteristics.

480 Data presented as Mean (SD)

481 BMI - Body mass index; WC – waist circumference; WHR – waist-to-hip ratio; WHtR – waist-to-height ratio;
482 WHT.5R – WC/height^{0.5}; fat mass (FM); visceral adipose tissue (VAT).

483 For VAT mass, which was log-transformed prior to analysis, the geometric mean is shown, with the
484 dispersion given as a \times/\div factor standard deviation (SD) [36].

485

486 **S2 Table. Prediction of whole body fat percentage from anthropometric measures.**

487 *AIC - Akaike's Information Criterion; BMI - Body mass index; WC – waist circumference; WHR – waist-to-*
488 *hip ratio; WHtR – waist-to-height ratio; WHT.5R – WC/height^{0.5}*

489 *The 95% confidence interval for the standard error of the estimate is \times/\div a factor of 1.25 at these degrees
490 of freedom.

491

492 **S3 Table. Prediction of VAT mass (Log) from anthropometric measures.**

493 *AIC - Akaike's Information Criterion; BMI - Body mass index; WC – waist circumference; WHR – waist-to-*
494 *hip ratio; WHtR – waist-to-height ratio; WHT.5R - WC/height^{0.5}*

495 *8 females excluded due to undetectable levels of VAT mass leading to badly behaved residuals

496 **S1 File. PloSOne data set.**