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Validation of anthropometric and bioelectrical impedance equations for the prediction of fat mass amongst South African children

M. T. Hudda PhD[1] | E. van Niekerk PhD[2] | C. M. Sedumedi PhD[2] | L. Moeng-Mahlangu PhD[2] | P. H. Whincup PhD[3] | J. J. Reilly PhD[4] | H. S. Kruger PhD[5] | M. A. Monyeki PhD[2]

[1]Department of Population Health, Dasman Diabetes Institute, Kuwait City, Kuwait

[2]Physical Activity, Sport and Recreation Research Focus Area (PhASRec), Faculty of Health Sciences, North-West University, Potchefstroom, South Africa

[3]Population Health Research Institute, St George's School of Health & Medical Sciences, City St. George's University of London, London, UK

[4]Physical Activity for Health Group, School of Psychological Sciences and Health, University of Strathclyde, Glasgow, Scotland

[5]Centre of Excellence for Nutrition, North-West University, Potchefstroom, South Africa

Correspondence
M. A. Monyeki, Physical Activity, Sport and Recreation Research Focus Area (PhASRec), Faculty of Health Sciences, North-West University, Potchefstroom, South Africa.
Email: andries.monyeki@nwu.ac.za

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Abstract

Background/Aims: While several prediction equations which combine anthropometric, demographic, and/or bioelectrical impedance (BIA) variables to estimate childhood fat mass (FM) are available, comprehensive comparisons of their performance are lacking. We validated FM estimates for children from a range of published equations against reference-standard deuterium dilution observed FM.

Methods: This cross-sectional study was based on 323 children (42% male) from South Africa of Black African ethnic origins aged 5 to 8 years with information on age, sex, ethnicity, height, weight, deuterium dilution observed FM, triceps and subscapular skinfold thickness, and BIA observed FM, resistance, and impedance. We extracted all equations from three systematic reviews of childhood FM prediction equations that used the above available predictors and were developed on more than 100 males and females. FM estimates from each equation were calculated and the performance of each, as well as FM reported from the BIA manufacturer software, was compared with deuterium dilution observed FM using statistics of R^2, Calibration (slope and calibration-in-the-large), and root mean square error (RMSE).

Results: Nineteen equations (1 based on basic anthropometry, 12 on skinfold thickness, 6 on BIA) were validated. R^2 and RMSE values ranged between 58.3% (BIA manufacturer equation) and 89.0% (Britz et al. (2017) skinfold thickness equation), and between 1.1 kg (Wendel et al. (2016) skinfold thickness equation) and 3.4 kg (Horlick et al. (2002) BIA equation), respectively. Calibration varied considerably across the equations. From the basic anthropometry, skinfold thickness, and BIA

categories, the best performing equations from each category were by: Hudda et al. (2019) (basic anthropometry), Wickramasinghe et al. (2008) (skinfold thickness), and Ramirez et al. (2012) (BIA).

Conclusions: The performance of published equations varied considerably upon external validation in this South African childhood population. Notably, the Hudda et al. (2019) equation, which relies solely on readily available information of weight, height, sex, age and ethnicity, produced one of the highest R^2 values, was well calibrated, and produced a low RMSE value (1.4 kg). Alternative equations which also performed very well relied on additional measurements of skinfold thickness and/or BIA which require equipment, training, extra costs and additional time to obtain.

KEYWORDS
meta-analysis, obesity care, observational study, population study

1 | INTRODUCTION

Assessment of body composition is an important component in assessing health and nutritional status, including monitoring fat mass (FM) at one timepoint and changes in FM over time.[1,2] Overweight and obesity are defined by the World Health Organization as excessive fat accumulation that presents a risk to health.[3] Historically, due to the absence of direct body composition assessment techniques, proxy indirect markers of body fat such as body mass index (BMI; weight/height^2), waist circumference and skinfold thickness were adopted.[4–7] Thresholds of BMI-for-age have been used to define overweight and obesity in children.[8,9]

However, several more direct techniques now exist to assess body composition which utilize underlying prediction equations to estimate body composition.[4] Examples of such approaches include magnetic resonance imaging (MRI) scanning, dual-energy X-ray absorptiometry (DXA), bioelectric impedance (BIA), the four-component model and the deuterium dilution technique.[4–7] While MRI, the four-component model and deuterium dilution approaches have been shown to produce estimates of body composition with very low errors,[10,11] these methods are costly, time consuming, and/or require specialised expertise and thus may not be feasible for implementation at routine field, clinical, or population level.[4,7,12,13]

The use of BIA in the assessment of body composition has increased as the technology has advanced in recent years. Assessment is safe, relatively inexpensive, rapid, and observer independent, requiring little training. However, despite it being used more frequently, concerns have been raised about the precision and accuracy of BIA in children,[4,10,14,15] which may vary by the choice of the underlying software/equations.[10,16,17] It is for this reason, as well as potential age and sex variations in the chemical maturity of children, that many population-, age-, sex-, and ethnic-specific BIA prediction equations have been developed and discussed in the literature.[18–20] Thus, the published BIA equations, in addition to the several published algorithms for the prediction of body composition based on anthropometry (e.g., height, weight, BMI, skinfold thickness),[21] require validation against a reference-standard technique for FM assessment, such as the four-component model or deuterium dilution, to assess their performance in new populations.

We therefore aimed to validate the available equations for predicting childhood FM based on skinfold thickness, BIA, and anthropometry, using deuterium dilution observed FM as the reference standard.

2 | METHODS

This study is reported in accordance with The Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) reporting guidelines.[22] All analyses were conducted in Stata (version 18).

2.1 | Model selection process

To increase research efficiency and avoid duplication, as opposed to conducting a new review of existing prediction models, existing prediction models for estimation of FM using predictors obtained from BIA in children were identified from a literature summary by Kyle et al.[20] and a systematic review conducted by Chula de Castro et al.[19] In addition, we validated FM estimates reported from the Bodystat 1500MDD BIA machine (Bodystat Inc., Douglas, UK). Prediction equations based on anthropometric predictors (height, weight, BMI, skinfold thickness) were obtained from a systematic review conducted by Cerqueira et al.[21] Full details of the search strategy and selection procedures are given in the reports of the original reviews.[18–21]

For the present study, two researchers (E van Niekerk, MT Hudda) sought initial publications of the studies included in the three reviews and independently extracted model details (included variables, outcome definition, model equation) from each study. Studies were included in this external validation study if their suggested model(s): (i) were developed on study populations of more than

100 individuals, (ii) were developed on both males and females, (iii) included predictors of readily available basic anthropometry (weight, height, BMI), and/or skinfold thickness (triceps and/or subscapular) and/or variables obtained from BIA (resistance, impedance). Where eligible studies proposed more than one model that were all using the same predictors with differing coefficients, only the model with the highest reported performance was selected for validation. If, however, studies proposed more than one model where models utilized different predictors (i.e. one model using skinfold thickness predictors and one using BIA predictors), then both were selected for validation.

2.2 | Data source and study population used for external validation

A total of 323 African children 5 to 8-year-olds of predominantly Sotho-Tswana ethnic group, who are part of the larger body composition using isotope technique (BC–IT study) study, were selected from four urban township primary schools in North West Province, South Africa. More details of the BC–IT study are published elsewhere.[23] A sample was randomly selected from children within the 5 to 8-year age range between 2017 and 2018; whereby every third healthy (i.e., not on chronic medications, no form of physical disorders, no heart and lung disorders) child had an opportunity to participate in the study. The International Atomic Energy Agency (IAEA) protocol for administering the isotope technique to assess total body water (and then body composition thereafter) was followed. In summary, after an overnight fast, pre-dose saliva samples were obtained from participants. Based on their respective body weights, the appropriate dose of deuterium oxide-labelled water was calculated and given to the children to consume using drinking straws to avoid potential spillage. Each child's dose bottle was rinsed twice with water (50 mL per rinse) and the rinsing water was consumed to ensure complete intake of the dose. The time of dose administration was recorded for each child. Two further saliva samples were collected at 2 and 3 h post-dose. Between the first and last saliva sample collections, children were asked to stay in the study location and were required to avoid physical activity. Children were not allowed to eat or drink anything apart from the light snack provided after completion of the sample collection, but they were permitted to go to the bathroom at any time. After the saliva samples were processed using Fourier transform infrared spectroscopy and total body water was estimated, fat-free mass was estimated using age- and gender-specific Lohman constants for hydration factors for children.[24,25] Finally, FM was estimated as fat-free mass/weight * 100. Permission was received from the Department of Education, school principals and parents of the participating schools. The parents and their children gave consent and assent to participate in the study. The study was granted permission by the Health Research Ethics Committee (Ethic no: NWU-00025-17-S1) of the Faculty of Health Sciences (HREC) of the North-West University.

2.3 | Outcome and predictor assessment

All eligible identified and included models were applied to this population of South African children to evaluate their performance by assessing the generalizability of each model to this population. All participants in the external validation data underwent body composition assessments using the reference-standard isotope deuterium dilution method. This method involves administering a known dose of deuterium enriched water and measuring its equilibrium concentration to estimate total body water. Using the assumed percent hydration of fat-free mass, the amount of total body water is used to estimate fat-free mass, and thereafter FM by subtraction from weight.[4,26] Details of the standardized protocol used are published elsewhere.[24] The outcomes of included models were either FM (kg) or BF% (FM/weight * 100). To make fair comparisons across all the models and to ease interpretation, the external validation of the models was performed in terms of FM on the kilograms scale. Height (cm), weight (kg), triceps and subscapular skinfolds (mm) were measured by the same individual for all participants according to standard procedures.[23] BIA was performed using the Bodystat 1500MDD machine with a measurement frequency of 50 kHz. BIA involves the passing of a low-level current through the body to measure the resistance and reactance of different tissues. These values are then used to estimate total body water and thereafter fat-free mass (using assumed percent hydration of fat-free mass) and FM.[4,6,27] In accordance with standard procedures, prior to the BIA assessment, each child participant was instructed to empty their bladder. Measures of body mass, height, sex and age were entered manually. Body mass was automatically adjusted by 0.5 kg for clothing weight in all subjects. The Bodystat1500 software required predictors of FM and impedance (resistance and reactance). One individual had missing FM from BIA and was excluded from analysis.

2.4 | Statistical analysis: Assessment of predictive performance

The predictive performance of each model equation was assessed in the validation data through comparison of the predicted values, on the FM scale, with the observed outcome (deuterium dilution observed FM). Model performance was quantified through the following measures of calibration and overall model fit:

1. Calibration
   a. Calibration slope—a measure of the spread of predicted FM values in relation to the observed FM values.
   b. Calibration-in-the-large (CITL)—a measure of the average under- or over-estimation of FM from the prediction across the range of observed FM values. A CITL of zero implies no systematic under- or over-estimation is observed, while CITL values greater than or less than zero imply predicted FM values from the equation are systematically too low or too high respectively.

c. Calibration plot—a scatter plot of observed deuterium dilution observed FM values against predicted values of FM, with a smoothed curve through the data points.
2. R^2—the percentage of the variation in the observed deuterium dilution observed FM values that can be explained by the predicted value of FM.
3. Root mean squared error (RMSE): the average distance between predicted FM values from the model and the observed deuterium dilution observed FM, in kg.

Predictive performance was first assessed overall and then separately by sex and age (5 to 6-years-olds, 7-year-olds, and 8-year-olds) subgroups. To assess heterogeneity in model performance by subgroups, performance in each subgroup was pooled via random-effects meta-analyses using restricted maximum likelihood estimation (REML)[28] with the Hartung-Knapp[29] approach used to derive confidence intervals. Tau,[2] the estimate of between-study variance, was used to summarise heterogeneity for the three pooled performance measures.[30]

3 | RESULTS

3.1 | Included model equations

Of the 742 model equations identified from the three earlier reports[19,20,29] (58 by Kyle et al.,[20] 91 by De Castro et al.,[19] and 593 by Cerqueira et al.[29]), 18 equations from 17 independent publications met the inclusion criteria of this study and were included for external validation (Figure S1).[31–47] Of the 18 equations meeting our inclusion criteria, 1 included only predictors of basic anthropometry,[47] 12 equations additionally included predictors of skinfold thicknesses,[31–42] and 5 equations included predictors obtained from BIA in addition to basic anthropometry.[40,43–46] The Bodystat manufacturer BIA equation was also validated, resulting in a total of 19 equations for external validation (Figure S1). The model equations included for external validation are detailed in Table S1.

3.2 | External validation study population

Characteristics of the external validation population are summarised, by sex, in Table 1. The external validation data consisted of 323 children (42% males) with an average age of 7.7 years. While the average height and weight was similar among males and females, average levels of deuterium dilution observed FM were higher on average amongst females (median = 6.0 kg) compared to males (median = 4.9 kg).

3.3 | Assessment of predictive performance

FM estimates were obtained in the external validation data using each of the 19 equations. Table 2 provides a summary of the overall predictive performance of each of the model equations grouped by the primary predictor type on which the model equation is based upon (basic anthropometry only, Skinfold thicknesses, or BIA).

TABLE 1 Summary statistics of external validation analysis population.

Variable	Males ($n = 136$) Median (lower quartile—upper quartile)	Females ($n = 187$) Median (lower quartile—upper quartile)
Age (years)	7.7 (6.9–8.3)	7.7 (6.8–8.3)
Height (m)	1.21 (1.17–1.25)	1.20 (1.14–1.26)
Weight (kg)	22.3 (20.3–25.2)	22.2 (19.2–26.0)
BMI z-score	−0.25 (−0.93 to 0.44)	−0.16 (−0.88 to 0.64)
D_2O total body water (L)	13.13 (12.15–14.86)	12.26 (11.18–13.89)
D_2O fat mass (kg)	4.90 (4.03–6.05)	5.99 (4.55–7.94)
D_2O lean mass (kg)	17.09 (15.78–19.33)	15.91 (14.50–18.11)

Note: D_2O fat mass and lean mass relate to fat mass and lean mass observed using the deuterium dilution technique.

There was only one equation, the model by Hudda et al.,[47] which was based on basic anthropometry only and it provided a very high R^2 value (86.93%), excellent calibration of observed and predicted FM, and a low RMSE of 1.4 kg. Calibration plots, presented in Figure 1, graphically demonstrate the calibration performance of the equation.

Of the 12 equations utilizing skinfold thicknesses (Table 2, Figure 2), the vast majority provided R^2 values above 80%. However, the majority of the equations were miscalibrated in terms of the slope term and/or the CITL, with only five of the 95% confidence intervals for the calibration slope containing the ideal value of 1 and none of the 95% confidence intervals for the CITL values containing the ideal value of 0. The equation by Wickramasinghe et al.[36] provided the best overall calibration with a slope of 0.96 (95% CI: 0.90–1.03) and a CITL value of 0.71 (95% CI: 0.54–0.87). The RMSE values were relatively low from the majority of the equations, ranging between 1.1 kg (Wendel et al.)[41] and 3.2 kg (Yao et al.).[33]

The six equations which incorporated BIA assessed predictors had variable predictive performance (Table 2, Figure 3). Four of the model equations produced R^2 values of >80%, but the majority demonstrated marked miscalibration in terms of the slope and/or CITL. Models by Wickramasinghe et al.[45] and Ramírez et al.[40] had the highest predictive performance overall, with R^2 values of 84.69% and 82.83%, calibration slopes of 0.91 and 1.00, calibration-in-the-large values of −0.35 and 0.40 kg, and RMSE values of 1.2 and 1.2 kg, respectively. Notably, the Bodystat manufacturer BIA equation had poor predictive performance of FM, with a low R^2 value (58.98%), a poor calibration slope which is far from the ideal value of 1 (slope = 0.67), and a RMSE of 2.1 kg. However, the calibration-in-the-large value from this equation of 0.09 kg was very close to the ideal value of 0.

Sex-specific analyses demonstrated that for the majority of model equations from all three of the predictor type models, there were sex differences in the predictive performance. R^2 values were higher amongst females than males (Tables S2, S3, Figures S2–S4),

TABLE 2 Performance statistics of all equations for estimation of fat mass in kilograms.

Fat mass equation, author, year	*N*	R^2 (%)	Calibration slope	Calibration-in-the-large (kg)	RMSE (kg)
Basic anthropometry					
Hudda et al.[47]	323	86.93 (84.27, 89.59)	1.04 (0.99, 1.08)	0.98 (0.87, 1.09)	1.42
Skinfold thickness					
Frerichs et al.[31]	323	86.03 (83.20, 88.86)	1.14 (1.09, 1.19)	0.17 (0.04, 0.29)	1.12
Slaughter et al.[32]	322	84.41 (81.28, 87.54)	1.18 (1.12, 1.23)	2.79 (2.66, 2.92)	3.03
Yao et al.[33]	323	85.34 (82.39, 88.30)	1.57 (1.49, 1.64)	2.82 (2.67, 2.98)	3.17
Dezenberg et al.[34]	323	87.33 (84.75, 89.91)	1.03 (0.99, 1.07)	1.62 (1.51, 1.73)	1.91
Bray et al.[35]	323	84.23 (81.07, 87.38)	1.14 (1.09, 1.19)	1.80 (1.67, 1.93)	2.15
Wickramasinghe et al.[36]	323	72.22 (67.07, 77.37)	0.96 (0.90, 1.03)	0.71 (0.54, 0.87)	1.66
Kriemler et al.[37]	323	87.79 (85.29, 90.28)	1.04 (0.99, 1.08)	1.15 (1.04, 1.26)	1.52
Yeung and Hui[38]	323	84.58 (81.49, 87.67)	1.00 (0.95, 1.04)	1.18 (1.06, 1.31)	1.62
Pallaro et al.[39]	323	85.88 (83.03, 88.73)	0.98 (0.93, 1.02)	1.33 (1.21, 1.45)	1.71
Ramírez et al.[40]	323	86.01 (83.18, 88.84)	0.88 (0.84, 0.92)	1.96 (1.84, 2.09)	2.26
Wendel et al.[41]	323	88.06 (85.62, 90.50)	1.11 (1.06, 1.15)	0.35 (0.24, 0.46)	1.07
Britz et al.[42]	323	89.04 (86.78, 91.30)	1.06 (1.02, 1.10)	1.02 (0.91, 1.12)	1.39
BIA					
BIA manufacturer equation[a]	322	58.98 (52.10, 65.86)	0.67 (0.61, 0.74)	0.09 (−0.14, 0.32)	2.10
Deurenberg et al.[43]	323	87.38 (84.80, 89.95)	1.27 (1.21, 1.32)	0.15 (0.02, 0.28)	1.16
Horlick et al.[44]	323	86.84 (84.17, 89.52)	0.87 (0.83, 0.91)	3.26 (3.14, 3.38)	3.44
Wickramasinghe et al.[45]	323	84.69 (81.61, 87.76)	0.91 (0.86, 0.95)	−0.35 (−0.47, −0.22)	1.19
Khan et al.[46]	323	58.34 (51.40, 65.28)	0.87 (0.79, 0.95)	1.70 (1.50, 1.91)	2.52
Ramírez et al.[40]	323	82.83 (79.42, 86.23)	1.00 (0.95, 1.05)	0.40 (0.27, 0.53)	1.24

[a]Manufacturer equation from Bodystat1500MDD, MultiScan 5000 software.

calibration slopes from some models demonstrated greater miscalibration amongst males, while others among females (Tables S2, S3, Figures S1, S2, S5, S6), CITL values were largely closer to the ideal value of zero amongst males than females (Tables S2, S3, Figures S2, S7, S8), and RMSE values were lower amongst males compared to females for the majority of equations (Tables S2, S3). Model performances by age groups (5- to 6-year-olds, 7-year-olds, and 8-year-olds) are presented in Tables S4–S6. Model equations generally performed better in terms of their R^2 and calibration slope values at older ages compared to the youngest age group. CITL was generally similar across each age group with low levels of variation. However, the RMSE was marginally higher in the older age groups compared to the youngest children.

4 | DISCUSSION

4.1 | Summary of principal findings

In this study, we perform a systematic external validation of an extensive number of published prediction model equations for the estimation of childhood FM, in order to assess their performance and generalizability in this South African population of children of Black African ethnic origins. Model equations that were validated were of three groups: those based upon basic anthropometric predictors only, those that additionally used skinfold thickness measurements as predictors, and those that additionally used predictors obtained from BIA. The equations with the highest predictive performance from each of the three categories of equations were by Hudda et al.,[47] Wickramasinghe et al.,[36] and Ramírez et al.[40] The overall predictive performances of these three equations were similar, with excellent calibration (agreement) of model estimated FM with deuterium dilution observed FM, and relatively low levels of average error. Notably, one of the highest performing model equations is the one by Hudda et al., which was based on basic anthropometry and demographics alone.

4.2 | Comparison with other studies

The majority of studies did not report model calibration statistics and typically just the R^2 and RMSE values were available, making comparisons difficult. Comparable statistics were available for the Hudda et al.,[47,48] Dezenberg et al.,[34] Wickramasing et al.,[36] and Pallaro et al.[39] models. The performance of the Hudda et al. model was very similar to that observed from earlier external validations within the United Kingdom ($R^2 = 90.0\%$, calibration slope $= 1.02$, CITL $= -1.58$ kg, RMSE $= 2.6$ kg)[47] and South African ($R^2 = 83.3\%$, calibration slope $= 1.03$, CITL $= 0.82$ kg,

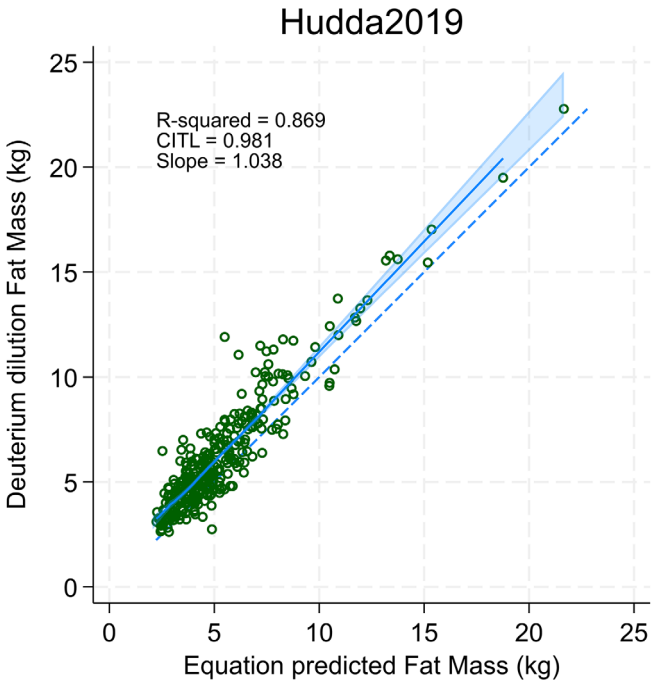

FIGURE 1 Calibration plot of equations based on basic anthropometry predictors. Deuterium dilution fat mass relates to fat mass observed using the deuterium dilution technique. RMSE from this model is 1.42 kg. Dashed line represents the line of equality. Solid line is a symmetric nearest neighbour through the individual data points. Slope = calibration slope; CITL = calibration-in-the-large.

RMSE = 1.4 kg)[48] childhood settings. The performance of the Dezenberg et al.,[34] Wickramasing et al.,[36] and Pallaro et al.[39] models was marginally poorer in this validation population compared to within their respective original development populations, which is likely due to model overfitting (and optimism) in the performance of models when assessed in the data used to develop them. Furthermore, differences in model performance across development and validation data can also occur due to underlying differences in the respective populations.[22] For example, models developed on populations of white European origins may not perform as well in this population of black African children. Of all included models, only those proposed by Hudda et al. and Dezenberg et al. included ethnicity as a predictor within their model equations. The findings of this study re-emphasise the poor performance of BIA manufacturer model equations reported in earlier studies.[10,15,19] In particular, the calibration slope of 0.67 reported here in this population when assessing the BIA manufacturer model equation further strengthens previous findings that these manufacturer equations overestimate FM for children with lower levels of FM and underestimate FM at the upper end of the FM distribution.[14,15,49]

4.3 | Strengths and limitations

The present study has several strengths in its approach to validating several published childhood FM prediction equations in this specific South African childhood population. Firstly, each prediction equation was assessed by comparing its performance at predicting FM to FM observed from the deuterium dilution of stable nuclear reference-standard technique. This technique is known to provide accurate, safe, and minimally invasive measurements of total body water (and fat-free mass) with very low error.[10,11] The IAEA standard protocol for administering the isotope technique was followed to ensure. Secondly, the sample size of 323 is suitable enough to provide predictive performance metrics with a high level of precision as per recent sample size guidelines for the external validation of prediction models with a continuous outcome, within which FM models were used as an applied example.[50] Thirdly, this study validated a large number of available prediction equations which used predictors of basic anthropometry, skinfold thickness measurements, or BIA. Finally, we followed the TRIPOD guideline for the reporting of studies validating a multivariable prediction model[22] to ensure robust statistical methods were used for the calculation of the prediction performance statistics. However, there are some limitations of this study to note. The validation population contained black children of South African origin and of a fairly narrow age group only, and thus findings need further validation in data resources with a wider age range and South African children of other ethnic origins. There were several additional prediction models based on predictors of skinfold thickness, which could not be included as they required four skinfold measurements to have been taken, whereas the external validation data used in this study only contained two of the four measurements. Moreover, the systematic reviews which were used to source the available skinfold thickness and BIA prediction models[18–20] were published between 2013 and 2017, and thus there may be additional more recent prediction equations which were not included here. However, the addition of these equations is unlikely to have changed the conclusion and recommendation that the Hudda et al. equation should be utilized in this population due to its high predictive performance at the individual level (due to its low RMSE value) and population level (due to its high R^2 value and high levels of calibration) and crucially, that it only requires basic anthropometry predictors of weight, height, sex, age, and ethnicity. The systematic review by Cerqueira et al.[21] which was used to source prediction equations based on anthropometric predictors was performed more recently (December 2019). Finally, the current validation dataset contained a wide range of FM values across the distribution, which allowed us to examine the performance of the models across the whole distribution for children of this age range. Therefore, although the data were collected in 2017 to 2018, it is likely model performance would be the same in more contemporary data.

4.4 | Implications

BMI-for-age is widely used because of its simplicity and reliance solely on measures of height and weight though its limitations are widely recognised.[51–59] As a weight-based proxy marker of body fat, BMI is unable to discriminate between FM and fat-free/lean mass, which has

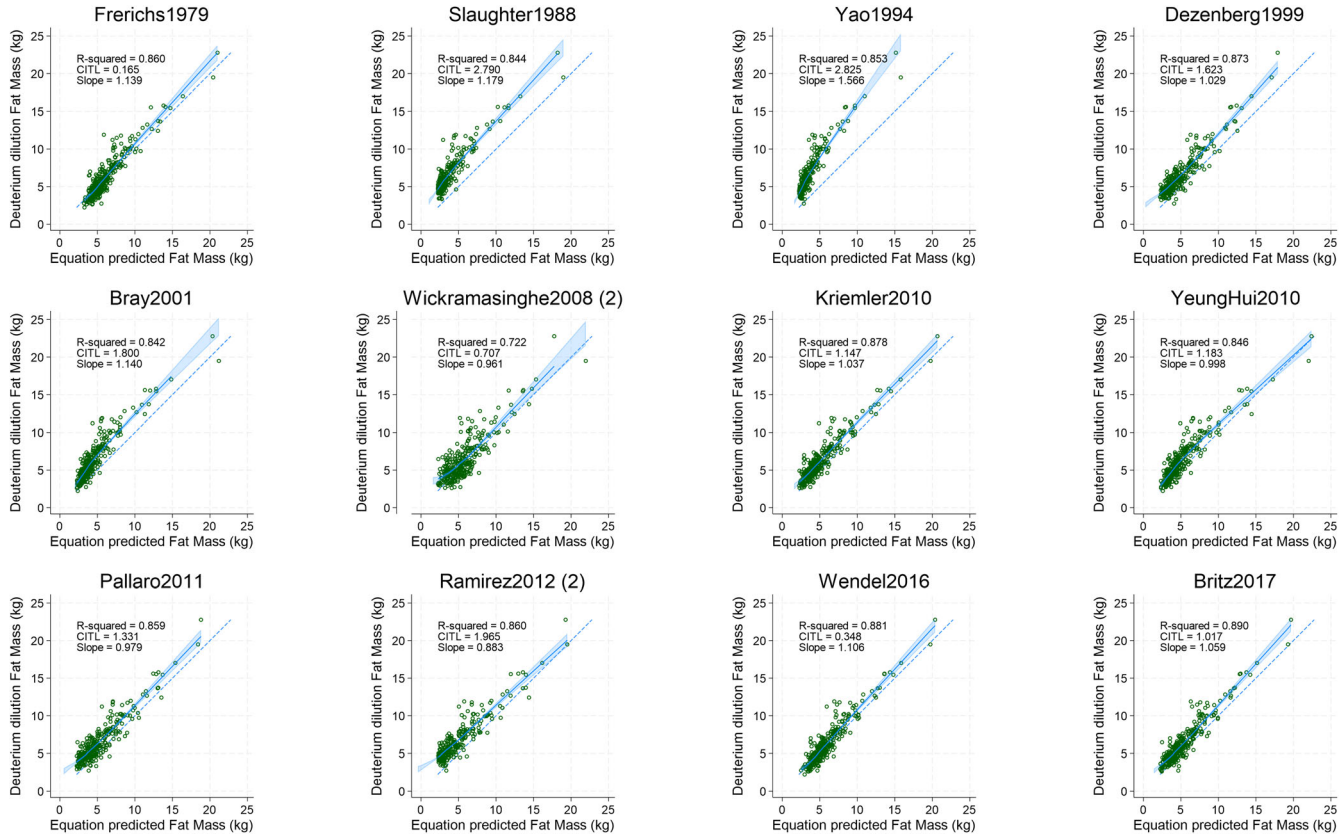

FIGURE 2 Calibration plot of equations based on skinfold thickness measurements. Deuterium dilution fat mass relates to fat mass observed using the deuterium dilution technique. Dashed line represents the line of equality. Solid line is a symmetric nearest neighbour through the individual data points. Slope = calibration slope; CITL = calibration-in-the-large.

been shown to vary markedly in individuals with a given BMI.[53] Additionally, the use of weight-for-height classifications enforces the misconception that body weight is more important than fatness. However, there is an important distinction to be made between being thin and being lean. While thinness is related to body weight, leanness is associated with body composition. Thin individuals may weigh less than the recommended value in height-weight tables, whereas lean individuals with little body fat may weigh more than the ideal.[60] Crucially, childhood BMI is not a consistent marker of body fat across different ethnic groups, underestimating body fat among South Asian children and overestimating it amongst Black African children.[16,56,61,62] Given the World Health Organization's definition of obesity is "excessive fat deposits that can impair health,"[63,64–66] accurate yet simple methods for direct FM assessment are crucial for the advancement of the field of childhood adiposity. All in vivo techniques to assess FM (such as DXA, MRI or BIA) are based upon a predictive model equation which each require validation to assess their performance. The findings of this study demonstrate that out of all 19 equations externally validated within this South African population, the model proposed by Hudda et al. (which only requires information on childhood age, sex, weight, height, and ethnicity) has great potential for both individual/clinical- and population-level implementation for the assessment of childhood FM in South African children due to its high accuracy and simplicity. Notably, this model has demonstrated very good performance upon external validation within several multi-ethnic childhood settings including from South Africa.[48,67,68] While models by Wickramasinghe et al.[36] and Ramírez et al.[40] also produced similar accuracy in terms of their FM estimates in this population, these equations required additional measurements of skinfold thickness and bioimpedance respectively making them more difficult to recommend for clinical or population health practice where these parameters are often not available.

4.5 | Further Research

Further validation of the included models within a wider age range and children of additional ethnic origins among South African children would add to the generalizability of the findings. Additionally, population-, sex-, and age-specific reference values of childhood FM are needed, based upon prospectively associated disease risks as opposed to current centile-based approaches,[69] would allow individuals to be classified into groups based on future disease risk attributable to their current FM levels.

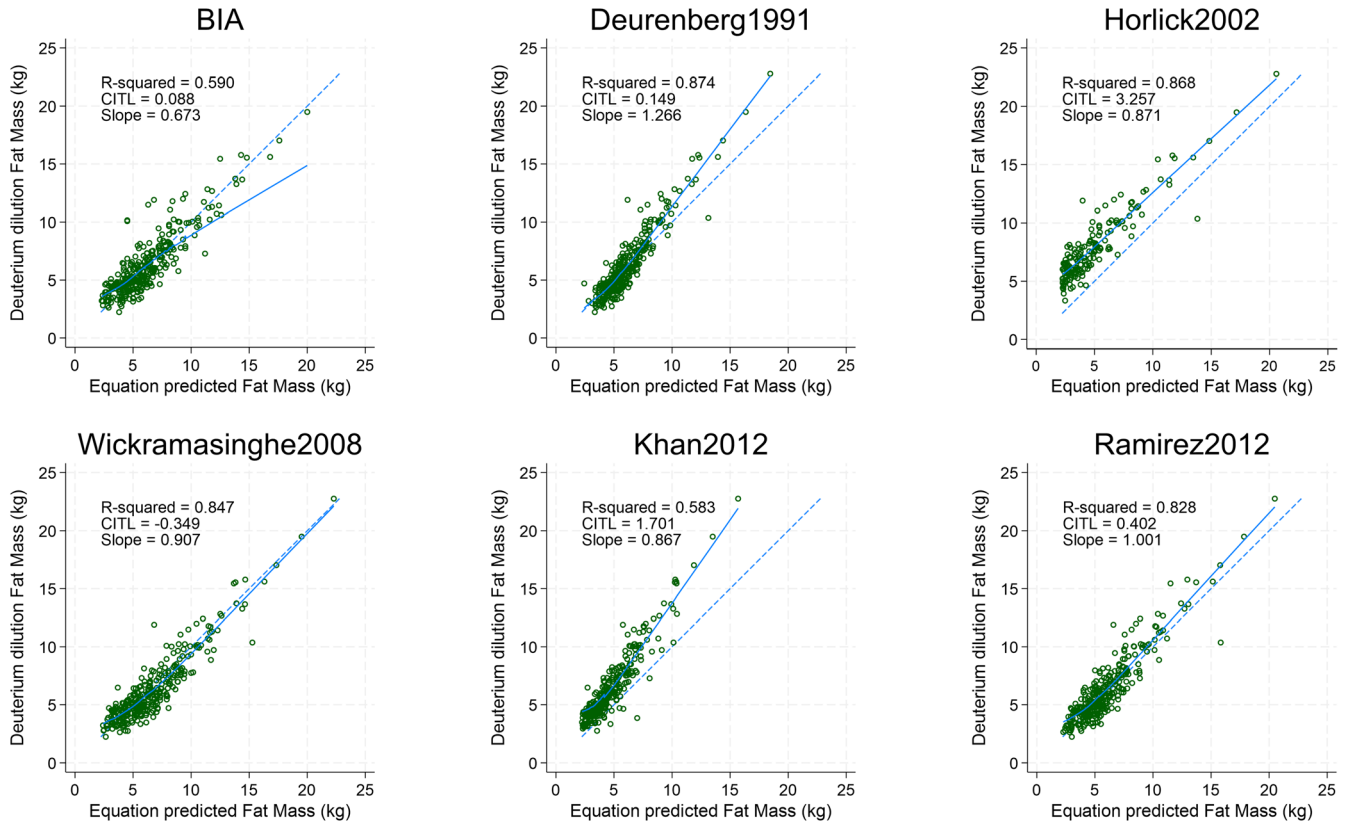

FIGURE 3 Calibration plot of equations based on bioelectrical impedance analysis. Deuterium dilution fat mass relates to fat mass observed using the deuterium dilution technique. BIA relates to FM observed by the BIA manufacturer model into the Bodystat1500MDD, MultiScan 5000 software. Dashed line represents the line of equality. Solid line is a symmetric nearest neighbour through the individual data points. Slope = calibration slope; CITL = calibration-in-the-large.

AUTHOR CONTRIBUTIONS

Study design—MT Hudda, MA Monyeki. Data analysis—MT Hudda. Data interpretation—all authors. Drafting manuscript—MT Hudda. Critical evaluation and revision of manuscript—all authors.

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CONFLICT OF INTEREST STATEMENT

The authors have no competing interests to declare.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/dom.70129.

DATA AVAILABILITY STATEMENT

The dataset analysed during the current study is available from the corresponding author on reasonable request, and permission will be followed in accordance with the NWU policies, and Research Data management policy: RDM Policy & Legislation-; https://libguides.nwu.ac.za/research-data-management/rdm-policy-legislation.

ETHICAL STATEMENT

The parents and their children gave informed consent and assent, respectively, to participate in the study. The study was granted

permission by the Health Research Ethics Committee (Ethic no: NWU-00025-17-S1) of the Faculty of Health Sciences (HREC) of the North-West University.

ORCID

M. T. Hudda https://orcid.org/0000-0001-7894-1159

REFERENCES

1. Macias N, Aleman-Mateo H, Esparza-Romero J, Valencia ME. Body fat measurement by bioelectrical impedance and air displacement plethysmography: a cross-validation study to design bioelectrical impedance equations in Mexican adults. *Nutr J*. 2007;6:18.
2. Hill GL. Jonathan E. Rhoads lecture. Body composition research: implications for the practice of clinical nutrition. *JPEN J Parenter Enteral Nutr*. 1992;16(3):197-218.
3. World Health Organisation. Obesity. https://www.who.int/health-topics/obesity. Accessed August 27, 2025
4. Wells JC, Fewtrell MS. Measuring body composition. *Arch Dis Child*. 2006;91(7):612-617.
5. Duren DL, Sherwood RJ, Czerwinski SA, et al. Body composition methods: comparisons and interpretation. *J Diabetes Sci Technol*. 2008;2(6):1139-1146.
6. Lee SY, Gallagher D. Assessment methods in human body composition. *Curr Opin Clin Nutr Metab Care*. 2008;11(5):566-572.
7. Lukaski HC. Methods for the assessment of human body composition: traditional and new. *Am J Clin Nutr*. 1987;46(4):537-556.
8. Cole TJ, Freeman JV, Preece MA. Body mass index reference curves for the UK, 1990. *Arch Dis Child*. 1995;73(1):25-29.
9. Cole TJ, Lobstein T. Extended international (Iotf) body mass index cut-offs for thinness, overweight and obesity. *Pediatr Obes*. 2012;7(4):284-294.
10. Wells JC, Fuller NJ, Dewit O, Fewtrell MS, Elia M, Cole TJ. Four-component model of body composition in children: density and hydration of fat-free mass and comparison with simpler models. *Am J Clin Nutr*. 1999;69(5):904-912.
11. Deurenberg P, Yap M. The assessment of obesity: methods for measuring body fat and global prevalence of obesity. *Baillieres Best Pract Res Clin Endocrinol Metab*. 1999;13(1):1-11.
12. Prentice AM, Jebb SA. Beyond body mass index. *Obes Rev*. 2001;2(3):141-147.
13. Clasey JL, Hartman ML, Kanaley J, et al. Body composition by Dexa in older adults: accuracy and influence of scan mode. *Med Sci Sports Exerc*. 1997;29(4):560-567.
14. Reilly JJ, Gerasimidis K, Paparacleous N, et al. Validation of dual-energy X-ray absorptiometry and foot-foot impedance against deuterium dilution measures of fatness in children. *Int J Pediatr Obes*. 2010;5(1):111-115.
15. Hudda MT, Owen CG, Rudnicka AR, Cook DG, Whincup PH, Nightingale CM. Quantifying childhood fat mass: comparison of a novel height-and-weight-based prediction approach with Dxa and bioelectrical impedance. *Int J Obes*. 2020;45:99-103.
16. Nightingale CM, Rudnicka AR, Owen CG, et al. Are ethnic and gender specific equations needed to derive fat free mass from bioelectrical impedance in children of south Asian, black African-Caribbean and white European origin? Results of the assessment of body composition in children study. *PLoS One*. 2013;8(10):e76426.
17. Shypailo RJ, Butte NF, Ellis KJ. Dxa: can it be used as a criterion reference for body fat measurements in children? *Obesity (Silver Spring)*. 2008;16(2):457-462.
18. Silva AM, Fields DA, Sardinha LB. A Prisma-driven systematic review of predictive equations for assessing fat and fat-free mass in healthy children and adolescents using multicomponent molecular models as the reference method. *J Obes*. 2013;2013:148696.
19. Chula de Castro JA, Lima TR, Silva DAS. Body composition estimation in children and adolescents by bioelectrical impedance analysis: a systematic review. *J Bodyw Mov Ther*. 2018;22(1):134-146.
20. Kyle UG, Earthman CP, Pichard C, Coss-Bu JA. Body composition during growth in children: limitations and perspectives of bioelectrical impedance analysis. *Eur J Clin Nutr*. 2015;69(12):1298-1305.
21. Cerqueira MS, Amorim PRS, Encarnacao IGA, et al. Equations based on anthropometric measurements for adipose tissue, body fat, or body density prediction in children and adolescents: a scoping review. *Eat Weight Disord*. 2022;27(7):2321-2338.
22. Moons KM, Altman DG, Reitsma JB, et al. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (tripod): explanation and elaboration. *Ann Intern Med*. 2015;162(1):W1-W73.
23. Moeng-Mahlangu LT, Monyeki MA, Reilly JJ, et al. Level of agreement between objectively determined body composition and perceived body image in 6- to 8-year-old south African children: the body composition-isotope technique study. *PLoS One*. 2020;15(8):e0237399.
24. International Atomic Energy Agency. *Introduction to Body Composition Assessment Using the Deuterium Dilution Technique with Analysis of Saliva Samples by Fourier Transform Infrared Spectrometry*. Iaea: Human Health Series No. 12; 2011.
25. Lohman T. Assessment of body composition in children. *Pediatr Exerc Sci*. 1989;1(1):19-30.
26. Fomon SJ, Haschke F, Ziegler EE, Nelson SE. Body composition of reference children from birth to age 10 years. *Am J Clin Nutr*. 1982;35(5 Suppl):1169-1175.
27. de Beer M, Timmers T, Weijs PJM, Gemke RJBJ. Validation of total body water analysis by bioelectrical impedance analysis with deuterium dilution in (pre)school children. *E-Spen Eur E J Clin Nutr Metab*. 2011;6(5):e223-e226.
28. Viechtbauer W. Bias and efficiency of meta-analytic variance estimators in the random-effects model. *J Educ Behav Stat*. 2005;30(3):261-293.
29. Hartung J, Knapp G. On tests of the overall treatment effect in meta-analysis with normally distributed responses. *Stat Med*. 2001;20(12):1771-1782.
30. Riley RD, Higgins JPT, Deeks JJ. Interpretation of random effects meta-analyses. *Br Med J*. 2011;342:d549.
31. Frerichs RR, Harsha DW, Berenson GS. Equations for estimating percentage of body fat in children 10-14 years old. *Pediatr Res*. 1979;13(3):170-174.
32. Slaughter MH, Lohman TG, Boileau RA, et al. Skinfold equations for estimation of body fatness in children and youth. *Hum Biol*. 1988;60(5):709-723.
33. Yao XJ, Chen Z, Zhang GY. A study on body fat in children aged 7-12. *Zhonghua Yu Fang Yi Xue Za Zhi*. 1994;28(4):213-215.
34. Dezenberg CV, Nagy TR, Gower BA, Johnson R, Goran MI. Predicting body composition from anthropometry in pre-adolescent children. *Int J Obes Relat Metab Disord*. 1999;23(3):253-259.
35. Bray GA, DeLany JP, Harsha DW, Volaufova J, Champagne CC. Evaluation of body fat in fatter and leaner 10-y-old African American and white children: the Baton Rouge Children's study. *Am J Clin Nutr*. 2001;73(4):687-702.
36. Wickramasinghe VP, Lamabadusuriya SP, Cleghorn GJ, Davies PS. Assessment of body composition in Sri Lankan children: validation of a skin fold thickness equation. *Ceylon Med J*. 2008;53(3):83-88.
37. Kriemler S, Puder J, Zahner L, Roth R, Meyer U, Bedogni G. Estimation of percentage body fat in 6- to 13-year-old children by skinfold thickness, body mass index and waist circumference. *Br J Nutr*. 2010;104(10):1565-1572.
38. Yeung DC, Hui SS. Validity and reliability of skinfold measurement in assessing body fatness of Chinese children. *Asia Pac J Clin Nutr*. 2010;19(3):350-357.

39. Pallaro A, Vidueiros S, Morea G, et al. Validation of body fat mass prediction models for Argentinian children using anthropometry. *Ann Nutr Metab*. 2011;58:356-357.
40. Ramírez E, Valencia ME, Bourges H, et al. Body composition prediction equations based on deuterium oxide dilution method in Mexican children: a national study. *Eur J Clin Nutr*. 2012;66(10):1099-1103.
41. Wendel D, Weber D, Leonard MB, et al. Body composition estimation using skinfolds in children with and without health conditions affecting growth and body composition. *Ann Hum Biol*. 2016;44(2):108-120.
42. Britz M, Aznarez A, Santa ANA. Desarrollo Y Validación De Ecuaciones Para Estimar Composición Corporal En Niños De 4 a 6 Años De Uruguay. *Rev Chil Nutr*. 2017;44:9.
43. Deurenberg P, van der Kooy K, Leenen R, Weststrate JA, Seidell JC. Sex and age specific prediction formulas for estimating body composition from bioelectrical impedance: a cross-validation study. *Int J Obes*. 1991;15(1):17-25.
44. Horlick M, Arpadi SM, Bethel J, et al. Bioelectrical impedance analysis models for prediction of total body water and fat-free mass in healthy and Hiv-infected children and adolescents. *Am J Clin Nutr*. 2002;76(5):991-999.
45. Wickramasinghe VP, Lamabadusuriya SP, Cleghorn GJ, Davies PS. Assessment of body composition in Sri Lankan children: validation of a bioelectrical impedance prediction equation. *Eur J Clin Nutr*. 2008;62(10):1170-1177.
46. Khan AI, Hawkesworth S, Hawlader MD, et al. Body composition of Bangladeshi children: comparison and development of leg-to-leg bioelectrical impedance equation. *J Health Popul Nutr*. 2012;30(3):281-290.
47. Hudda MT, Fewtrell MS, Haroun D, et al. Development and validation of a prediction model for fat mass in children and adolescents: meta-analysis using individual participant data. *Br Med J*. 2019;366:l4293.
48. Hudda MT, Wells JCK, Adair LS, et al. External validation of a prediction model for estimating fat mass in children and adolescents in 19 countries: individual participant data meta-analysis. *Br Med J*. 2022;378:e071185.
49. Eisenkölbl J, Kartasurya M, Widhalm K. Underestimation of percentage fat mass measured by bioelectrical impedance analysis compared to dual energy X-ray absorptiometry method in obese children. *Eur J Clin Nutr*. 2001;55(6):423-429.
50. Archer L, Snell KIE, Ensor J, Hudda MT, Collins GS, Riley RD. Minimum sample size for external validation of a clinical prediction model with a continuous outcome. *Stat Med*. 2020;40:133-146.
51. Chinn S, Rona RJ, Gulliford MC, Hammond J. Weight-for-height in children aged 4-12 years. A new index compared to the normalized body mass index. *Eur J Clin Nutr*. 1992;46(7):489-500.
52. Fung KP, Lee J, Lau SP, Chow OK, Wong TW, Davis DP. Properties and clinical implications of body mass indices. *Arch Dis Child*. 1990;65(5):516-519.
53. Wells JC. A Hattori chart analysis of body mass index in infants and children. *Int J Obes Relat Metab Disord*. 2000;24(3):325-329.
54. Benn RT. Some mathematical properties of weight-for-height indices used as measures of adiposity. *J Epidemiol Community Health*. 1971;25(1):42-50.
55. Johnson W, Norris T, Bann D, et al. Differences in the relationship of weight to height, and thus the meaning of Bmi, according to age, sex, and birth year cohort. *Ann Hum Biol*. 2020;47(2):199-207.
56. Hudda MT, Nightingale CM, Donin AS, et al. Body mass index adjustments to increase the validity of body fatness assessment in UK black African and South Asian children. *Int J Obes*. 2017;41(7):1048-1055.
57. L'Abee C, Visser GH, Liem ET, Kok DE, Sauer PJ, Stolk RP. Comparison of methods to assess body fat in non-obese six to seven-year-old children. *Clin Nutr*. 2010;29(3):317-322.
58. Hudda MT, Aarestrup J, Owen CG, Baker JL, Whincup PH. Varying optimal power for height-standardisation of childhood weight, fat mass and fat-free mass across the obesity epidemic. *Int J Obes*. 2024;49:84-92.
59. Müller MJ, Bosy-Westphal A. Has the Bmi had its day? *Int J Obes*. 2025;49(1):1-3.
60. Heyward VH. *Applied Body Composition Assessment*. Human Kineties; 1996:2-20.
61. Nightingale CM, Rudnicka AR, Owen CG, Cook DG, Whincup PH. Patterns of body size and adiposity among UK children of south Asian, black African-Caribbean and white European origin: child heart and health study in England (chase study). *Int J Epidemiol*. 2011;40(1):33-44.
62. Shaw NJ, Crabtree NJ, Kibirige MS, Fordham JN. Ethnic and gender differences in body fat in British schoolchildren as measured by Dxa. *Arch Dis Child*. 2007;92(10):872-875.
63. World Health Organisation. Obesity and Overweight 2022. https://www.who.int/en/news-room/fact-sheets/detail/obesity-and-overweight. Accessed August 27, 2025
64. Busetto L, Dicker D, Frühbeck G, et al. A new framework for the diagnosis, staging and management of obesity in adults. *Nat Med*. 2024;30(9):2395-2399.
65. Reinehr T, Dieris B. New clinical practice guideline for evaluation and treatment of children and adolescents with obesity: paradigm shifts. *Lancet Diabetes Endocrinol*. 2023;11(4):222-223.
66. Rubino F, Cummings DE, Eckel RH, et al. Definition and diagnostic criteria of clinical obesity. *Lancet Diabetes Endocrinol*. 2025;13:221-262.
67. Choy CC, Johnson W, Duckham RL, et al. Prediction of fat mass from anthropometry at ages 7 to 9 years in Samoans: a cross-sectional study in the Ola Tuputupua'e cohort. *Eur J Clin Nutr*. 2023;77(4):495-502.
68. Al-Ati T, El Kari K, Nasreddine L, et al. External validation of a prediction model for estimating fat mass in Arab children and adolescents. *Diabetes Obes Metab*. 2025;27:2740-2749.
69. McCarthy HD, Cole TJ, Fry T, Jebb SA, Prentice AM. Body fat reference curves for children. *Int J Obes*. 2006;30(4):598-602.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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