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Validity between dual-energy x-ray absorptiometry and bioelectrical impedance for segmental fat analysis and a novel low-cost model developed using anthropometry in young adults

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Abstract

Background Accurate body fat distribution assessment is essential for managing cardiovascular disease and metabolic disorders. Although several methods are available for segmental fat analysis, few studies have examined the validity of affordable methods such as Bioelectrical Impedance Analysis (BIA) against the reference method, Dual-Energy X-ray Absorptiometry (DXA). This study aimed to assess the validity of BIA as compared to DXA for segmental fat mass assessment, and to develop anthropometric multivariate regression models that offer a cost-effective alternative for health professionals in clinical and public health settings.

Methods Cross-sectional study that included 264 young adults (161 males, mean age = 23.04 ± 5.61 years; and 103 females, mean age = 22.29 ± 5.98 years). Segmental fat mass was measured using DXA and BIA, and anthropometric measurements were collected following the ISAK protocol.

Results Significant differences were found between DXA and BIA for segmental fat mass ($p < 0.001$). Sex significantly influenced the results ($p < 0.05$), while BMI and hydration status had no significant impacts. The Bland-Altman analysis revealed significant differences ($p < 0.001$) between BIA and DXA for fat mass in the upper and lower limbs. Trunk fat mass also differed significantly in males and females ($p < 0.001$), except for the overall sample ($p = 0.088$). Anthropometric multivariate regression models showed a high predictive accuracy for both females ($R^2 = 0.766-0.910$; $p < 0.001$) and males ($R^2 = 0.758-0.887$; $p < 0.001$). Key predictors of segmental fat mass included body mass ($r = 0.606-0.867$; $p < 0.001$), skinfold thickness ($r = 0.688-0.893$; $p < 0.001$), and waist girth ($r = 0.883-0.810$; $p < 0.001$). Peripheral skinfolds were highly predictive for upper and lower limbs, while waist girth was relevant for trunk fat mass.

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Conclusions DXA and BIA are not interchangeable for segmental fat analysis due to the significant differences observed. However, the anthropometric multivariate regression models developed provide a cost-effective and reliable alternative for predicting segmental fat mass in clinical settings where DXA is unavailable.

Trial registration Not applicable.

Keywords Body composition, Fat mass, Body segment, Dual-energy x-ray absorptiometry, Bioelectrical impedance analysis, Anthropometry, Health

Introduction

Accurately quantifying body fat is critical in public health. It provides essential information for strategies aimed at mitigating the risk of chronic diseases such as obesity, diabetes, and cardiovascular conditions [1–3]. Furthermore, understanding fat distribution, beyond total body fat, is essential due to its heterogeneous distribution throughout the body, which can lead to varying health outcomes [4, 5]. Notably, visceral fat accumulation, particularly in the abdominal area, is strongly associated with metabolic and cardiovascular diseases [6, 7], and challenges in balance and stability, increasing the risk of falls [8]. Additionally, excess fat accumulation in the trunk or lower limbs can impair daily activities, limiting autonomy and diminishing overall functional capacity [9].

Dual-energy X-ray absorptiometry (DXA), bioelectrical impedance analysis (BIA), and anthropometry are the most commonly used methods for assessing body fat [10, 11]. DXA is widely regarded as the benchmark due to its high accuracy, particularly in the assessment of bone mineral content. However, its high operational costs and limited accessibility restrict its use to well-funded institutions [10, 12]. BIA is a more affordable and portable alternative that provides segmental data, but is limited by its reliance on pre-established equations, which may reduce accuracy in certain populations [13–15]. In addition, its reliability may depend on the technology used, the position in which the assessment is performed, or differences in the placement of the electrodes [16, 17]. Anthropometry, which estimates subcutaneous adiposity through skinfold measurements, is an accessible and cost-effective method for assessing body fat [18]. Its affordability and portability make it especially valuable in both athletic and clinical settings [15]. Furthermore, it can be consistently replicated by trained practitioners following standardized protocols [19].

BIA and DXA devices frequently provide detailed segmental reports on fat and other body components, highlighting their usefulness in clinical and sports studies [20, 21]. While numerous studies have validated BIA against DXA for overall fat estimation [22–24], research at the segmental level remains scarce. Consequently, the validity of BIA as compared to DXA for segmental fat analysis is not well established. In contrast, anthropometry

has received limited attention in segmental fat analysis. To date, only two studies have attempted to estimate segmental fat using anthropometry, both of which faced significant methodological shortcomings [25, 26]. In one study, some of the included anthropometric variables were not part of the standardized International Society for the Advancement on Kinanthropometry (ISAK) protocol; and it included the use of only 31 anthropometric variables, omitting key measurements outlined in the ISAK protocol, which likely reduced the accuracy of their predictive models [25]. The other study employed a broad age range (21–82 years), introducing variability in fat distribution across life stages and limiting the applicability of their findings to more homogeneous populations [26]. Additionally, both studies exclusively measured the right side of the body, failing to capture potential asymmetries between dominant and non-dominant limbs [25, 26]. To the authors' knowledge, no study has yet conducted a comprehensive analysis of segmental fat using anthropometry in a large, homogeneous young sample, with measurements taken bilaterally and following the updated ISAK protocol. This gap highlights the need for further research to explore the potential of anthropometry as a reliable tool for segmental fat estimation.

In addition, differences in fat distribution related to sex, adiposity accumulation and hydration status, should be taken into account when performing segmental fat analysis. Not surprisingly, previous studies have demonstrated the influence of this factor on the comparability between different methods of estimating fat mass from a global point of view [27–30]. With respect to sex-related differences, males typically exhibit a visceral fat accumulation pattern, often described as an 'apple-shaped' distribution, while females tend to have a 'pear-shaped' pattern characterized by subcutaneous fat predominantly stored around the hips and thighs, and a lower visceral fat accumulation, especially in their pre-menopausal stage [29, 31]. Furthermore, BMI, a widely recognized indicator of overall adiposity, has been shown to significantly affect the precision of fat mass estimates and agreement with the different body composition calculation methods, particularly in individuals with extreme body mass indices [32]. Finally, hydration status has been shown to have a direct impact on the electrical properties measured by BIA, as fluctuations in total body water alter resistance

and reactance values, influencing fat mass estimates, which could affect the estimation of the body composition with one of these methods [12, 33, 34]. However, no studies have analyzed the influence of these factors on the agreement between methods that address body composition from a segmental point of view.

Recognizing these gaps, this study aims to address the need for accessible and accurate methods to estimate segmental fat distribution. Specifically, anthropometry, as an accessible and cost-effective method, can provide valuable insights into segmental fat distribution without the need for expensive equipment such as DXA. Such models can improve health outcomes by facilitating early interventions in order to address health disparities in populations with limited access to advanced medical technology.

Therefore, the objectives of the present study were: (a) to analyze the differences between DXA and BIA in measuring segmental fat, and to determine the influence of BMI, hydration status, and sex, on the differences between methods; and (b) to develop anthropometric formulas through multivariate regression to predict the kg of fat in each body segment (right and left upper limbs, trunk, and right and left lower limbs), as compared with DXA.

With regard to the hypotheses of the present research, (a) given the known discrepancies between DXA and BIA in general body fat analysis, it is hypothesized that significant differences will be observed in segmental fat measurements between these two methods, with a significant effect of the co-variables. (b) Additionally, considering the high predictive power of certain anthropometric variables, such as skinfold thicknesses, as demonstrated in previous studies [35], it is hypothesized that accurate multivariate regression models can be developed to estimate segmental fat mass using anthropometric measurements.

Materials and methods

Design

This study utilized a descriptive, cross-sectional design. Participants were recruited through non-probabilistic convenience sampling. The minimum sample size was calculated using Rstudio 3.15.0 software (Rstudio Inc., Boston, MA, USA), with a significance level set at $\alpha=0.05$. The standard deviation (SD) for fat mass percentage was determined from previous studies ($SD=5.19$) [18, 36]. Based on this methodology, the minimum required sample size was 103 participants per group, assuming an error (d) of 1.00% for fat mass percentage within a 95% confidence interval (CI). The study aimed for a statistical power greater than 0.80, achieving a calculated power of 0.96, which is considered high.

The Ethics Committee of the Catholic University San Antonio of Murcia (Murcia, Spain) reviewed and approved the data collection protocol, adhering to the World Medical Association Code (CE062103). The study followed all recommendations from the Declaration of Helsinki. Participants were informed about the study procedures and provided written consent prior to participation.

Participants

A total of 264 participants volunteered to take part in the study. Of these, 161 were males (mean age= 23.04 ± 5.61 years) and 103 were females (mean age= 22.29 ± 5.98 years). The flow diagram of the sample selection process can be consulted in Fig. 1. The inclusion criteria were: (1) to be a student in any of the university subjects related to body composition in the Nutrition, Physiotherapy and Sports Sciences degree of the Universidad Católica San Antonio de Murcia, UCAM (Murcia, Spain); (2) being 18–35 years of age; and (3) fasting for at least 8 h prior to the measurements. The exclusion criteria were: (1) engaging in vigorous exercise within 24 h, or any physical activity on the same day; (2) consumption of diuretics or heavy meals within 24 h before the session; (3) any injury or condition affecting the measurements; (4) diseases influencing body fat; (5) hormonal or corticosteroid treatment in the past three months (excluding menstrual regulation); (6) for females, not being between the second half of the follicular phase and the first half of the late phase; (7) use of sports supplements affecting fat distribution or composition estimation; and (8) failure to complete all measurements (Fig. 1).

Protocol

Within the university subjects related to body composition in the degree of Nutrition, Physiotherapy, and Sport Sciences at the Universidad Católica San Antonio de Murcia, UCAM (Murcia, Spain), an announcement was posted in the virtual classroom to invite students to participate in the study. Interested individuals completed an initial questionnaire, and those meeting the inclusion criteria were contacted for further instructions. Informed consent was obtained from each participant, and measurement appointments were scheduled, considering the menstrual cycle for female participants. All the sessions were conducted in the morning between 8am and 10am, with participants fasting from the previous night. The females' appointments were arranged to avoid variations due to different stages of their menstrual cycle. For this, an online questionnaire asking for the total length of the menstrual cycle and the date of the last menstrual period was previously completed by each of the female participants.

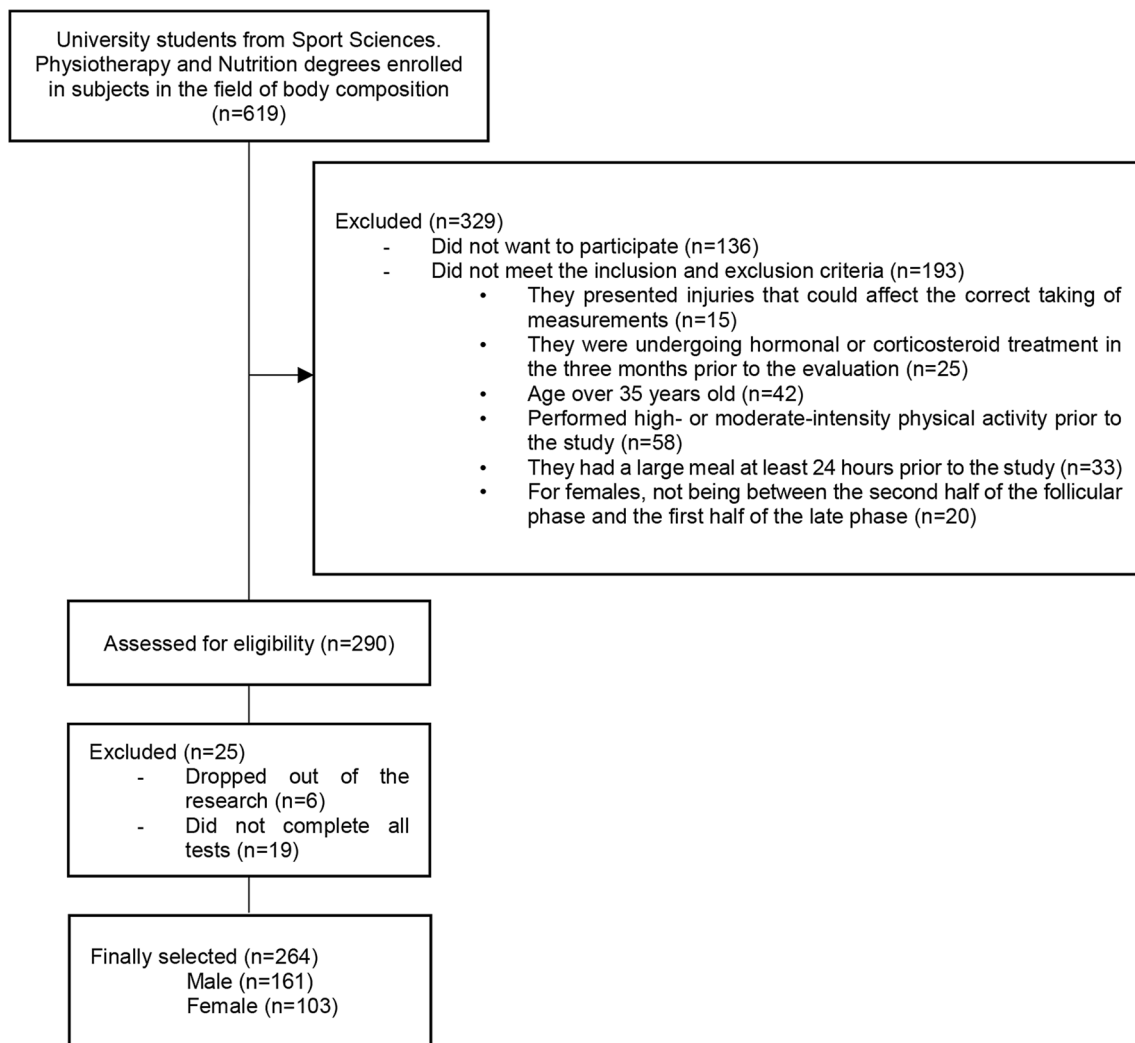


Fig. 1 Participants' flow chart

To determine the hydration status of the participants, urine specific gravity (USG) was measured using a MASTER-URC/N α refractometer (Atago, Japan) (mean=1020.26 \pm 8.52 specific gravity). This assessment followed the protocol outlined in previous research, which involves a urine sample collected in the 30 min prior to the measurements in a sterile, unused container. Hydration status was then classified according to the following USG criteria: well-hydrated (USG: \leq 1.020), moderately dehydrated (USG: 1.021–1.024), and significantly dehydrated (USG: $>$ 1.024). These categories are based on established urinary density benchmarks [37, 38].

The participants also completed a questionnaire on sociodemographic data, including health status, medication, menstrual cycle information for females, dietary intake (24-hour recall), and exercise habits (48-hour recall) [39]. Furthermore, information on regular sports supplement use was also collected using a questionnaire

that had been previously used in research for similar purposes [22].

Body composition measurements using DXA, BIA, and anthropometry were performed in a single session in a controlled environment at 24 °C. Tests were conducted in a randomized order, with each measurement taken by the same technician to eliminate inter-rater variability.

Dual-energy x-ray absorptiometry (DXA)

Segmental fat mass was assessed using a Hologic Horizon system (Hologic Inc., Bedford, MA, USA) which was calibrated daily using an anthropometric spine phantom supplied by the manufacturer. All the measurements were taken by the same experienced technician who was specialized in body composition analysis following standardized protocols, including the removal of all metallic items and ensuring that participants urinated within 30 min before the assessment [40, 41]. The participants were positioned with their hands in a lateral position,

and feet at a 15° internal angle [42]. To measure subjects whose stretch stature was greater than the scanner dimensions, sum-of-scans protocols were used following the protocol used in previous research [42]. Data analysis was performed using the Hologic APEX 13.6.0.5:5 software, and segmental fat mass (right and left upper limbs, trunk and right and left lower limbs) in kg and percentage was measured using the Hologic software (Hologic Inc., Bedford, MA, USA).

Bioelectrical impedance analysis (BIA)

Bioelectrical impedance analysis (BIA) measurements were taken using a TANITA MC-780-MA scale (Tanita Corporation, Tokyo, Japan), a device that utilizes segmental multi-frequency analysis through eight electrodes (measuring at 5 kHz, 50 kHz, and 250 kHz). The precision of this device has been analyzed in previous studies ($p < 0.001$; $r = 0.852$; ICC 95% CI = 0.84 (0.75–0.90)) [43, 44]. The technical error of measurement (TEM) of the TANITA MC-780-MA has been reported to range between 1.5% and 2.5%, depending on the population and body segment being evaluated, highlighting the precision of the TANITA MC-780-MA scale in both total and segmental body fat assessments [44].

The participants stood on the device, following the technical instructions provided in the user manual, which included the removal of all metallic items and urination within 30 min prior to assessment [45]. The participants wore sports tights to minimize interference with the readings [33].

The TANITA MC-780-MA scale measures raw bioimpedance parameters, including resistance, reactance, and phase angle, which are key variables for determining total body water and estimating fat mass values. The use of multiple frequencies enhances the device's ability to differentiate between intracellular and extracellular water, which is crucial for providing a more complete assessment of body composition [34]. However, this device does not provide this raw data. On the contrary, the TANITA MC-780-MA software provided both total and segmental (right and left upper limbs, trunk and right and left lower limbs) fat mass data in kilograms and percentages. The equation used was chosen by the software itself, based on the characteristics of the individual.

The device used underwent a systematic calibration to ensure the validity of its measurements. An automatic calibration was performed before each session, and a periodic verification using standardized resistors was conducted to maintain precision. These procedures followed international guidelines for BIA devices, minimizing potential errors and ensuring that the measurements remained accurate over time.

The TANITA MC-780-MA scale, as other BIA devices, may be sensitive to daily factors such as hydration status

[22]. While the device provides an estimate of both intracellular and extracellular water, variations in body water levels—due to factors such as physical activity, dehydration, or food intake—have been shown to influence the accuracy of the fat mass estimations. In this study, these variables were supervised by ensuring that participants followed a standardized protocol, but it is still a factor that could affect results in other settings [45].

Anthropometry

Anthropometric measurements were performed by a level 3 anthropometrist accredited by the ISAK [19]. All indications from the ISAK protocol were followed to measure both the right and left sides of the body. One researcher measured the right side and another the left side, maintaining their positions during all the measurements to avoid inter-rater TEM. A complete measurement profile was used, which included basic measurements (body mass, stretch stature, sitting height, and arm span), skinfolds (triceps, subscapular, biceps, iliac crest, supraspinale, abdominal, thigh, and calf), girths (head, neck, arm relaxed, arm flexed and tensed, forearm, wrist, chest, waist, hips, thigh 1 cm gluteal, thigh middle, calf and ankle), lengths and heights (acromiale-radiale, radiale-styilion, midstylium-dactylium, iliospinale height, trochanterion height, trochanterion-tibiale laterale, tibiale laterale height, foot, and tibiale mediale-sphyrion tibiale), breadths and depths (biacromial, antero-posterior abdominal depth, biiliocrystal, transverse chest, antero-posterior chest depth, humerus, bi-styloid, femur and bimalleolar). Measurements were taken twice, and if discrepancies exceeded 1% for basic measurements or 5% for skinfolds, a third measurement was taken. The final value used for analysis was the mean of two measurements or the median when three measurements were taken. The intra-evaluator technical error of measurement (TEM) was 0.01% for basic measurements, 1.12% for skinfolds, 0.6% for girths, and 0.3% for lengths and heights and 0.4% for breadths and depths.

The instruments used included a TANITA MC-780-MA scale (Tanita Corporation, Tokyo, Japan), with an accuracy of 0.1 mm, for body mass; a SECA portable stadiometer (SECA, Hamburg, Germany), with an accuracy of 0.1 cm, for stretch stature and sitting height; a Harpenden caliper (Harpenden, London, UK), with an accuracy of 0.2 mm, for skinfolds; an inextensible tape with an accuracy of 0.1 cm for girths (Lufkin, USA), a segmometer for lengths and heights with an accuracy of 0.1 cm (Cescorf, Brazil); and large and small sliding calipers for breadths with an accuracy of 0.1 cm (Realmet, Spain).

Statistical analysis

The normal distribution of the variables was assessed using the Kolmogorov-Smirnov test, as well as with the analysis of kurtosis and skewness. Levene's test was performed to evaluate the homogeneity of the variances at the beginning of the study. The analysis indicated a platykurtic distribution for all variables (-0.34 to -0.597) and a symmetric tendency (0.034 to -0.067). The Kolmogorov-Smirnov test showed that the data had a normal distribution ($p < 0.067$ -0.200), and Levene's test showed the homogeneity of the variances ($F = 0.191$ to 8.550; $p = 0.084$ to 0.999). Given the normality and homogeneity of the data, parametric tests were deemed appropriate. Descriptive statistics were computed for the analyzed variables. The differences between the fat mass segmental results, depending on the method used, were examined using a repeated-measures ANOVA. A repeated-measures ANCOVA was used to evaluate the impact of the variables "BMI", "sex", and "hydration status" on the observed differences. The effect size for pairwise comparisons was calculated using partial Eta-squared (η^2_p). To assess the robustness of the data, 95% confidence intervals (95% CI) were calculated for all analyses. The Bland-Altman test was used to determine the validity of BIA's fat mass segmental values (right and left upper limbs, trunk and right and left lower limbs) in kg as compared to DXA values. The trend to overestimate or underestimate the values with respect to the reference method and the multivariate regression equation for the model was also calculated.

The correlation between the DXA-measured fat mass in kg and anthropometric measurements was evaluated using both Pearson's and partial correlation tests for male and female subgroups. Partial correlations were calculated to control for the influence of BMI and hydration status, ensuring that the observed associations were not affected by these variables. Subsequently, a multivariate stepwise regression was performed with the variables that demonstrated significant correlations, to identify which anthropometric variables could predict the fat mass values of the left and right upper limbs, trunk, and right and left lower limbs depending on sex. The multicollinearity of the variables in the different models was also analyzed using the variance inflation factor (VIF). Based on established guidelines in the literature, a VIF threshold of ≤ 5 was used to confirm the absence of significant multicollinearity; a range between 5 and 10 was considered a moderate collinearity, while a significant collinearity was considered if the $VIF > 10$ [46].

The MedCalc Statistical Software v.20.106 (Maraikkerke, Belgium) was used to perform the Bland-Altman test. The rest of the statistical analyses were performed using SPSS software (v.23. IBM. Endicott. NY, USA). The

significance level for all statistical tests was set a priori at $p \leq 0.05$.

Results

Descriptive analysis

The descriptive statistics for fat mass kilograms and percentages across body segments, measured by DXA and BIA, are presented in Table 1. In the general sample, fat mass in the right upper limb was 0.92 ± 0.37 kg by DXA and 1.10 ± 0.40 kg by BIA; in the left upper limb, it was 0.94 ± 0.39 kg by DXA and 1.12 ± 0.42 kg by BIA; in the trunk, it was 7.80 ± 3.61 kg by DXA and 10.23 ± 4.07 kg by BIA; in the right lower limb, it was 3.95 ± 1.41 kg by DXA and 4.25 ± 1.58 kg by BIA; and in the left lower limb, it was 3.85 ± 1.38 kg by DXA and 4.15 ± 1.53 kg by BIA. Regarding the percentage of fat mass, in the right upper limb, it was $4.96 \pm 0.70\%$ by DXA and $6.03 \pm 0.85\%$ by BIA; in the left upper limb, it was $5.05 \pm 0.68\%$ by DXA and $6.20 \pm 0.87\%$ by BIA; in the trunk, it was $41.42 \pm 5.85\%$ by DXA and $49.57 \pm 7.29\%$ by BIA; in the right lower limb, it was $21.58 \pm 3.11\%$ by DXA and $23.97 \pm 3.85\%$ by BIA; and in the left lower limb, it was $21.04 \pm 3.14\%$ by DXA and $23.54 \pm 3.79\%$ by BIA).

Analysis of differences in fat mass (kg and percentage) by body segments between DXA and BIA

Table 2 presents the results of the ANOVA and ANCOVA analyses performed to evaluate the effects of the covariates BMI, hydration status, and sex on segmental fat mass estimation in both kilograms (kg) and percentage (%), using DXA and BIA.

Significant differences between DXA and BIA were observed in the general sample for most segments when estimating fat mass in both kg and percentage, reflecting small to moderate effect sizes ($p = 0.000$ -0.024; $\eta^2_p = 0.019$ -0.073). In the male subgroup, significant differences in fat mass percentage were detected in all segments, with small to large effect sizes ($p = 0.000$ -0.007; $\eta^2_p = 0.038$ -0.154). For females, significant differences were found in absolute fat mass for the right and left lower limbs, with a small effect size ($p = 0.018$ -0.020; $\eta^2_p = 0.030$ -0.034), and in the fat mass percentage of the left upper limb, with a moderate effect size ($p = 0.004$; $\eta^2_p = 0.043$).

Sex showed significant effects on fat mass estimation in multiple segments. For fat mass in kg, significant effects were observed, with a small effect size for the right upper limb ($p = 0.002$; $\eta^2_p = 0.045$), a moderate effect size for the left upper limb ($p = 0.000$; $\eta^2_p = 0.078$), and a large effect size for the trunk ($p = 0.000$; $\eta^2_p = 0.199$). When considering fat mass percentage, significant effects were found, showing moderate to large effect sizes for the right upper limb ($p = 0.005$; $\eta^2_p = 0.037$), left upper limb ($p = 0.000$; $\eta^2_p = 0.083$), trunk ($p = 0.000$; $\eta^2_p = 0.463$), right lower

Table 1 Descriptive analysis of kg and percentages of fat mass by body segments estimated by DXA and BIA in the general sample and divided by sex

Variable	General sample (n = 264)		Male sample (n = 161)		Female sample (n = 103)	
	Mean ± SD	Min.-Max.	Mean ± SD	Min.-Max.	Mean ± SD	Min.-Max.
Body mass (kg)	71.55 ± 13.93	42.54;111.5	78.37 ± 11.47	56.40;111.50	60.94 ± 10.33	42.54;102.80
Stretch Stature (cm)	172.46 ± 9.58	147.44;198.4	177.90 ± 7.02	161.54;198.40	163.97 ± 6.33	147.44;180.14
BMI	23.91 ± 3.42	16.16;36.75	24.77 ± 3.18	18.37;36.75	22.58 ± 3.36	16.16;36.75
Sitting height (cm)	91.15 ± 4.53	80.14;101.29	93.60 ± 3.43	85.60;101.29	87.33 ± 3.20	80.14;95.00
Arm span (cm)	174.80 ± 11.37	147.09;203.99	181.38 ± 8.10	162.70;203.99	164.54 ± 7.44	147.09;180.14
% DXA right upper limb	4.96 ± 0.70	2.49;8.94	4.96 ± 0.67	3.72;8.94	4.96 ± 0.74	2.49;6.80
% DXA left upper limb	5.05 ± 0.68	3.50;8.80	5.00 ± 0.65	3.85;8.80	5.13 ± 0.73	3.50;7.08
% DXA trunk	41.42 ± 5.85	25.83;56.18	43.64 ± 4.60	33.07;56.18	37.95 ± 5.92	25.83;53.58
% DXA right lower limb	21.58 ± 3.11	14.98;30.16	20.18 ± 2.29	14.98;30.16	23.75 ± 2.97	14.98;30.16
% DXA left lower limb	21.04 ± 3.14	14.39;30.90	19.66 ± 2.38	14.39;30.90	23.19 ± 2.96	14.39;30.90
% BIA right upper limb	5.48 ± 0.64	5.57;8.10	5.57 ± 0.70	3.57;8.10	5.34 ± 0.52	3.57;6.77
% BIA left upper limb	5.75 ± 0.74	3.90;9.25	5.87 ± 0.83	4.08;9.25	5.57 ± 0.53	3.90;6.89
% BIA trunk	53.32 ± 10.28	17.18;68.51	59.86 ± 4.28	40.00;68.51	43.12 ± 8.44	17.18;68.47
% BIA right lower limb	17.62 ± 5.45	7.40;37.50	14.37 ± 3.01	7.40;37.50	22.70 ± 4.42	7.40;37.50
% BIA left lower limb	17.86 ± 5.34	7.40;37.50	14.73 ± 2.96	7.40;37.50	22.74 ± 4.51	7.40;37.50
Kg. DXA right upper limb	0.92 ± 0.37	0.30;2.51	0.84 ± 0.33	0.30;2.22	1.03 ± 0.40	0.30;2.51
Kg. DXA left upper limb	0.94 ± 0.39	0.31;2.51	0.85 ± 0.35	0.31;2.26	1.07 ± 0.41	0.38;2.51
Kg. DXA trunk	7.80 ± 3.61	2.63;25.88	7.62 ± 3.54	2.75;25.88	8.07 ± 3.73	2.63;23.06
Kg. DXA right lower limb	3.95 ± 1.41	1.13;8.65	3.44 ± 1.31	1.13;8.65	4.75 ± 1.16	2.26;8.57
Kg. DXA left lower limb	3.85 ± 1.38	1.06;8.65	3.35 ± 1.29	1.06;8.65	4.64 ± 1.14	2.29;8.09
Kg. BIA right upper limb	0.80 ± 0.33	0.10;2.70	0.75 ± 0.28	0.10;1.80	0.87 ± 0.38	0.20;2.70
Kg. BIA left upper limb	0.83 ± 0.32	0.10;2.70	0.79 ± 0.28	0.10;1.80	0.90 ± 0.37	0.20;2.70
Kg. BIA trunk	7.98 ± 3.80	1.00;26.70	8.41 ± 3.81	1.00;26.70	7.30 ± 3.70	1.10;20.50
Kg. BIA right lower limb	2.55 ± 1.16	0.40;8.10	1.94 ± 0.77	0.40;5.40	3.50 ± 1.03	1.20;8.10
Kg. BIA left lower limb	2.58 ± 1.15	0.40;8.10	1.99 ± 0.78	0.40;5.60	3.50 ± 1.03	1.20;8.10

Kg: kilogram; %: percentage; BMI: Body Mass Index; DXA: Dual-energy X-ray Absorptiometry; BIA: Bioelectrical Impedance

limb ($p=0.000$; $\eta^2p=0.314$), and left lower limb ($p=0.000$; $\eta^2p=0.288$).

BMI significantly influenced fat mass estimation in the general sample for the lower limbs and trunk in kg, with small effect sizes ($p=0.007-0.043$; $\eta^2p=0.020-0.030$). Additionally, BMI had a significant impact on fat mass percentage, showing small to moderate effect sizes in the right and left upper limbs ($p=0.000-0.011$; $\eta^2p=0.027-0.071$) and in the trunk ($p=0.004$; $\eta^2p=0.040$). When analyzed separately by sex, BMI showed a significant effect in males for trunk fat mass in kg, with a small effect size ($p=0.004$; $\eta^2p=0.039$). Significant moderate effects were observed for the right ($p=0.000$; $\eta^2p=0.086$) and left lower limbs ($p=0.000$; $\eta^2p=0.063$). For fat mass percentage, BMI had a significant small effect on the right upper limb ($p=0.004$; $\eta^2p=0.038$) and trunk ($p=0.004$; $\eta^2p=0.039$), while the left upper limb showed a moderate effect size ($p=0.000$; $\eta^2p=0.062$). In females, BMI significantly affected the fat mass percentage of the left upper limb, with a small effect size ($p=0.031$; $\eta^2p=0.025$).

No significant effects of hydration status were observed for any segment in the general sample ($p=0.284-0.971$; $\eta^2p<0.006$) or when the sample was stratified by sex ($p=0.161-0.971$; $\eta^2p<0.009$).

Bland-Altman analysis of agreement between DXA and BIA

Table 3 presents the Bland-Altman analysis results, showing the agreement between DXA and BIA for segmental fat mass measurements in kilograms across the right and left upper limbs, trunk, and lower limbs. To ensure the robustness of the findings, the Bland-Altman analysis was supplemented by confidence interval assessments, with narrower ranges indicating a higher precision. For the general sample, the limits of agreement for trunk segment measurements ranged from -3.53 to 3.17 , being the widest interval, while the right lower limb showed a narrower range (-0.27 to 3.08). Similar trends were observed in the segmented analyses by sex, with the trunk consistently exhibiting the broadest limits of agreement across all groups.

Using DXA as the reference method, significant differences ($p<0.001$) were observed between BIA and DXA for fat mass estimation in most of the segments analyzed for the overall sample, as well as in males and females separately.

The mean differences indicated a consistent overestimation by BIA for all limbs (mean difference= 1.40 kg to 0.10 kg; limits of agreement: -0.38 to 3.08) in the general sample. For males, BIA overestimated the values in

Table 2 Analysis of differences in fat mass (kg and percentage) by body segments between DXA and BIA for the general sample and divided by sex

	ANOVA			Variable*BMI			Variable*Hydration Status			Variable*Sex		
	F	p	η^2_p	F	p	η^2_p	F	p	η^2_p	F	p	η^2_p
General sample (n = 264)												
Right upper limb fat mass (kg)	2.760	0.098	0.011	0.007	0.932	0.000	0.001	0.971	0.000	9.971	0.002	0.037
Left upper limb fat mass (kg)	0.163	0.687	0.001	1.628	0.203	0.006	0.166	0.684	0.001	18.276	0.000	0.066
Trunk fat mass (kg)	5.142	0.024	0.019	1.640	0.202	0.006	0.129	0.719	0.000	52.496	0.000	0.168
Right lower limb fat mass (kg)	0.038	0.846	0.000	7.489	0.007	0.028	1.153	0.284	0.004	1.867	0.173	0.007
Left lower limb fat mass (kg)	0.385	0.536	0.001	4.155	0.043	0.016	0.703	0.402	0.003	1.865	0.173	0.007
Right upper limb fat mass (%)	8.862	0.003	0.033	6.594	0.011	0.025	0.135	0.714	0.001	7.914	0.005	0.030
Left upper limb fat mass (%)	20.570	0.000	0.073	16.990	0.000	0.061	0.012	0.911	0.000	19.998	0.000	0.071
Trunk fat mass (%)	16.345	0.000	0.059	8.531	0.004	0.032	0.382	0.537	0.001	186.500	0.000	0.418
Right lower limb fat mass (%)	0.765	0.382	0.003	0.401	0.527	0.002	0.421	0.517	0.002	102.901	0.000	0.284
Left lower limb fat mass (%)	0.506	0.478	0.002	0.503	0.479	0.002	0.151	0.698	0.001	89.798	0.000	0.257
Males (n = 161)												
Right upper limb fat mass (kg)	0.036	0.850	0.000	0.513	0.475	0.003	0.377	0.540	0.002			
Left upper limb fat mass (kg)	0.442	0.507	0.003	1.772	0.185	0.011	0.135	0.714	0.001			
Trunk fat mass (kg)	3.630	0.059	0.022	8.657	0.004	0.052	0.074	0.787	0.000			
Right lower limb fat mass (kg)	2.206	0.139	0.014	18.025	0.000	0.102	0.109	0.742	0.001			
Left lower limb fat mass (kg)	1.134	0.289	0.007	13.473	0.000	0.079	0.001	0.970	0.000			
Right upper limb fat mass (%)	10.235	0.002	0.061	8.385	0.004	0.050	1.982	0.161	0.012			
Left upper limb fat mass (%)	18.591	0.000	0.105	13.477	0.000	0.080	1.335	0.250	0.008			
Trunk fat mass (%)	46.879	0.000	0.229	8.411	0.004	0.051	0.015	0.904	0.000			
Right lower limb fat mass (%)	8.145	0.005	0.049	0.290	0.591	0.002	0.354	0.553	0.002			
Left lower limb fat mass (%)	7.438	0.007	0.045	0.408	0.524	0.003	0.009	0.924	0.000			
Females (n = 103)												
Right upper limb fat mass (kg)	1.971	0.163	0.019	0.371	0.544	0.004	0.557	0.457	0.006			
Left upper limb fat mass (kg)	0.090	0.765	0.001	0.248	0.620	0.002	1.250	0.266	0.012			
Trunk fat mass (kg)	0.121	0.729	0.001	2.008	0.160	0.020	0.422	0.517	0.004			
Right lower limb fat mass (kg)	5.612	0.020	0.053	0.595	0.442	0.006	1.096	0.298	0.011			
Left lower limb fat mass (kg)	5.777	0.018	0.055	1.168	0.282	0.012	1.058	0.306	0.010			
Right upper limb fat mass (%)	2.475	0.119	0.024	0.505	0.479	0.005	1.310	0.255	0.013			
Left upper limb fat mass (%)	8.833	0.004	0.081	4.764	0.031	0.045	1.673	0.199	0.016			
Trunk fat mass (%)	2.929	0.090	0.028	1.542	0.217	0.015	0.589	0.445	0.006			
Right lower limb fat mass (%)	0.248	0.620	0.002	0.128	0.722	0.001	0.102	0.750	0.001			
Left lower limb fat mass (%)	0.063	0.802	0.001	0.111	0.740	0.001	0.202	0.654	0.002			

Kg: kilogram; %: percentage

Table 3 Bland–Altman results for the agreement between DXA and BIA for estimating kilograms of fat mass in each segment for the general sample and divided by sex

	Mean diff.	95% CI	95% Limits of agreement		p	Regression equation	p
			Lower limit	Upper limit			
General sample (n = 264)							
Right upper limb	0.11	0.09 to 0.14	-0.26	0.50	<0.001	y=0.004687+0.1322*x	0.0002
Left upper limb	0.10	0.08 to 0.13	-0.30	0.51	<0.001	y=-0.06366+0.1915*x	<0.0001
Trunk	-0.18	-0.38 to 0.02	-3.53	3.17	0.088	y=0.2458+0.05403*x	0.0645
Right lower limb	1.40	1.30 to 1.50	-0.27	3.08	<0.001	y=0.7163+0.2115*x	<0.0001
Left lower limb	1.27	1.17 to 1.37	-0.38	2.93	<0.001	y=0.6351+0.1986*x	<0.0001
Males (n = 161)							
Right upper limb	0.08	0.057 to 0.11	-0.29	0.46	<0.001	y=-0.05551+0.1783*x	0.0004
Left upper limb	0.06	0.033 to 0.09	-0.34	0.47	0.001	y=-0.1309+0.2382*x	<0.0001
Trunk	-0.78	-1.03 to -0.54	-3.86	2.28	<0.001	y=-0.1613+0.07824*x	0.0228
Right lower limb	1.50	1.36 to 1.63	-0.24	3.24	<0.001	y=-0.07568+0.5850*x	<0.0001
Left lower limb	1.36	1.22 to 1.49	-0.33	3.06	<0.001	y=-0.1047+0.5485*x	<0.0001
Females (n = 103)							
Right upper limb	0.16	0.13 to 0.20	-0.19	0.53	<0.001	y=0.1087+0.06426*x	0.196
Left upper limb	0.17	0.13 to 0.20	-0.21	0.55	<0.001	y=0.07246+0.09989*x	0.0499
Trunk	0.78	0.49 to 1.07	-2.12	3.69	<0.001	y=0.6774+0.01434*x	0.7272
Right lower limb	1.24	1.09 to 1.40	-0.28	2.77	<0.001	y=0.7338+0.1251*x	0.1063
Left lower limb	1.13	0.97 to 1.28	-0.44	2.70	<0.001	y=0.7337+0.09807*x	0.2293

all limbs (mean difference=0.06 kg to 1.50 kg; limits of agreement: -0.34 to 3.24), and underestimated the trunk value (mean difference = -0.78 kg; limits of agreement: -3.86 to 2.28). For females, BIA overestimated values both in the trunk and limbs (mean difference=0.16 kg to 1.24 kg; limits of agreement: -2.12 to 3.69). The broad limits of agreement highlight the substantial variability between methods, reinforcing the non-interchangeability between DXA and BIA, particularly in the upper and lower limbs.

Generation of predictive models for the analysis of segmental body composition by anthropometry

In Tables 4 and 5, the Pearson and partial correlation analyses revealed strong associations between anthropometric variables and DXA-measured segmental fat mass across both sexes. After controlling for BMI and hydration status, the correlations generally remained significant, although the strength of some associations was slightly reduced.

These analyses served as the basis for developing the predictive models. The stepwise multivariate regression method ensured that only significant variables were included in the models, with multicollinearity tested. Between one and six models were found for the fat mass in each segment (Tables 6 and 7), with R² values ranging from 0.758 to 0.887 for males (p<0.001) and between 0.766 and 0.910 for females (p<0.001), demonstrating strong predictive capacities.

In the case of the upper limbs in the sample of males, four multivariate regression models were obtained

(R²=0.758–0.812; p<0.001). Trunk and left lower limb fat mass can be predicted by four models as well (R²=0.783–0.887; p<0.001); and the right lower limb by three models (R²=0.794–0.819; p<0.001). For the right upper limb, the triceps skinfold, body mass, and biceps skinfold were the highest predictive variables (VIF value=1.170–4.409). For the left upper limb, the triceps skinfold, arm relaxed girth, and arm flexed and tensed girth were the highest predictive variables (VIF value=1.648–18.028). For the trunk, the variable with the highest predictive ability was the left supraspinale skinfold (VIF value=1.000). The thigh skinfold was shown to be most influential for the right and left lower limbs, followed by body mass for the right lower limb and thigh 1 cm gluteal girth for the left lower limb (VIF value=1.140–8.643).

In the female sample, six multivariate regression models were obtained for the left upper limb (R²=0.853–0.910; p<0.001), and three for the right upper limb (R²=0.766–0.899; p<0.001). Trunk fat mass can be predicted by five models (R²=0.780–0.907; p<0.001), while the left and right lower limbs fat mass by three models (R²=0.776–0.840; p<0.001). Body mass showed a high degree of determination, being the most important variable for determining the kg of fat in the left upper limb and for both lower limbs, followed by biceps skinfold for left upper limb and calf skinfold for both lower limbs (VIF value=1.559–27.238). In the case of the right upper limb, the triceps skinfold was the most important determinant factor (VIF value=1.000). In the trunk, waist girth was shown to be most influential (VIF value=1.000).

Table 4 (continued)

Partial correlations with hydration status as a control variable

Right lower limb fat mass (kg)	$r = 0.617$ $p < 0.001$	Sitting height	$r = 0.179$ $p = 0.024$	Right Thigh skinfold	$r = 0.820$ $p < 0.001$	Right Thigh 1 cm gluteal girth	$r = 0.743$ $p < 0.001$	Right Thigh middle girth	$r = 0.657$ $p < 0.001$	Right Calf skinfold	$r = 0.778$ $p < 0.001$	Right Calf 1 cm gluteal girth	$r = 0.743$ $p < 0.001$	Right Thigh middle girth	$r = 0.657$ $p < 0.001$	Right Calf girth	$r = 0.541$ $p < 0.001$	Right Ankle girth	$r = 0.418$ $p < 0.001$	Right Trochanterion-Tibiale	$r = 0.449$ $p < 0.001$	Right Femur breadth	$r = 0.449$ $p < 0.001$
Left lower limb fat mass (kg)	$r = -0.156$ $p = 0.049$	Sitting height	$r = -0.035$ $p = 0.661$	Left Thigh skinfold	$r = 0.258$ $p < 0.001$	Left Thigh 1 cm gluteal girth	$r = -0.045$ $p = 0.573$	Left Thigh middle girth	$r = -0.067$ $p = 0.400$	Left Calf skinfold	$r = 0.338$ $p < 0.001$	Left Calf girth	$r = -0.005$ $p = 0.955$	Left Ankle girth	$r = 0.194$ $p = 0.014$	Left Femur breadth	$r = 0.083$ $p = 0.298$	Left Trochanterion-Tibiale	$r = -0.186$ $p = 0.019$	Left Femur breadth	$r = 0.083$ $p = 0.298$	Left Tibiale Laterale length	$r = -0.186$ $p = 0.019$

Kg: kilogram; %: percentage

Discussion

The first objective of this research was to analyze the differences between DXA and BIA in estimating segmental fat mass. Significant differences were observed in most body segments across the general sample. Specifically, discrepancies were found in trunk fat mass, both in kilograms and percentages, as well as in the percentages of the right and left upper limbs. When analyzing the male subgroup, differences were identified in all body segments, both in kilograms and percentages (upper limbs, trunk, and lower limbs). In contrast, in the female subgroup, significant differences were found in the kilograms of fat in the lower limbs and the percentage of fat in the left upper limb.

One of the possible sources of these differences could be attributed to the methodology used in each technique. DXA measures molecular density, differentiating between soft lean mass, fat mass, and bone mineral content with a high accuracy [47]. In contrast, BIA estimates body composition through predictive equations based on the body's electrical impedance, which can be strongly influenced by factors such as hydration status, fasting conditions, glycogen levels, and body temperature, leading to potential variations in the measurements [48]. Furthermore, BIA does not always adequately capture regional fat distribution differences, as its accuracy can vary depending on the technology used (leg-to-leg, hand-to-hand, etc.), and the subject's posture [49].

Additionally, differences between segmental DXA and BIA measurements may arise from how each method defines body segments. DXA allows technicians to manually delineate specific body segments, providing a high degree of customization and precision [40, 41]. In contrast, BIA determines these segments automatically through its software, without the possibility for manual adjustment, which can introduce variability in body composition estimates made by the BIA apparatus [45].

Moreover, a critical limitation of the BIA device used was its inability to provide raw impedance values, a factor that significantly restricts the application of alternative BIA equations that might be better aligned with DXA values [50]. This limitation hinders the ability to refine or adjust BIA estimations for a greater accuracy in comparison to the reference method [51]. Thus, in the current research, the BIA device used employed proprietary equations based on raw bioimpedance parameters to estimate fat mass. These equations were supposed to have been validated in multiple populations, showing a good agreement with DXA [52, 53]. However, the manufacturer's proprietary equations are not disclosed in detail, which presents a limitation when attempting to understand the underlying assumptions and variables used in the estimations [50]. This is also particularly relevant to consider when using BIA's software values to analyze

Table 5 Pearson and partial correlations between DXA segmental fat mass and anthropometric variables in the female sample, controlling for BMI and hydration status

Body segment		Pearson's correlation												
Right upper limb fat mass (kg)	Body mass	Stretch	Arm span	Right Triceps skinfold	Right Biceps skinfold	Right Arm relaxed girth	Right Arm flexed and tensed girth	Right Forearm girth	Right Wrist girth	Right Acromiale length	Right Humerus breadth	Right Bi-styloid breadth		
		$r=0.852$ $p<0.001$	$r=0.293$ $p=0.003$	$r=0.875$ $p<0.001$	$r=0.874$ $p<0.001$	$r=0.828$ $p<0.001$	$r=0.750$ $p<0.001$	$r=0.735$ $p<0.001$	$r=0.627$ $p<0.001$	$r=0.327$ $p=0.001$	$r=0.564$ $p<0.001$	$r=0.351$ $p<0.001$		
Left upper limb fat mass (kg)	Body mass	Stretch	Arm span	Left Triceps Skinfold	Left Biceps Skinfold	Left Arm relaxed girth	Left Arm flexed and tensed girth	Left Forearm girth	Left Wrist girth	Left Acromiale length	Left Radiale-Styloid length	Left Bistyloid breadth	Left Humerus breadth	
		$r=0.863$ $p<0.001$	$r=0.308$ $p=0.002$	$r=0.815$ $p<0.001$	$r=0.831$ $p<0.001$	$r=0.832$ $p<0.001$	$r=0.728$ $p<0.001$	$r=0.766$ $p<0.001$	$r=0.675$ $p<0.001$	$r=0.401$ $p<0.001$	$r=0.270$ $p=0.006$	$r=0.343$ $p<0.001$	$r=0.529$ $p<0.001$	
Trunk fat mass (kg)	Body mass	Stretch	Sitting Height	Right Subscapular skinfold	Right Iliac Crest skinfold	Right Subscapular skinfold	Right Abdominal skinfold	Left Subscapular skinfold	Left Iliac Crest skinfold	Left Subscapular skinfold	Left Abdominal skinfold	Chest girth	Waist girth	Hips girth
		$r=0.867$ $p<0.001$	$r=0.251$ $p<0.001$	$r=0.869$ $p<0.001$	$r=0.839$ $p<0.001$	$r=0.826$ $p<0.001$	$r=0.750$ $p<0.001$	$r=0.865$ $p<0.001$	$r=0.731$ $p<0.001$	$r=0.791$ $p<0.001$	$r=0.711$ $p<0.001$	$r=0.871$ $p<0.001$	$r=0.883$ $p<0.001$	$r=0.830$ $p<0.001$
Right lower limb fat mass (kg)	Body mass	Stretch	Sitting Height	Right Thigh skinfold	Right Calf skinfold	Right Thigh 1 cm girth	Right Thigh middle girth	Right Calf girth	Right Ankle girth	Right Iliospinale height	Right Trochanterion height	Right Tibiale Laterale height	Right Femur breadth	Right Bimalleolar breadth
		$r=0.853$ $p<0.001$	$r=0.494$ $p<0.001$	$r=0.688$ $p<0.001$	$r=0.688$ $p<0.001$	$r=0.742$ $p<0.001$	$r=0.742$ $p<0.001$	$r=0.744$ $p<0.001$	$r=0.656$ $p<0.001$	$r=0.422$ $p<0.001$	$r=0.361$ $p<0.001$	$r=0.430$ $p<0.001$	$r=0.784$ $p<0.001$	$r=0.508$ $p<0.001$
Left lower limb fat mass (kg)	Body mass	Stretch	Sitting Height	Left Thigh skinfold	Left Calf skinfold	Left Thigh 1 cm girth	Left Thigh middle girth	Left Calf girth	Left Ankle girth	Left Iliospinale height	Left Trochanterion height	Left Tibiale Laterale Height	Left Femur breadth	Left Bimalleolar breadth
		$r=0.846$ $p<0.001$	$r=0.494$ $p<0.001$	$r=0.719$ $p<0.001$	$r=0.750$ $p<0.001$	$r=0.818$ $p<0.001$	$r=0.731$ $p<0.001$	$r=0.759$ $p<0.001$	$r=0.697$ $p<0.001$	$r=0.384$ $p<0.001$	$r=0.485$ $p<0.001$	$r=0.483$ $p<0.001$	$r=0.787$ $p<0.001$	$r=0.429$ $p<0.001$

Body segment		Partial correlation with BMI as a control variable												
Right upper limb fat mass (kg)	Body mass	Stretch	Arm span	Right Triceps skinfold	Right Biceps skinfold	Right Arm relaxed girth	Right Arm flexed and tensed girth	Right Forearm girth	Right Wrist girth	Right Acromiale length	Right Humerus breadth	Right Bi-styloid breadth		
		$r=0.472$ $p<0.001$	$r=0.465$ $p=0.001$	$r=0.753$ $p<0.001$	$r=0.722$ $p<0.001$	$r=0.336$ $p<0.001$	$r=0.092$ $p<0.001$	$r=0.218$ $p<0.001$	$r=0.311$ $p=0.001$	$r=0.487$ $p<0.001$	$r=0.218$ $p=0.028$	$r=0.075$ $p=0.454$		
Left upper limb fat mass (kg)	Body mass	Stretch	Arm span	Left Triceps Skinfold	Left Biceps Skinfold	Left Arm relaxed girth	Left Arm flexed and tensed girth	Left Forearm girth	Left Wrist girth	Left Acromiale length	Left Radiale-Styloid length	Left Bistyloid breadth	Left Humerus breadth	
		$r=0.507$ $p<0.001$	$r=0.495$ $p=0.001$	$r=0.650$ $p<0.001$	$r=0.679$ $p<0.001$	$r=0.348$ $p<0.001$	$r=0.053$ $p=0.595$	$r=0.249$ $p=0.012$	$r=0.272$ $p=0.006$	$r=0.503$ $p=0.002$	$r=0.309$ $p=0.002$	$r=0.061$ $p=0.545$	$r=0.234$ $p=0.018$	
Trunk fat mass (kg)	Body mass	Stretch	Sitting Height	Right Subscapular skinfold	Right Iliac Crest skinfold	Right Subscapular skinfold	Right Abdominal skinfold	Left Subscapular skinfold	Left Iliac Crest skinfold	Left Subscapular skinfold	Left Abdominal skinfold	Chest girth	Waist girth	Hips girth
		$r=0.449$ $p<0.001$	$r=0.429$ $p=0.001$	$r=0.661$ $p<0.001$	$r=0.657$ $p<0.001$	$r=0.613$ $p<0.001$	$r=0.568$ $p<0.001$	$r=0.631$ $p<0.001$	$r=0.552$ $p<0.001$	$r=0.597$ $p<0.001$	$r=0.614$ $p<0.001$	$r=0.503$ $p<0.001$	$r=0.505$ $p<0.001$	$r=0.340$ $p<0.001$

Table 5 (continued)

Partial correlation with BMI as a control variable													
Right lower limb fat mass (kg)	Body mass	Stretch Stature	Sitting Height	Right Thigh skinfold	Right Thigh 1 cm gluteal girth	Right middle thigh girth	Right Calf girth	Right Ankle girth	Right iliospinal height	Right Trochanterion height	Right Tibiale Laterale height	Right Femur breadth	Right Bimalleolar breadth
$r = 0.674$ $p < 0.001$	$r = 0.678$ $p < 0.001$	$r = 0.575$ $p < 0.001$	$r = 0.404$ $p < 0.001$	$r = 0.446$ $p < 0.001$	$r = 0.650$ $p < 0.001$	$r = 0.294$ $p = 0.003$	$r = 0.412$ $p < 0.001$	$r = 0.443$ $p < 0.001$	$r = 0.608$ $p < 0.001$	$r = 0.474$ $p < 0.001$	$r = 0.548$ $p < 0.001$	$r = 0.538$ $p < 0.001$	$r = 0.429$ $p < 0.001$
Left lower limb fat mass (kg)	Body mass	Stretch Stature	Sitting Height	Left Thigh skinfold	Left Thigh 1 cm gluteal girth	Left middle thigh girth	Left Calf girth	Left Ankle girth	Left iliospinal height	Left Trochanterion height	Left Tibiale Laterale Height	Left Femur breadth	Left Bimalleolar breadth
$r = 0.097$ $p = 0.334$	$r = 0.104$ $p = 0.300$	$r = 0.071$ $p = 0.479$	$r = 0.007$ $p = 0.946$	$r = 0.080$ $p = 0.426$	$r = 0.265$ $p = 0.007$	$r = 0.424$ $p < 0.001$	$r = 0.351$ $p < 0.001$	$r = 0.327$ $p = 0.001$	$r = 0.161$ $p = 0.106$	$r = 0.052$ $p = 0.604$	$r = 0.064$ $p = 0.522$	$r = 0.305$ $p = 0.002$	$r = 0.258$ $p = 0.009$
Partial correlations with hydration status as control variable													
Right upper limb fat mass (kg)	Body mass	Stretch Stature	Arm span	Right Triceps skinfold	Right Arm relaxed girth	Right Arm flexed and tensed girth	Right Forearm girth	Right Wrist girth	Right Acromiale-Radi-ale length	Right Humerus breadth	Right Bi-styloid breadth	Right Humerus breadth	Right Bimalleolar breadth
$r = 0.852$ $p < 0.001$	$r = 0.299$ $p = 0.002$	$r = 0.252$ $p = 0.010$	$r = 0.875$ $p < 0.001$	$r = 0.873$ $p < 0.001$	$r = 0.829$ $p < 0.001$	$r = 0.753$ $p < 0.001$	$r = 0.736$ $p < 0.001$	$r = 0.626$ $p < 0.001$	$r = 0.334$ $p = 0.001$	$r = 0.561$ $p < 0.001$	$r = 0.347$ $p < 0.001$	$r = 0.561$ $p < 0.001$	$r = 0.538$ $p < 0.001$
Left upper limb fat mass (kg)	Body mass	Stretch Stature	Arm span	Left Triceps skinfold	Left Arm relaxed girth	Left Arm flexed and tensed girth	Left Forearm girth	Left Wrist girth	Left Acromiale-Radi-ale length	Left Radiale-Styloid length	Left Bistyloid breadth	Left Humerus breadth	Left Bimalleolar breadth
$r = 0.864$ $p < 0.001$	$r = 0.314$ $p = 0.001$	$r = 0.248$ $p = 0.012$	$r = 0.815$ $p < 0.001$	$r = 0.830$ $p < 0.001$	$r = 0.835$ $p < 0.001$	$r = 0.730$ $p < 0.001$	$r = 0.766$ $p < 0.001$	$r = 0.674$ $p < 0.001$	$r = 0.411$ $p < 0.001$	$r = 0.281$ $p = 0.004$	$r = 0.339$ $p = 0.001$	$r = 0.526$ $p < 0.001$	$r = 0.437$ $p < 0.001$
Trunk fat mass (kg)	Body mass	Stretch Stature	Sitting Height	Right Subscapular skinfold	Right Subscapular skinfold	Right Abdominal skinfold	Left Subscapular skinfold	Left Iliac Crest skinfold	Left Subscapular skinfold	Left Abdominal skinfold	Chest girth	Waist girth	Hips girth
$r = 0.865$ $p < 0.001$	$r = 0.260$ $p = 0.008$	$r = 0.370$ $p < 0.001$	$r = 0.868$ $p < 0.001$	$r = 0.838$ $p < 0.001$	$r = 0.825$ $p < 0.001$	$r = 0.751$ $p < 0.001$	$r = 0.865$ $p < 0.001$	$r = 0.731$ $p < 0.001$	$r = 0.790$ $p < 0.001$	$r = 0.718$ $p < 0.001$	$r = 0.870$ $p < 0.001$	$r = 0.883$ $p < 0.001$	$r = 0.828$ $p < 0.001$
Right lower limb fat mass (kg)	Body mass	Stretch Stature	Sitting Height	Right Calf skinfold	Right Thigh 1 cm gluteal girth	Right middle thigh girth	Right Calf girth	Right Ankle girth	Right iliospinal height	Right Trochanterion height	Right Tibiale Laterale height	Right Femur breadth	Right Bimalleolar breadth
$r = 0.860$ $p < 0.001$	$r = 0.494$ $p < 0.001$	$r = 0.530$ $p < 0.001$	$r = 0.698$ $p < 0.001$	$r = 0.696$ $p < 0.001$	$r = 0.851$ $p < 0.001$	$r = 0.753$ $p < 0.001$	$r = 0.749$ $p < 0.001$	$r = 0.658$ $p < 0.001$	$r = 0.422$ $p < 0.001$	$r = 0.361$ $p < 0.001$	$r = 0.432$ $p < 0.001$	$r = 0.796$ $p < 0.001$	$r = 0.514$ $p < 0.001$
Left lower limb fat mass (kg)	Body mass	Stretch Stature	Sitting Height	Left Calf skinfold	Left Thigh 1 cm gluteal girth	Left middle thigh girth	Left Calf girth	Left Ankle girth	Left iliospinal height	Left Trochanterion height	Left Tibiale Laterale Height	Left Femur breadth	Left Bimalleolar breadth
$r = 0.853$ $p < 0.001$	$r = 0.495$ $p < 0.001$	$r = 0.527$ $p < 0.001$	$r = 0.728$ $p < 0.001$	$r = 0.752$ $p < 0.001$	$r = 0.828$ $p < 0.001$	$r = 0.744$ $p < 0.001$	$r = 0.762$ $p < 0.001$	$r = 0.702$ $p < 0.001$	$r = 0.384$ $p < 0.001$	$r = 0.484$ $p < 0.001$	$r = 0.484$ $p < 0.001$	$r = 0.800$ $p < 0.001$	$r = 0.437$ $p < 0.001$

Kg: kilogram; %: percentage

Table 6 Multivariate regression models using anthropometric variables in males

	Model	R ²	Variable included	VIF	F	p	Equation
Right upper limb fat mass (kg)	1	0.758	Right Triceps skinfold	3.484	164.123	p < 0.001	-0.473 + 0.025 * Right Triceps skinfold + 0.011 * Body mass + 0.041 * Right Biceps skinfold
			Body mass	1.170			
	2	0.774	Right Triceps skinfold	3.528	133.191	p < 0.001	0.403 + 0.024 * Right Triceps skinfold + 0.015 * Body mass + 0.039 * Right Biceps skinfold - 0.071 * Right Wrist girth
			Body mass	2.337			
			Right Biceps skinfold	3.514			
			Right Wrist girth	2.006			
	3	0.781	Right Triceps skinfold	3.535	110.252	p < 0.001	0.131 + 0.023 * Right Triceps skinfold + 0.011 * Body mass + 0.040 * Right Biceps skinfold - 0.065 * Right Wrist girth + 0.014 * Right Arm relaxed girth
			Body mass	4.321			
			Right Biceps skinfold	3.521			
			Right Wrist girth	2.034			
	4	0.798	Right Triceps skinfold	3.781	101.241	p < 0.001	0.160 + 0.019 * Right Triceps skinfold + 0.010 * Body mass + 0.035 * Right Biceps skinfold - 0.050 * Right Wrist girth + 0.080 * Right Arm relaxed girth - 0.065 * Right Arm flexed and tensed girth
			Body mass	4.409			
			Right Biceps skinfold	3.580			
			Right Wrist girth	2.119			
			Right Arm relaxed girth	26.315			
	Left upper limb fat mass (kg)	1	0.782	Left Triceps skinfold	1.648	187.391	p < 0.001
Left Arm relaxed girth				17.460			
Left Arm flexed and tensed girth				16.312			
2	0.796	0.806	Left Triceps skinfold	2.896	152.164	p < 0.001	-0.909 + 0.032 * Left Triceps skinfold + 0.124 * Left Arm relaxed girth - 0.078 * Left Arm flexed and tensed girth + 0.026 * Left Biceps skinfold
			Left Arm relaxed girth	18.028			
			Left Arm flexed and tensed girth	16.765			
			Left Biceps skinfold	2.632			
3	0.806	0.812	Left Triceps skinfold	2.899	129.106	p < 0.001	-0.847 + 0.031 * Left Triceps skinfold + 0.107 * Left Arm relaxed girth - 0.076 * Left Arm flexed and tensed girth + 0.023 * Left Biceps skinfold + 0.006 * Body mass
			Left Arm relaxed girth	20.142			
			Left Arm flexed and tensed girth	16.796			
			Left Biceps skinfold	2.669			
			Body mass	2.881			
4	0.812	0.883	Left Triceps skinfold	2.971	110.859	p < 0.001	-0.371 + 0.030 * Left Triceps skinfold + 0.096 * Left Arm relaxed girth - 0.068 * Left Arm flexed and tensed girth + 0.022 * Left Biceps skinfold + 0.008 * Body mass - 0.099 * Left Bi-styloid breadth
			Left Arm relaxed girth	21.925			
			Left Arm flexed and tensed girth	17.758			
			Left Biceps skinfold	2.696			
			Body mass	3.812			
Trunk fat mass (kg)	1	0.797	Left Supraspinale skinfold	1.000	625.670	p < 0.001	1.345 + 0.580 * Left Supraspinale skinfold - 11.625 + 0.415 * Left Supraspinale skinfold + 0.180 * Waist girth
			Left Supraspinale skinfold	1.943			
			Waist girth	1.943			
			Left subscapular skinfold	4.192			
2	0.866	0.887	Left Supraspinale skinfold	3.824	393.298	p < 0.001	-9.881 + 0.300 * Left Supraspinale skinfold + 0.146 * Waist girth + 0.202 * Left subscapular skinfold
			Waist girth	2.230			
			Left subscapular skinfold	4.192			
			Left Supraspinale skinfold	3.833			
			Waist girth	6.613			
3	0.887	0.887	Left Supraspinale skinfold	3.833	304.629	p < 0.001	-7.983 + 0.304 * Left Supraspinale skinfold + 0.081 * Waist girth + 0.219 * Left subscapular skinfold + 0.041 * Body mass
			Waist girth	6.613			
			Left subscapular skinfold	4.319			
4	0.887	0.887	Left Supraspinale skinfold	4.207	304.604	p < 0.001	-1.862 + 0.117 * Right Thigh skinfold + 0.044 * Body mass
			Body mass	4.207			
Right lower limb fat mass (kg)	1	0.794	Right Thigh skinfold	1.140	304.604	p < 0.001	-1.754 + 0.084 * Right Thigh skinfold + 0.041 * Body mass + 0.063 * Right Calf skinfold
			Body mass	1.140			
			Right Calf skinfold	3.081			
2	0.813	0.819	Right Thigh skinfold	3.045	228.086	p < 0.001	-2.909 + 0.077 * Right Thigh skinfold + 0.028 * Body mass + 0.060 * Right Calf skinfold + 0.038 * Right Thigh 1 cm gluteal girth
			Body mass	1.164			
			Right Calf skinfold	3.081			
			Right Thigh 1 cm gluteal girth	4.752			
3	0.819	0.819	Right Thigh skinfold	3.352	176.038	p < 0.001	-2.909 + 0.077 * Right Thigh skinfold + 0.028 * Body mass + 0.060 * Right Calf skinfold + 0.038 * Right Thigh 1 cm gluteal girth
			Body mass	3.642			
			Right Calf skinfold	3.107			
4	0.819	0.819	Right Thigh skinfold	4.752	176.038	p < 0.001	-2.909 + 0.077 * Right Thigh skinfold + 0.028 * Body mass + 0.060 * Right Calf skinfold + 0.038 * Right Thigh 1 cm gluteal girth
			Right Thigh 1 cm gluteal girth	4.752			

Table 6 (continued)

	Model	R ²	Variable included	VIF	F	p	Equation
Left lower limb fat mass (kg)	1	0.783	Left Thigh skinfold Left Thigh 1 cm gluteal girth	1.499 1.499	285.257	p < 0.001	-4.554 + 0.102 * Left Thigh skinfold + 0.106 * Left Thigh 1 cm gluteal girth
	2	0.826	Left Thigh skinfold Left Thigh 1 cm gluteal girth Left Calf skinfold	2.711 1.565 2.605	247.744	p < 0.001	-3.962 + 0.061 * Left Thigh skinfold + 0.092 * Left Thigh 1 cm gluteal girth + 0.087 * Left Calf skinfold
	3	0.836	Left Thigh skinfold Left Thigh 1 cm gluteal girth Left Calf skinfold Left Thigh middle girth	2.850 10.035 2.616 8.643	199.523	p < 0.001	-3.749 + 0.055 * Left Thigh skinfold + 0.169 * Left Thigh 1 cm gluteal girth + 0.090 * Left Calf skinfold - 0.087 * Left Thigh middle girth
	4	0.845	Left Thigh skinfold Left Thigh 1 cm gluteal girth Left Calf skinfold Left Thigh middle girth Body mass	2.976 12.785 2.619 8.887 4.715	169.005	p < 0.001	-2.652 + 0.060 * Left Thigh skinfold + 0.130 * Left Thigh 1 cm gluteal girth + 0.092 * Left Calf skinfold - 0.100 * Left Thigh middle girth + 0.023 * Body mass

Kg: kilogram; %: percentage; VIF: variance inflation factor

different populations, as the accuracy of these equations may vary based on factors such as ethnicity, activity level, or age [50].

Another limitation is the inability of BIA to differentiate between visceral and subcutaneous fat with the same precision as imaging methods such as magnetic resonance imaging (MRI) or DXA [54]. This can lead to variability in the assessment of fat distribution, particularly in populations with central obesity or conditions that affect fat accumulation. Previous studies have suggested that while BIA may be effective for general fat mass assessment, it should be complemented with more direct methods such as DXA or MRI, when precise information about visceral fat is required, as this will affect the trunk values [55]. These may explain the differences obtained in this study.

An analysis of whether the covariates BMI, sex and hydration status affected the differences between methods was also performed. Concerning BMI, although it has historically been considered a strong indicator of nutritional status and levels of overweightness [56, 57], in the present study, it did not have an influence on the comparison of segmental fat as a function of the method used for its assessment in most cases. This could be because BMI does not distinguish between fat mass and fat-free mass, taking for granted that an excess of total weight is related to an excess of fat, which could be an erroneous conclusion, especially in the health field [58]. In addition, BMI does not include any variables at the segmental level in its calculation, only general body mass and stretch stature. This indicates that BMI could be considered when assessing the general condition of a person, but would not be related to fat in different body segments [59].

Hydration status also showed no effects on the differences in estimated segmental fat mass. Previous studies have found that body water levels could be a contaminating factor in the estimation of fat mass, especially in

methods based on electrical conductivity such as BIA [12]. However, in the current research, most of the factors that could influence the participants' hydration status were carefully controlled for [58], such as physical activity, training, and food intake, which can help reduce the impact of hydration levels [22]. Despite these controls, the Bland-Altman analysis revealed that even under adequate hydration and normal BMI conditions, significant differences persisted between BIA and DXA across various body segments. This highlights that those discrepancies are not solely attributable to hydration variability or extreme body composition, but are likely inherent to the methodological differences between these techniques. Consequently, the reliability of BIA could deteriorate further in populations with abnormal hydration states, such as individuals with lymphedema, edema, or chronic kidney disease, as well as in elderly populations, where hydration status can vary significantly [60, 61]. This underscores the need for alternative methods, such as anthropometry, which demonstrated a greater robustness under ad libitum conditions.

In contrast, sex had a significant influence on the differences between DXA and BIA in the different body segments. Body fat distribution significantly differs between males and females, as it is influenced by hormonal and physiological factors. Females tend to accumulate more subcutaneous fat, especially in the hips and thighs, while males generally have more visceral fat [28, 29, 31]. This differential distribution can influence the accuracy of BIA, as the method is sensitive to the distribution and fluctuation of body water. During the menstrual cycle, females experience hormonal changes that affect the retention of fluids, which can alter BIA measurements [62]. For instance, the luteal phase of the menstrual cycle is associated with a higher retention of water, which can influence body fat estimates obtained through BIA [63]. These hormonal and water fluctuations do not affect

Table 7 Multivariate regression models using anthropometric variables in females

	Model	R ²	Variable included	VIF	F	p	Equation
Right upper limb fat mass (kg)	1	0.766	Right Triceps skinfold	1.000	330.473	p < 0.001	-0.093 + 0.055 * Right Triceps skinfold
	2	0.876	Right Triceps skinfold Body mass	1.988 1.988	353.597	p < 0.001	-0.792 + 0.034 * Right Triceps skinfold + 0.018 * Body mass
	3	0.899	Right Triceps skinfold Body mass Right Biceps skinfold	4.237 2.142 4.234	292.986	p < 0.001	-0.620 + 0.020 * Right Triceps skinfold + 0.016 * Body mass + 0.031 * Right Biceps skinfold
Left upper limb fat mass (kg)	1	0.853	Body mass Left Biceps Skinfold	1.888 1.888	290.396	p < 0.001	-0.715 + 0.022 * Body mass + 0.045 * Left Biceps Skinfold
	2	0.871	Body mass Left Biceps Skinfold Left Bi-styloid breadth	2.397 1.895 1.433	223.765	p < 0.001	0.087 + 0.026 * Body mass + 0.044 * Left Biceps Skinfold - 0.212 * Left Bi-styloid breadth
	3	0.881	Body mass Left Biceps Skinfold Left Bi-styloid breadth Left Triceps skinfold	2.571 4.126 1.467 4.024	181.217	p < 0.001	-0.091 + 0.025 * Body mass + 0.030 * Left Biceps Skinfold - 0.189 * Left Bi-styloid breadth + 0.017 * Left Triceps skinfold
	4	0.888	Body mass Left Biceps Skinfold Left Bi-styloid breadth Left Triceps skinfold Left Arm relaxed girth	5.771 4.152 1.565 4.032 4.291	153.711	p < 0.001	-0.519 + 0.019 * Body mass + 0.028 * Left Biceps Skinfold - 0.155 * Left Bi-styloid breadth + 0.016 * Left Triceps skinfold + 0.024 * Left Arm relaxed girth
	5	0.905	Body mass Left Biceps Skinfold Left Bi-styloid breadth Left Triceps skinfold Left Arm relaxed girth Left Arm flexed and tensed girth	5.928 4.176 1.640 4.176 26.657 18.373	152.254	p < 0.001	-0.576 + 0.017 * Body mass + 0.026 * Left Biceps Skinfold - 0.108 * Left Bi-styloid breadth + 0.012 * Left Triceps skinfold + 0.109 * Left Arm relaxed girth - 0.083 * Left Arm flexed and tensed girth
	6	0.910	Body mass Left Biceps Skinfold Left Bi-styloid breadth Left Triceps skinfold Left Arm relaxed girth Left Arm flexed and tensed girth Left Acromiale-Radiale length	7.514 4.188 1.672 4.180 27.238 18.375 1.627	137.592	p < 0.001	-1.272 + 0.013 * Body mass + 0.027 * Left Biceps Skinfold - 0.125 * Left Bi-styloid breadth + 0.011 * Left Triceps skinfold + 0.117 * Left Arm relaxed girth - 0.083 * Left Arm flexed and tensed girth + 0.025 * Left Acromiale-Radiale length
Trunk fat mass (kg)	1	0.780	Waist girth	1.000	358.541	p < 0.001	-24.423 + 0.461 * Waist girth
	2	0.850	Waist girth Right Subscapular skinfold	2.870 2.870	282.990	p < 0.001	-14.360 + 0.273 * Waist girth + 0.213 * Right Subscapular skinfold
	3	0.883	Waist girth Right Subscapular skinfold Body mass	5.438 2.873 3.416	248.738	p < 0.001	-8.814 + 0.053 * Waist girth + 0.228 * Right Subscapular skinfold + 0.159 * Body mass
	4	0.901	Waist girth Right Subscapular skinfold Body mass Left Abdominal skinfold	5.555 4.239 3.487 2.170	226.007	p < 0.001	-10.065 + 0.058 * Waist girth + 0.152 * Right Subscapular skinfold + 0.161 * Body mass + 0.136 * Left Abdominal skinfold
	5	0.906	Waist girth Right Subscapular skinfold Body mass Left Abdominal skinfold Biacromial breadth	7.882 4.431 3.697 2.187 5.894	189.333	p < 0.001	-4.745 + 0.068 * Waist girth + 0.140 * Right Subscapular skinfold + 0.184 * Body mass + 0.127 * Left Abdominal skinfold - 0.194 * Biacromial breadth
Right lower limb fat mass (kg)	1	0.776	Body mass Right Calf skinfold	1.559 1.559	173.450	p < 0.001	-0.909 + 0.078 * Body mass + 0.046 * Right Calf skinfold
	2	0.800	Body mass Right Calf skinfold Stretch Stature	2.080 1.638 1.357	131.782	p < 0.001	-5.824 + 0.066 * Body mass + 0.053 * Right Calf skinfold + 0.034 * Stretch Stature
	3	0.840	Body mass Right Calf skinfold Stretch Stature Right 1 cm gluteal girth	9.891 1.638 1.559 7.857	128.556	p < 0.001	-12.114 + 0.002 * Body mass + 0.053 * Right Calf skinfold + 0.051 * Stretch Stature + 0.126 * Right 1 cm gluteal girth

Table 7 (continued)

	Model	R ²	Variable included	VIF	F	p	Equation
Left lower limb fat mass (kg)	1	0.792	Body mass	1.674	190.441	p < 0.001	-0.782 + 0.069 * Body mass + 0.068 * Left Calf skinfold
			Left Calf skinfold	1.674			
	2	0.822	Body mass	2.080	152.040	p < 0.001	-4.895 + 0.057 * Body mass + 0.081 * Left Calf skinfold + 0.051 * Left Iliospinale Height
			Left Calf skinfold	1.817			
			Left Iliospinale Height	1.243			
	3	0.840	Body mass	2.460	128.360	p < 0.001	-5.781 + 0.048 * Body mass + 0.059 * Left Calf skinfold + 0.060 * Left Iliospinale Height + 0.036 * Left Thigh skinfold
			Left Calf skinfold	2.510			
			Left Iliospinale Height	1.319			
			Left Thigh skinfold	2.668			

Kg: kilogram; %: percentage; VIF: variance inflation factor

DXA in the same manner, which can therefore provide more stable and accurate body composition measurements, specifically fat measurements, regardless of these variations [64]. Additionally, the hormonal environment in males contributes to an android pattern of fat distribution, characterized by a greater fat accumulation in the abdominal region. Hormones such as testosterone and growth hormone play crucial roles in this process. Testosterone is known to promote the development of lean body mass and to reduce fat mass [65, 66]. Growth hormone also supports muscle growth and fat metabolism, with higher levels in males especially during the growth stage [67]. This hormonal context leads to a body composition where fat is more centrally located in males, and as a result, sex is a modulating factor in the differences shown in segmental fat between methods (67).

As mentioned, one of the primary challenges faced in this study was the notable discrepancy between BIA and DXA when estimating segmental fat mass. Given these constraints, a second objective was pursued: developing anthropometric-based predictive models for segmental fat mass in kg, using multivariate regression equations with DXA as the reference method. Anthropometry has many distinct advantages in this context, particularly within public health settings [68, 69]. It is a highly accessible, low-cost method that can be employed in large-scale studies and across various population groups [70, 71]. Therefore, by leveraging anthropometric data, this study aimed to bridge the gap left by the limitations of BIA, to offer a more feasible and scalable solution for body fat analysis in resource-constrained environments. Furthermore, the current study strictly adhered to the most current ISAK protocols, by including all 45 variables, and accounting for bilateral asymmetries in the predictive models. This comprehensive approach not only improves the robustness of the models, but also enhances their applicability and replicability in both research and public health settings [19, 42, 72]. The results of the predictive models differed between males and females, when using DXA as the reference. The models developed showed a higher prediction capacity in females. These findings are consistent with previous studies that suggested that

anthropometric measurements can be reliable predictors of body composition, particularly in females [73, 74].

In males, the predictive models for both the right and left upper limbs included triceps and biceps skinfolds, confirming the relationship between subcutaneous fat and segmental fat [75]. In addition, skinfolds, as well as body mass, have shown the lowest multicollinearity values when generating the models and this enhances their predictive capacity. In the right upper limb, body mass also contributed to the prediction equation. This demonstrates the high predictive power of this basic variable, and in fact, several general fat mass estimation formulae include this variable in their analysis. However, arm relaxed girth and arm flexed and tensed girth were determinant variables in left upper limb fat prediction. Arm relaxed girth reflects not only muscle mass but also subcutaneous fat [76], which could explain why this variable is a positive determinant of upper limb fat mass, although with a higher multicollinearity, what could weaken the predictive power of this variable. On the other hand, arm flexed and tensed girth negatively predicted segmental fat mass, which could be because this variable is highly correlated with muscle mass development, instead of fat [77].

Focusing on the left upper limb in females, the multivariate regression model highlighted the importance of variables such as triceps skinfold for the right upper limb, and biceps skinfold for the left upper limb, also indicating a strong relationship between subcutaneous fat and segmental fat mass in the upper limbs [75]. Body mass has been shown to have a high predictive power in the left arm in women. This is consistent with previous studies, thereby showing the high predictive power of body mass on total fat, especially in populations where there is no prominent muscular presence that could act as a contaminating factor. In addition, considering that the left arm tends to be the least dominant in the general population worldwide, the prediction of fat mass could be made from body mass, although this variable does not distinguish between fat mass and lean mass [73].

For the trunk, in both males and females, the key predictor variables included the supraspinale skinfold and

waist girth, respectively. These variables emphasize the relevance of central adiposity and visceral fat distribution in predicting trunk fat. Similar findings were reported in previous research, where waist girth was a strong predictor of trunk fat, emphasizing its usefulness in clinical and fitness assessments [63, 78].

In the lower limbs, the models underscored the influence of the thigh skinfold, thigh 1 cm gluteal girth, and body mass. The thigh skinfold provides a direct assessment of subcutaneous fat in one of the primary regions where fat accumulates in the lower limbs [79]. This localized fat is closely associated with overall lower limb fat mass, making the thigh skinfold a strong predictor of total fat in this area [79]. Similarly, the gluteal girth at 1 cm below the fold captures both subcutaneous fat and underlying muscle mass. Given the high proportion of fat stored in the glutes and thighs as compared to other body regions [80], this measurement indirectly reflects overall fat accumulation in these areas, while also detecting variations in leg circumference influenced by fat content [81]. Although body mass is a more general measurement, it correlates positively with total fat content, especially in populations with a higher BMI [59, 82, 83], and can thus serve as an indicator of the total fat deposited in the lower limbs. For females, the most precise model for both lower limbs included body mass and calf skinfold. The findings that calf skinfold and body mass are the strongest predictors of leg fat in females can be attributed to the unique physiological and anthropological factors influencing fat distribution in females. They typically exhibit a greater accumulation of subcutaneous fat, particularly in the gluteo-femoral region, including the calves, due to the regulatory effects of estrogen [84]. This regional fat deposition is thought to serve as an energy reserve for reproductive functions such as gestation and lactation, reflecting an evolutionary adaptation [85]. The calf skinfold measurement, which captures the subcutaneous fat in this area, therefore becomes a reliable indicator of overall leg fat. Additionally, body mass correlates with a higher body fat percentage in females, particularly in areas prone to subcutaneous fat storage, such as the lower limbs [28, 67].

However, these conclusions should be taken with caution. In all cases, the main predictor variable had a VIF below 5, which is the value determined by previous research to establish that there is no multicollinearity in its predictive ability [46]. However, some of the covariates included obtained a VIF above 10; considering that they may have some multicollinearity with other variables, it is recommended to eliminate or group variables with scores above this value [46], so perhaps it would be more appropriate to choose predictive models in which all factors have a $VIF < 5$.

Strengths, limitations and future lines of research

The current study reveals the complex interplay between various anthropometric measurements and segmental fat distribution. The variables related to skinfolds, girths, and body mass, have been the most important determinants in the different segmental fat prediction equations for both males and females. Understanding these relationships is crucial for developing accurate models for body composition analysis, which have significant implications for health, sports, and aesthetic assessments. These insights support the use of comprehensive anthropometric assessments in clinical and fitness settings, promoting a nuanced approach to evaluating and optimizing segmental body composition. This work seeks to fill the gap in the literature by providing comparative data between methods, and by developing practical tools for assessing segmental fat, thereby contributing to a better understanding and management of adiposity in various contexts.

Furthermore, the adherence to ISAK protocols and the inclusion of bilateral measurements provide a robust foundation for the proposed predictive models, and the results presented offer a strong foundation for further research. The simplicity and accessibility of the anthropometry-based models developed in this study highlight their potential to address gaps in body composition analysis, particularly in settings where DXA is unavailable or unsuitable. These findings represent an important step forward in creating practical tools for assessing segmental fat.

However, this study presents some limitations. Firstly, the sample included only young individuals with normal BMI ranges and an adequate hydration status. Although the findings are robust within the context of this study, they are primarily applicable to individuals with similar demographic and physiological profiles. Therefore, the findings of the present research cannot be generalized to other populations [74]. Future research should aim to include a more heterogeneous and representative population in terms of age, adiposity levels, and hydration status. This would enhance the external validity of the models and allow their application to broader groups, such as older adults, children, or individuals with extreme body composition characteristics, such as elite athletes or those with obesity.

Secondly, the sample was selected by convenience sampling. However, although the sample was very large as compared to previous studies [4], it was limited to university students of Caucasian ethnicity coming from mostly Southern and Eastern European countries. This may have meant that the sample was not representative of the young population, and the particular characteristics of the individuals accessible for the present research may have influenced the results obtained. These issues

may limit the generalization of the findings [18, 86], necessitating replication in future research in samples with diverse hydration statuses, BMI, age, ethnic backgrounds and metabolic conditions, among others, or randomly selected samples.

Thus, while the equations generated demonstrated a strong predictive power within the sample studied, their performance in diverse populations remains to be tested. Together with this, some of the variables showed a high multicollinearity, possibly affecting the predictive power of the model. Future research should prioritize the inclusion of independent validation groups and a broader range of individuals to confirm the reliability of these models for both group-level analysis and individual assessments, and to also confirm the specific weight of the predictive variables in the model.

Additionally, a standing BIA device was used, which, although widely accepted and frequently utilized in clinical and sports settings [87], may produce discrepancies as compared to supine BIA systems [49]. The eight-electrode placement on the hands and feet, standard for many BIA devices, has shown acceptable validity for total body composition estimation, but may not be optimal for body segment-specific analysis, especially in special populations such as those with fluid retention disorders or asymmetries [60]. Future studies should also explore whether the predictive models developed here maintain their accuracy under conditions of extreme BMI or abnormal hydration levels, as these factors are known to influence BIA-based estimations.

Practical implications

The findings of this study offer valuable insights for health professionals, particularly in clinical settings where DXA may not be available due to its high cost or limited accessibility. The Bland-Altman analysis demonstrated significant differences between BIA and DXA across various body segments. These findings reinforce the known fact that DXA and BIA are not interchangeable for segmental fat mass estimation, even in a well-hydrated, homogeneous population with normal BMI ranges. Given the observed variability and overestimation tendencies of the BIA, this raises concerns regarding the reliability of BIA. This concern could be even greater in populations with abnormal hydration states, such as individuals with lymphedema, edema, or chronic kidney disease, or in elderly populations where hydration status can vary significantly [61, 88]. Under such conditions, it is likely that the agreement between BIA and DXA would deteriorate further, limiting its usefulness as a reliable tool. In contrast, anthropometry has shown less variability under ad libitum conditions, reinforcing its robustness as a tool for segmental fat analysis [27, 30, 77]. By relying on simple, standardized measurements, anthropometry becomes

crucial for segmental fat analysis in contexts where DXA is unavailable.

Therefore, by developing predictive models for segmental fat estimation using simple anthropometric measurements, this research provides an effective and validated alternative for assessing fat distribution across the body. These models demonstrate that through the use of straightforward measurements, it is possible to predict fat mass in specific body segments such as the upper limbs, trunk, or lower limbs. More specifically, the determination of segmental fat mass in males can be achieved with just 10 variables (body mass, right and left triceps skinfolds, right biceps skinfold, left supraspinale skinfold, right and left thigh skinfolds, left arm relaxed girth, left arm flexed and tensed girth, and left thigh 1 cm gluteal girth), and in females with just 6 variables (body mass, right triceps skinfold, left biceps skinfold, right and left calf skinfolds, and waist girth). This simplicity not only reduces the need for complex and costly diagnostic tools but also makes these models highly accessible and feasible for implementation in diverse clinical and public health settings [68].

These anthropometry-based models also hold significant potential for public health initiatives, especially in underserved populations where the prevalence of obesity and associated comorbidities is high [79, 88, 89]. By providing a cost-effective solution for routine screening and monitoring, these models enable health professionals to identify individuals at risk of central fat accumulation, a critical predictor of chronic diseases such as cardiovascular conditions and metabolic syndrome. The simplicity of these models also ensures their applicability in resource-constrained environments, allowing for the collection of consistent and actionable data without the need for advanced imaging technologies [2, 90, 91].

In clinical and rehabilitation settings, these models offer additional value by enabling long-term monitoring of segmental fat distribution. The ability to predict fat mass in specific segments, such as the arms or legs, using simple variables such as skinfold thicknesses or girths, provides health professionals with a practical and reliable tool. This is particularly beneficial for individuals undergoing weight loss programs, rehabilitation after injuries, or managing chronic diseases that affect body composition [92]. The accurate tracking of changes in segmental fat allows clinicians to design personalized interventions, improve functional outcomes, and enhance quality of life [93, 94]. Furthermore, in conditions such as lymphedema or metabolic disorders, understanding fat distribution at the segmental level is crucial for tailoring treatment strategies effectively. These models are also useful in unique cases, such as individuals with amputations or asymmetrical fat distribution, where traditional methods face challenges in providing accurate assessments [95].

By addressing the limitations of methods such as BIA and offering a validated, simple, and reliable alternative for segmental fat analysis, this study underscores the usefulness of anthropometry as a cornerstone of accessible health care. It bridges the gap for populations and settings where access to advanced imaging techniques is limited, contributing to more equitable health outcomes and advancing the standard of care for diverse groups.

Conclusions

In conclusion, BIA demonstrated a limited validity for segmental fat mass estimation as compared to DXA. The current findings suggest that neither BMI nor hydration status significantly influenced the differences between BIA and DXA, although sex emerged as a crucial factor, highlighting the need for tailored approaches in both clinical and public health settings. As a consequence, this study underscores the importance of developing accessible, sex-specific methods for segmental fat mass assessment. The anthropometric multivariate regression models developed in the present research offer a reliable and cost-effective alternative for estimating fat mass in the upper limbs, trunk, and lower limbs, making them especially useful for extensive public health initiatives aimed at improving early detection and supporting individualized health care strategies across diverse communities.

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Authors' contributions

MM-C: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. MA-S: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. FE-R: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. NB: Writing – review & editing, Writing – original draft, Methodology, Investigation. RV-C: Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Data availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Declarations

Ethics approval and consent to participate

The studies involving humans were approved by the Ethics Committee from the Catholic University San Antonio de Murcia (Murcia, Spain), which reviewed and authorized the protocol designed for data collection, considering the World Medical Association Code (CE062103). The studies were conducted in accordance with the local legislation and institutional requirements.

Consent for publication

The participants provided their written informed consent to participate in this study.

Competing interests

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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