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Exploratory approach to speculate on body composition models for elite teenage basketball players

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The study of human body composition covers many fields, from clinical assessment to sports performance. Humans manifest different traits that set limitations in model estimation. This investigation aimed to (i) provide sport-specific densities for reducing biological variation in body composition assessment, and (ii) develop new regression models for body volume and density estimation by field applications. Thirty elite basketball players (16.84 ± 1.15 years; 188.48 ± 6.74 cm; 82.66 ± 12.23 kg) with a mean of 10.48 years of sport experience underwent anthropometric, bio-impedance (BIA) and air-displacement plethysmography (ADP) evaluations. Many models accounting for body fat percentage (BF) used the measured body mass (BM), volume (BV) and density (d) to analyse adipose and fat-free tissues. A new model payable for all players encompassed BF, with low error propagation (3.4% of BM). In addition, two new methods estimated BV by anthropometry (R^2 = 0.96, RMSE = 2.9%) or BIA (R^2 = 0.81, RMSE = 4.56%), with a high degree of precision (97.8 and 86.8%) and accuracy (100 and 99.6%). Body composition requires rigorous speculation, advanced instruments and high costs that could lead investigators to omit relevant concepts and produce estimation biases. Specific and easier methods may enhance its applicability.

Keywords Adipose tissue, Lean tissue, Sports, Applied physiology

The study of the human body found its origins in the valuation of populations using anthropometric and morphological techniques. With the born of empirical sciences and in vivo analysis, many far-sighted investigators applied well-known physical principles to discover human body composition[1–4]. To date, densitometry and nuclear analysis still be the main subjects accounting for body compartments from atomical up to tissue-system level[5,6]. Although compartmentation allows to reduce the number of assumptions accounted for describing individual body composition, a reference human is always needed for estimation[4]. Standards used for body evaluation come from in-vitro analysis of 51 cadavers of the last century, which defined properties and proportions considered unquestionable[7]. Siri defined general formulations and accounted for uncertainty due to experimental error and biological variability, suggesting that a residual percentage of body weight is always expected. Despite techniques and technologies improving daily, a more recent assessment by a six-compartment model confirmed an error propagation close to 3.5% in body fat estimation, and how it could vary according to 16 different methods compared among the same sample[8]. Interestingly, the three-compartment model designed by Siri showed the highest level of concordance, obtaining comparable results with easier approaches, while the simplest two-compartment model reached a 6–10% variation. Despite this, the four-compartment model is considered a gold standard for body composition evaluation[9], and many studies proposed total and fat-free body densities as new references for encompassing age and sex discrepancies[10–14]. In addition, several authors applied 3 or 4-C models to account for differences between sports and roles in the same discipline[15,16]. Independently of compartment number, densitometry models assumed constant densities in fat and fat-free bodies at measured temperature[3], settling a limit in error propagation due to variability in biological traits. Even when the number of measured components still be equal, agreement varies between model drawings within the same sample[8]. This highlights the need of reducing the heterogeneous body traits and properties manifested by humans' phenotypes and lifestyle habits such as sports[17–19]. Much evidence well-stated the strong relationship between body composition, metabolism and performance in sports[20]. For example, in high-level basketball players, anthropometrical sizes such as stature, hand length and wingspan were determinants in predicting future on-court performance[21]. In addition, international players exhibited reduced body fat profiles compared to national or regionals, with clear variations due to measurement methods, gender and age[22]. However, few sports institutes or clubs are equipped with sophisticated instruments such as neutron activation analysis (NAA), dual x-ray absorptiometry (DXA), underwater weighting or air displacement plethysmography (ADP), and technicians

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may evaluate body composition through bio-impedance analyser (BIA) or anthropometric[19]. Whilst cheaper and portable techniques are applied worldwide reducing laboratories' issues and easily allowing body composition applications, methods based on regression equations to account for body fat reported wider variability, likely due to unspecific models[16,23]. A recent meta-analysis found that SK and BIA always underestimate body fat in basketball players, up to a 10% discrepancy, compared to gold standard methods[22]. It leads to the demand for new models that increase accuracy and precision in estimating fat profiles of specific sports[24]. Recent findings showed that fat-free tissues exhibited density values higher than 1.1 kg/L in athletes, and only their identification allows us to account for biological variation[15,25]. Although basketball still be one of the most debated sports and fat profiles have been reported, no previous experiment provided a sport-specific model that uses elite players as a human reference, lacking property details such as density of fat-free mass[15,22].

In light of the above-mentioned statements, it is still clear that investigators may consider several aspects in body composition evaluation: (a) expertise and instruments available, (b) assumptions and model references, and (c) phenotypic features and sample variability. To date, no investigators defined body densities for their application in specific sports, and their definition may be a valid purpose to reduce biological variation with modern in-vivo methods. So, this study presented two main aims:

1) Defining densities for elite juvenile basketball players and applying that property to mathematical functions to create specific human references. These should allow setting of extreme cut-offs for fat and fat-free densities and reduce the propagation of errors.

2) Drawing new regression models for body volume estimation by anthropometry and BIA in the targeted sample. These should allow the application of the proposed method to investigators who use field instruments instead of laboratory ones.

Results

Body fat models

Table 1 shows the descriptive statistics divided by the age categories. Younger players exhibited a lower proportion of ICW (59.47% of TBW) compared to older (60.07%), associated with smaller reactance (Δ = −3.96, 95% CI: −6.527; −1.393).

As regards body composition models, the highest levels of BF were 21.66% (by 2-C Siri, U17) and 21.4% (by Brozek, U19) with relative d = 1.0495 and d = 1.0592 kg/L, respectively. The highest values of d_0 were 1.103 and 1.113 kg/L for younger and elder players. So, according to formula (6), references for the new model I were $f_0 = 0$, $f_1 = 0.21663$, $d_0 = 1.103$ kg/L, $d_1 = 1.0495$ kg/L for U17, and $f_0 = 0$, $f_1 = 0.214$, $d_0 = 1.113$ kg/L, $d_1 = 1.0592$ kg/L for U19, while the new model II settled highest values for f_1 and d_0. However, no significant differences appeared between categories in ADP variables and BF models.

Figure 1 (A) shows the relationship between each model for the total sample and each category, while Fig. 1 (B) shows the Bland and Altman graphs. The 3-C Siri model reported the strongest concordance with Lohman one (95% CI of CCC: 0.710, 0.923), with a high grade of precision (0.816) and accuracy (0.95). The new methods proposed reported low degrees of accuracy (I = 65% and II = 68%) due to wider differences in means (95% limit of agreement for new model I: −8.176, 0.651; 95% limit of agreement for new model II: −7.265, 0.616), but higher levels of precision. When analysed within groups, new model I reported the highest level of concordance with 3-C Siri in U17 (95% CI of CCC: 0.529, 0.905), whereas new model II in U19 (95% CI of CCC: 0.325, 0.846). New model I linearly correlated (Pearson) with the sum of skinfold thicknesses ($\rho = 0.686$, $p < 0.01$), specific resistance ($\rho = -0.398$, $p < 0.01$) and BV ($\rho = 0.664$, $p < 0.01$), while new model II related with thigh circumference ($\rho = 0.671$, $p < 0.01$) and specific reactance ($\rho = -0.485$, $p < 0.01$), with similar degree with the sum of skinfold thicknesses ($\rho = 0.679$, $p < 0.01$). However, the new model II showed better Pearson coefficients to both d and d_0 ($\rho = -0.999$ and $r = -0.272$) compared to the new model I ($\rho = -0.899$ and $r = -0.1$). Concerning propagation of uncertain (7), the new model I reached a mean error of 5.57% of body mass (6.35% in U17 and 4.79% in U19), while model II reported a lower error propagation (3.39% of BM). Concerning comparison between models I and II, Fig. 2 (A) shows the reduced major axis with the line of perfect agreement, where the Lin's concordance correlation coefficient was 0.88 (95% CI: 0.803, 0.958), while accuracy and precision were 0.98 and 0.898 respectively. The 95% limits of agreement varied between − 3.304 and 4.179 (Fig. 2B).

New models' functions follow:

New model I

$$BF = \left(\frac{4.6873}{d} - 4.24959\right) {*}100 = ((4.6873{*}BV) - (4.24959{*}BM)) {*}100 \tag{8}$$

Category U17

$$BF = \left(\frac{4.689264}{d} - 4.213175\right) {*}100 = ((4.689264{*}BV) - (4.213175{*}BM)) {*}100 \tag{9}$$

Category U19.

New model II (all players)

$$BF = \left(\frac{3.98495}{d} - 3.58037\right) {*}100 = ((3.98495{*}BV) - (3.58037{*}BM)) {*}100 \tag{10}$$

Variables	U17 ($n=16$)		U19 ($n=14$)		U19 vs. U17		Total ($n=30$)	
	Mean	SD	Mean	SD	$F_{(1, 28)}$	p	Mean	SD
age [years]	15.93	0.49	17.89	0.67	83.87	< 0.01*	16.84	1.15
experience [years]	8.99	2.61	12.17	3.07	9.41	< 0.01*	10.48	3.22
Anthropometry								
BM [kg]	80.74	11.66	84.86	8.18	1.22	0.279	82.66	10.23
stature [cm]	187	7.82	190.17	5	1.69	0.204	188.48	6.74
arm [cm]	29.57	2.71	31.39	1.86	4.46	0.044	30.42	2.49
thigh [cm]	56.05	4.95	55.16	3.09	0.34	0.565	55.63	4.14
calf [cm]	39.19	2.71	38.71	1.94	0.3	0.586	38.96	2.36
Skinfold thickness								
triceps [mm]	10.09	3.54	9.05	2.5	0.84	0.368	9.61	3.1
biceps [mm]	4.28	1.6	4.68	1.09	1.33	0.259	4.47	1.38
subscapular [mm]	8.53	2.65	8.98	1.32	0.33	0.57	8.74	2.12
sopra iliac [mm]	9.78	3.9	11.04	2.01	1.17	0.289	10.37	3.18
sopra spinal [mm]	7.48	2.66	6.98	2.57	0.29	0.594	7.25	2.58
thigh [mm]	11.25	3.44	11.84	3.28	0.23	0.636	11.53	3.32
calf [mm]	9.11	2.68	8.68	3.54	0.14	0.709	8.91	3.06
total sum [mm]	60.53	17.91	61.25	14.23	0.01	0.905	60.87	16.03
BIA								
R [Ω]	445.38	40.95	451.08	34.57	0.17	0.686	448.04	37.57
Xc [Ω]	54.05	3.89	58.01	2.95	9.67	< 0.01*	55.9	3.97
TBW [kg]	51.93	6.41	53.82	4.91	0.8	0.378	52.81	5.75
ECW [kg]	21.05	2.46	21.49	1.75	0.31	0.579	21.25	2.14
w/FFM [%]	74.24	2.6	72.07	3.76	3.44	0.074	73.22	3.32
ICW/ECW	1.47	0.04	1.5	0.03	7.82	< 0.01*	1.48	0.04
ADP								
BV [L]	75.6	11.51	79.08	7.97	0.9	0.351	77.23	10.01
d [kg/L]	1.069	0.011	1.074	0.009	1.34	0.257	1.071	0.01
d_0 [kg/L]	1.1	0.002	1.102	0.003	4.7	< 0.05*	1.101	0.003
Body composition								
BF Brožek [%]	12.94	4.39	11.78	4.32	0.53	0.471	12.4	4.32
BF 2-C Siri [%]	13.05	4.84	11.13	4.08	1.36	0.254	12.16	4.53
BF Lohman [%]	11.6	4.92	10.63	4.13	0.34	0.566	11.15	4.51
BF 3-C Siri [%]	10.54	3.89	10.87	2.42	0.07	0.791	10.7	3.29
BF_Mauro [%]	13.52	4.44	15.53	3.73	1.65	0.209	14.46	4.24
BF_Mauro_II [%]	14.74	3.77	13.2	3.17	1.36	0.254	14.02	6.87

Table 1. Descriptive statistics.

Body volume models

Figure 3 shows the scatterplot matrix based on the linear correlation between ADP parameters and anthropometry (A), skinfold thicknesses (B) and BIA (C). Highest Pearson coefficients appeared between body volume and body mass ($\rho=0.998$, $p<0.01$), arm ($\rho=0.826$, $p<0.01$) and thigh ($\rho=0.879$, $p<0.01$) circumferences, and specific resistance ($\rho=-0.818$, $p<0.01$), while body density strongly related to thigh ($\rho=-0.658$, $p<0.01$) and supraspinal skinfold thicknesses ($\rho=-0.606$, $p<0.01$). Regarding predicted values, volume strongly correlated with TBW ($\rho=0.982$, $p<0.01$), while body density was negatively related to TBW/FFM ($\rho=-0.824$, $p<0.01$).

According to linear correlation coefficients, two stepwise procedures have been performed considering separately anthropometrical and bioelectrical parameters. Due to correlation coefficient between BM and BV ~ 1, BM has not been considered as regressor. Table 2 shows the best anthropometrical model. White test excluded residuals heteroskedasticity ($\chi^2_{(1)}=0.02$, $p=0.888$), while VIF = 1.37 (1.37 for both regressors, with 1/VIF = 0.729) rejected the multicollinearity. Only one observation was considered as a leverage point (Cook's D = 0.15 > 0.133), and it was not removed from the model. In fact, residuals varied between −0.055 and 0.046, with a mean lower than 0.001. In addition, the residuals' curve distribution met normality. AIC and BIC equalled to −124.74 and −120.53, respectively. The mean model error was 2.89% (95% CI: 2.31%, 3.86%), where a variation of 1.47% (95% CI: 1.277, 1.662) in arm and thigh circumference induced a percental change in BV. Figure 4 and B shows the concordance level and Bland & Altman plot for anthropometrical developing model. The concordance correlation coefficient was 0.978 (95% CI: 0.962, 0.994), with levels of precision = 0.978 and accuracy ~ 1, whereas the average difference was 0.00 ± 0.03 and correlation between mean and difference = −0.106 ($p=0.854$). The prediction equation follows:

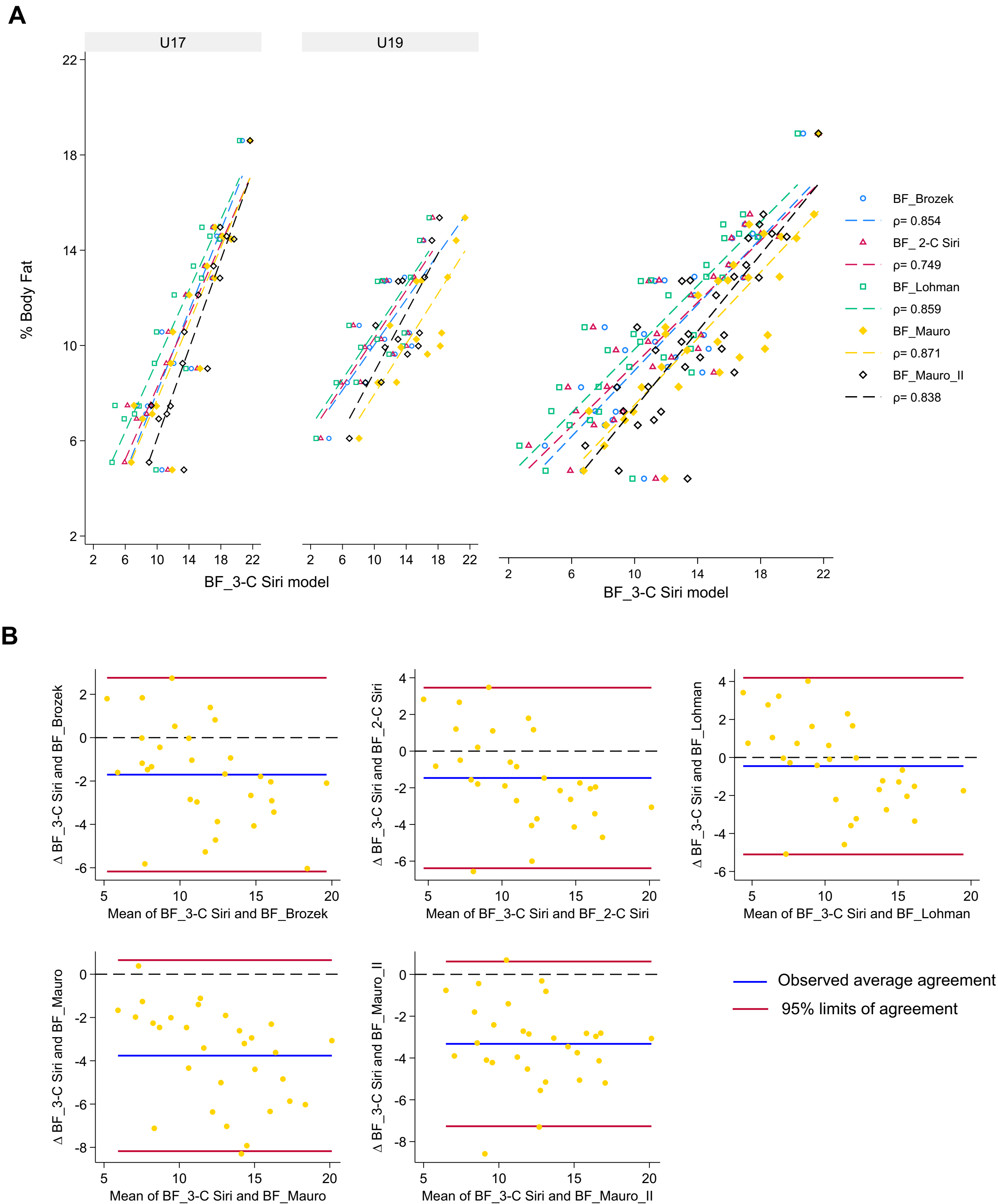

Fig. 1. Linear correlation between the 3-C Siri model and others (**A**) and Bland & Altman plots for models' agreement (**B**). Note: BF, body fat; ρ = Pearson Correlation coefficient; Δ, difference.

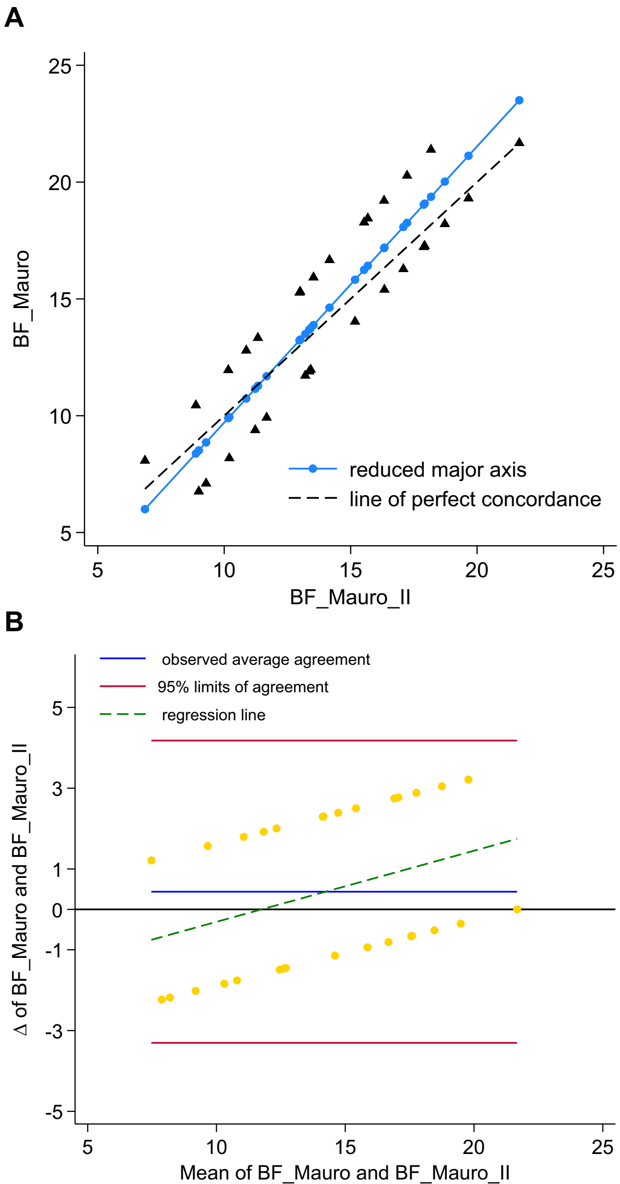

Fig. 2. Concordance (**A**) and Bland & Altman plot (**B**) for the new proposed models (Mauro and Mauro II). Note: BF, body fat; Δ, difference.

$$BV = (circum*1.344354) + e^{(stature*0.007504)-3.061758} \quad (11)$$

Where $circum = thigh + arm\ perimeters\ [cm]$ and stature was measured in centimetres.

The cross-validation group (re-test) included 13 players (16.91 ± 1.01 years). Table S1 showed descriptive statistics of re-tested players, where BM ($F_{(1,\ 24)} = 0.02$, $p = 0.902$), stature ($F_{(1,\ 24)} = 0.36$, $p = 0.554$), BV ($F_{(1,\ 24)} = 0.00$, $p = 0.997$), thigh ($F_{(1,\ 24)} = 0.69$, $p = 0.416$) and arm ($F_{(1,\ 24)} = 0.00$, $p = 0.950$) circumferences did not report significant differences. The Pearson correlation coefficient of test-retest was 0.999 (Table 2), with no significant differences between predicted BVs ($t_{12} = -1.63$, $p = 0.129$). Lin's CCC was 0.999 (95% CI: 0.998, 1.000), with perfect accuracy (99.99%) and precision (100.00%). Figure 4 shows the agreement axes (C) and Bland & Altman plot (D) for cross-validated, where the average difference was − 0.217 (95% LoA: −1.158, 0.724) and correlation between difference and mean was 0.877 ($p < 0.01$). The cross-validated model explained the 96.99% of BV variability, with a CV of 3.93%.

Table 3 shows the final linear model for predicting BV by BIA. The first model reported an outlier (observation Cook's D = 0.246, cut-off settled at 0.133) who negatively affected goodness of fit increasing AIC by 7.46% and decreasing BIC by 7.5%. The final model explained ~ 80% of BV variability, about 7% more than the first one. In addition, the mean error was reduced by 12.94% (95% CI RMSE: 3.694, 6.235). The VIF = 1.09 (for both regressors, 1/VIF = 0.914) and White test excluded residuals heteroskedasticity ($\chi^2_{(1)} = 0.49$, $p = 0.485$). Figure 5 shows the concordance agreement (A) and Bland & Altman plot (B) for BIA developing model. The concordance

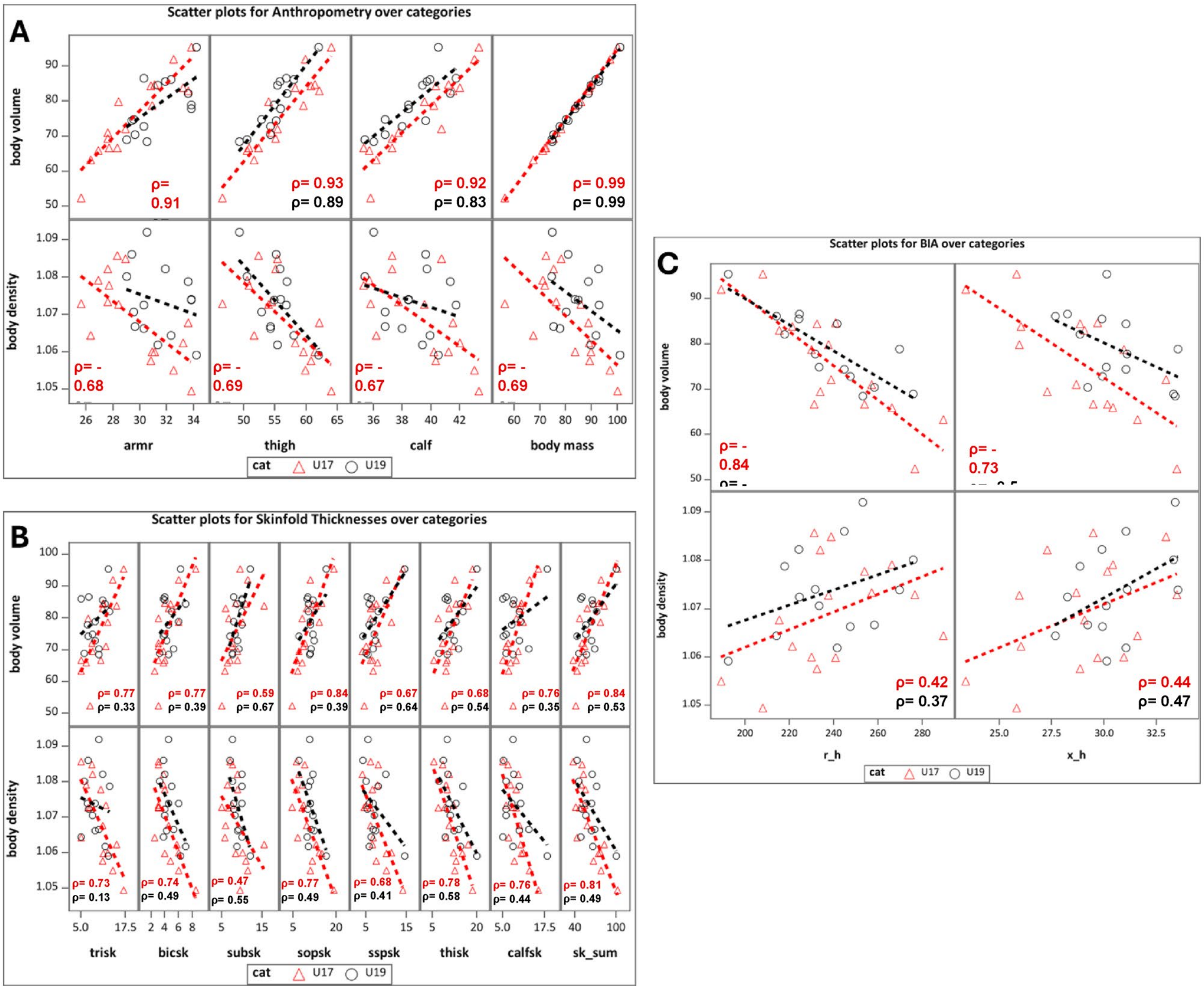

Fig. 3. Scatter plots for ADP parameters and anthropometry (**A**), skinfold thickness (**B**) and BIA (**C**). Note: ρ, Pearson correlation coefficient. Signes of correlations between body density and skinfold thicknesses were not reported for clarity but explain only negative relationship.

correlation coefficient = 0.865 (95% CI: 0.772, 0.957) with 86.8% precision and 99.6% accuracy. The 95% Limits of agreement ranged between −9.348 and 10.273, with an average difference of 0.462 ± 5.006 ($p = 0.648$). The prediction equation follows:

$$BV = (-0.1428512{*}R) + (0.9151765{*}stature) - 31.72532 \quad (12)$$

Where $R = BIA\ Resistance\ [\Omega]$ and stature was measured in centimetres.

BIA Resistance did not vary between developing and cross-validation ($F_{(1, 24)} = 3.91$, $p = 0.059$, Table S1). The Pearson correlation coefficient of test-retest was 0.928 (Table 3), with no significant differences between predicted BVs ($t_{12} = -1.48$, $p = 0.153$). Lin's CCC was 0.739 (95% CI: 0.542, 0.936), with 76.9% accuracy and 92.7% precision. Figure 5 shows the agreement axes (C) and Bland & Altman plot (D) for cross-validated model, where the average difference was 7.015 (95% LoA: −0.684, 14.715) and correlation between difference and mean was −0.126 ($p < 0.01$). The cross-validated model explained the 77.60% of BV variability, with a CV of 8.01%.

Discussion

The first aim of this study was to define body density values for elite adolescent basketball players who were expected to be selected for best national league clubs and use them to modulate body composition formulae and provide new equations for the specific sport and age. Our purpose considered detecting both fat and fat-free densities by ADP, assuming that the highest level of fat and fat-free physical traits (mass, volume and density) observed can approximate extreme values in samples with similar characteristics, such as elite category of a specific sport that requires homogeneous and defined bodies for performing best. Although participants of this study did not undergo on high-fat diet, the rationale of our assumption followed Keys, Anderson and Brožek[26]

Source	**SS**	**df**	**MS**	**$F_{(2, 27)}$**	**adj-R^2**	**RMSE**
Model	0.497	2	0.248	298.03	0.954	0.029
Residual	0.022	27	0.001	p	R^2	
Total	0.519	29	0.018	< 0.001	0.957	
ln_BV	β	se	t	p	95% CI	
intercept	−3.062	0.391	−10.55	< 0.001	−4.926	−3.322
ln_Circum	1.344	0.094	15.68	< 0.001	1.277	1.662
stature	0.008	0.001	7.81	< 0.001	0.005	0.009
Re-test (ρ = 0.999)						
Source	SS	df	MS	$F_{(2, 10)}$	adj-R^2	RMSE
Model	0.294	2	0.147	160.98	0.964	0.03
Residual	0.009	10	0.001	p	R^2	
Total	0.303	12	0.025	< 0.001	0.969	
ln_BV	β	se	t	p	95% CI	
intercept	−2.868	0.519	−5.52	< 0.001	−4.026	−1.71
ln_Circum	1.341	0.166	8.06	< 0.001	0.97	1.711
stature	0.007	0.002	3.76	0.004	0.003	0.01

Table 2. Linear regression for BV and anthropometry.

who registered the maximal increase in fat tissue (64% BF) after six months of simple overeating and used the density of the fat gain (0.9478 kg/L) as a standard for comparison. Setting asymptotic cut-offs takes with methods some limitations but should increase accuracy and precision compared to cadaveric "pure tissue" density standards. We computed the most common equations suggested by literature for adolescent samples[3,4,27] and collected the biggest value of the fat and fat-free mass. Then, to account for the validity of our models, we used as a reference the 3-C model, designed by Siri and suggested by Wang and colleagues[8]. We found that the fattest players were 21.67% (U17) and 21.4% (U19), while the densest were 1.103 (U17) and 1.113 kg/L (U19). These thresholds worked as thresholds in both new methods I, which considered the extreme values of each category, and II that considered widest fat and density. Thus, elite Young basketball players were supposed to vary in adipose tissue from 0% up to 21.67%, excluding extreme values of BF such as 64 or 100%. We found similar somatic features between Younger and elder players, which led to narrow BF estimates in models I and II. The lowest body density values for each category varied by 0.2%, while the highest by 0.09%, indicating that body densities in elite sport categories were not strongly affected by ~ 2 years of age and experience. However, density was different in fat-free bodies and matched with the lower amount of water in elder players. Many studies reported how the total body water (TBW) reduced with ageing, and its reduction affected FFM density (d_0) due to water is the fat-free component with lower density at a physiological temperature of about 37 °C [12]. The high level of negative correlation that we observed between body density and TBW/FFM ratio represents the variation sensitiveness age-related. Slaughter and colleagues[28] debated the massive biological variability in body composition due to age, and recent investigations are defining new references to fill gaps rooted in in-vitro analysis[14]. Whilst teenage males reported various profiles each year, particularly in terms of body's fat-free mass and densities, sportive samples are expected to report less consistent variation[20]. Silva and colleagues[25] found that males' variability may expand even when the adolescent athletic population was analysed, but they analysed five different disciplines together. Whilst also their level of fat-free tissue density was higher than the one proposed by Siri (1.1 kg/L), enhancing the need for define sport-specific cut-offs, a sport such as swimming requires a lower level of fat mass (10.1 ± 4.3%) due to its negative role in velocity, while sports such as gymnastic may take advantage of a stronger body independently of fat (20.8 ± 3.3%, + 5% of protein content)[29]. In fact, even if they assessed a 5-C model, the coefficient of variability for boys was 37.40%, 1.46 and 1.36 times wider than our U17 and U19, respectively. Considering that biological variability brings an amount of residual uncertainty of ~ 4% of body mass even if experimental error tends to be null[4], applying the best model and laboratory evaluations may yield less than recruiting homogeneous participants and provide many equations stratified for sport, gender and age. In fact, when we consider the whole sample, the coefficient of variation doubled. Nevertheless, the ADP reported a technical error lower than 1%[30] and we found an uncertainty propagation of ~ 3.4% of body mass in the new model II, with the highest degree of precision compared to the 3-C Siri, and lower variability when accounted for U17 and U19 separately, even if they concord at 88%. On the other hand, our proposed models reached the lowest degree of accuracy, overestimating BF compared to 3-C Siri and standard models[15]. The new models overestimated body fat by ~ 30%, and this effect could manifest due to the closer density values considered as cut-off (difference reduced by 0.2 to 0.05), and to the estimation of TBW by BIA equation. As Matias and colleagues debated, the presence of body mass and stature as regressors strongly affect the final estimation, and anthropometrical higher values led to overestimate TBW, reducing body fat percentage[31,32]. According to this expectation, our sample was about 5 kg heavier and 5 cm taller. BIA takes several assumptions based on body form and dimensions, and the variability of these traits hides estimation biases that led as again to the need of specific-population models. However, body fat reached with new models was closer (14.46 ± 4.24 and 14.02 ± 6.87) than 3-C Siri (10.7 ± 3.29) to previous results (13.84 ± 3.78%) that analysed 88 male collegial basketball players (19.83 ± 1.35 years) with DXA[15].

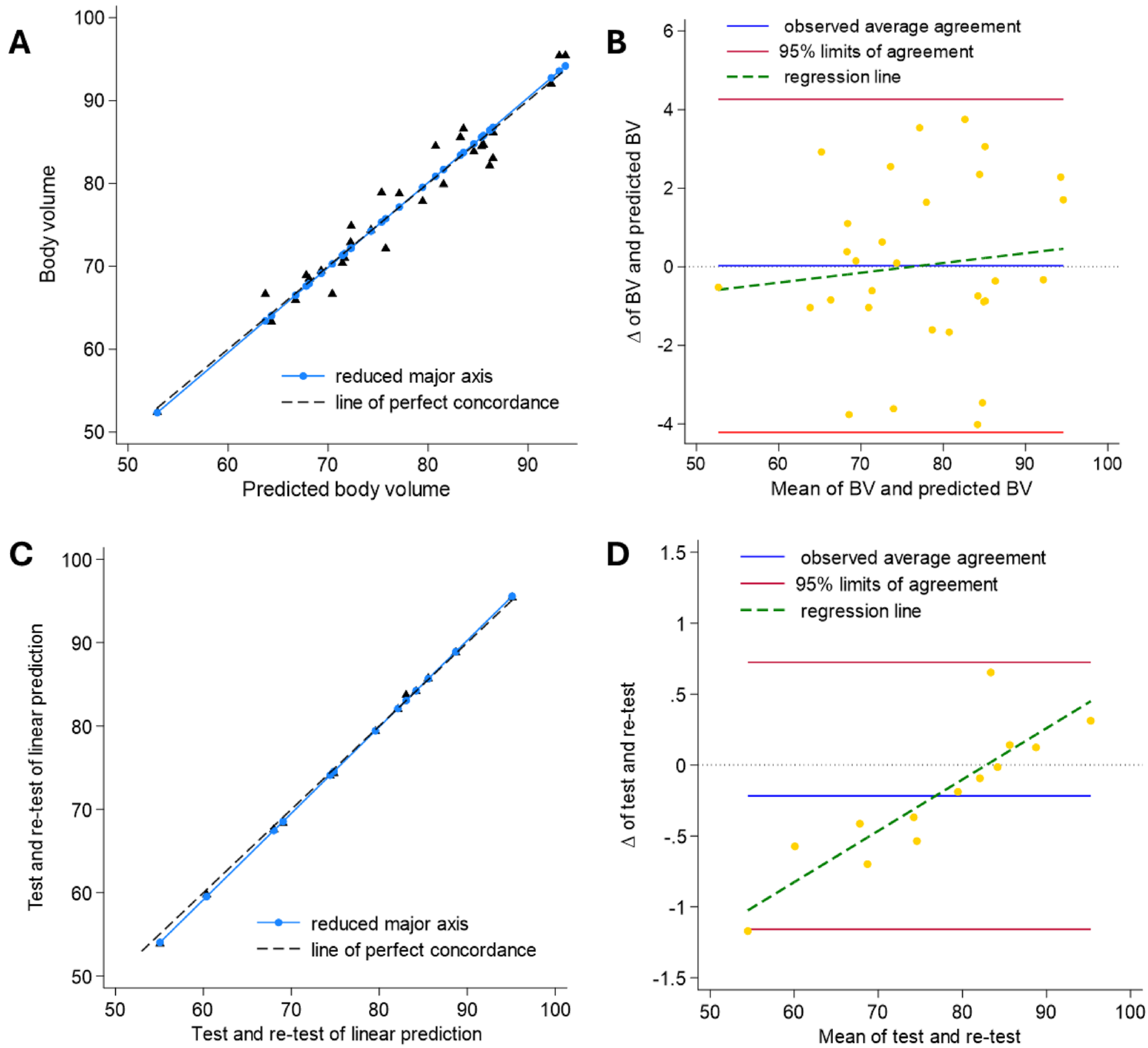

Fig. 4. Concordance line and Bland & Altman plots between observed and predicted body volume by anthropometry in developed (**A**, **B**) and cross-validated models (**C**, **D**). Note: BV, body volume; Δ, difference.

To the best of the author's knowledge, this is a novel study that projects the application of specific densities detected by ADP in a sample of elite players. Although the lack of instruments such as DXA and dilution to deeply investigate FFM compartments could have biased the estimation of fat-free densities, setting a relevant limitation in our proposal, we hope to purpose a new challenge and direction in sports physiology, in which investigators may contributing extending the evidence to many age categories and disciplines. The application of our model may allow basketball technicians to detect and monitor players body composition changes with smaller error variation, settling a direct comparison with specific elite bodies. The second aim of this study was to implement new regression models for body volume estimation by anthropometry and BIA in elite adolescent basketball players. Previous investigations debated the anthropometrical methods for assessing body composition, based on the observed linear relationship between subcutaneous adipose tissue, body density and external adipose tissue measured by skinfold thicknesses[33,34]. Thus, type I methods obtained by regression equations have been studied on the general population and athletes, and some diseases[5,33,34]. Most of the derived applications accounted for body density or body fat throughout skinfold thickness or BIA. However, both hydrostatic weighting and ADP directly measure BV against BF, which is subsequently obtained as previously debated. We proposed two different models to estimate BV from anthropometrical and BIA features, speculating that circumferences may strongly relate with BV than skinfold thicknesses. In accordance with our beginning hypothesis, we found a near-perfect linear relationship between BV and arm and thigh circumferences, and with high degrees of internal validity in body composition inspection. Despite BV and body density being inseparable measures bonded by body mass, and to date body mass is detectable with negligible error[35], to predict BV and

Source	**SS**	**df**	**MS**	**$F_{(2, 27)}$**	**adj-R^2**	**RMSE**
Model	2360.208	2	1180.104	56.75	0.799	4.56
Residual	540.664	26	20.795	p	R^2	
Total	2900.872	28	103.603	< 0.001	0.814	
BV	β	se	t	p	95% CI	
intercept	−31.752	29.644	−1.07	0.294	−92.66	29.209
R	−0.143	0.024	−5.96	< 0.001	−0.192	−0.094
stature	0.915	0.132	6.93	< 0.001	0.644	1.187
Re-test (ρ = 0.928)						
Source	SS	df	MS	$F_{(2, 10)}$	adj-R^2	RMSE
Model	1317.974	2	658.987	17.32	0.731	6.168
Residual	380.392	10	38.039	p	R^2	
Total	1698.366	12	141.53	< 0.001	0.776	
BV	β	se	t	p	95% CI	
intercept	−133.728	49.165	−2.72	0.022	−243.273	−24.182
R	−0.062	0.043	−1.43	0.184	−0.158	0.035
stature	1.236	0.226	5.46	< 0.001	0.731	1.74

Table 3. Linear regression for BV and BIA.

then compute body density as BM and BV ratio appears as a parsimonious and valid strategy with high level of precision (~ 98%), accuracy (~ 100%) and low error (< 3%), in both developed and cross-validate methods. Differently, concerning BIA we assumed that the human body acts as a perfect cylinder where the resistance opposing to current flow is proportional to body size (volume) and composition. According to what was expected by Ohm's laws, we found a negative correlation between BIA resistance and BV (inverse proportionality between R and body surface), and a simple model with two regressors (R and stature) was able to explain about 80% of BV variability, which reduced by 8.75% in cross-validated sample. Due to its high goodness of fit in predicting TBW in athletes[31] and considering that water in youths represents ~ 74% of FFM compounding a wide portion of BV[36], our results found physiological justification. Both the proposed equations allow us to reach a simple and useful 2-C model that has been validated in a wide range of individuals and applied worldwide[37]. In addition, body volume provides fundamental information in human morphology, and it has been applied in various clinical contexts. Liu and colleagues[38] designed different equations to predict BV by 3D scan technique through anthropometry. Also, Silva and colleagues[9] designed a novel equation to directly estimate BV by DXA in athletes, reducing costs and techniques needed and allowing them to assess 4-C by just one instrument. It is reasonable to look at body composition as a subject full of laboratory analyses and translate them to portable instruments such as skinfold callipers, elastic tape and impedance analysers to benefit sports investigators. Our results confirm that anthropometry fits better in predicting BV, with perfect accuracy and higher precision than BIA even in young elite basketball players. Despite this, accuracy (~ 1) and goodness of fit (R^2 = 0.8) reached by our model better predicted the desired component than previous equations that estimated BF in athletic (accuracy varied from 0.83 to 0.94, R^2 from 0.53 to 0.69) and sport-specific players (accuracy = 0.99, R^2 = 0.64). To date, few authors met the challenge of proposing specific methods for each sport[39], and direct comparisons were not available. So, unspecific models still be applied placing a cap in exposition to phenotype variability. It is not clear whether it depends on investigators' needs or journal requirements, but research should target smaller and more homogeneous samples than include hundreds of athletes enrolled from many disciplines. Sample size may be selected a priori based on the study hypothesis and design, detecting a magnitude of effect clinically relevant[40]. Once errors, statistical power and internal validation have been met, the experiment waits for replications under the same conditions (external validation). Our findings confirmed that homogeneous samples represent the key to reducing biological variation in body composition studies, where body and fat-free tissue densities varied less than 1% and body fat estimation reduce variability of 21.54% compared to previous 2-C models. This research provides many practical applications that reduce costs and limitations in body composition evaluations, from the estimation of body volume and density through field instruments up to its insertion to specific model that reflects precise body fat profiles. Coaches can easily obtain players body composition by measuring just arm and thigh circumferences, and stature, and applying their results to the purposed formulas.

Unfortunately, this study presented some limitations the authors would outline for future perspectives. Firstly, this study represents an exploratory idea investigated throughout a small sample, which restricts the generalizability of the findings. Further investigations on elite basketball players at different ages are needed to confirm or deny the external validity of our models.

Concerning the insight of our analysis, we could account for a two-compartment model with ADP or a three-compartment model adding water mass by BIA. Whilst we found it is enough to reduce error propagation compared to the previous two-compartment models (fat profile), we could not investigate the fat-free mass components. We hypothesise that experiments on four or 5-compartment models could boost biological variability reduction.

Finally, our models presented larger fat mass profiles compared to the references. Although it links to the proposed closer cutoff points and mathematical formulae, further observations are needed before recommending

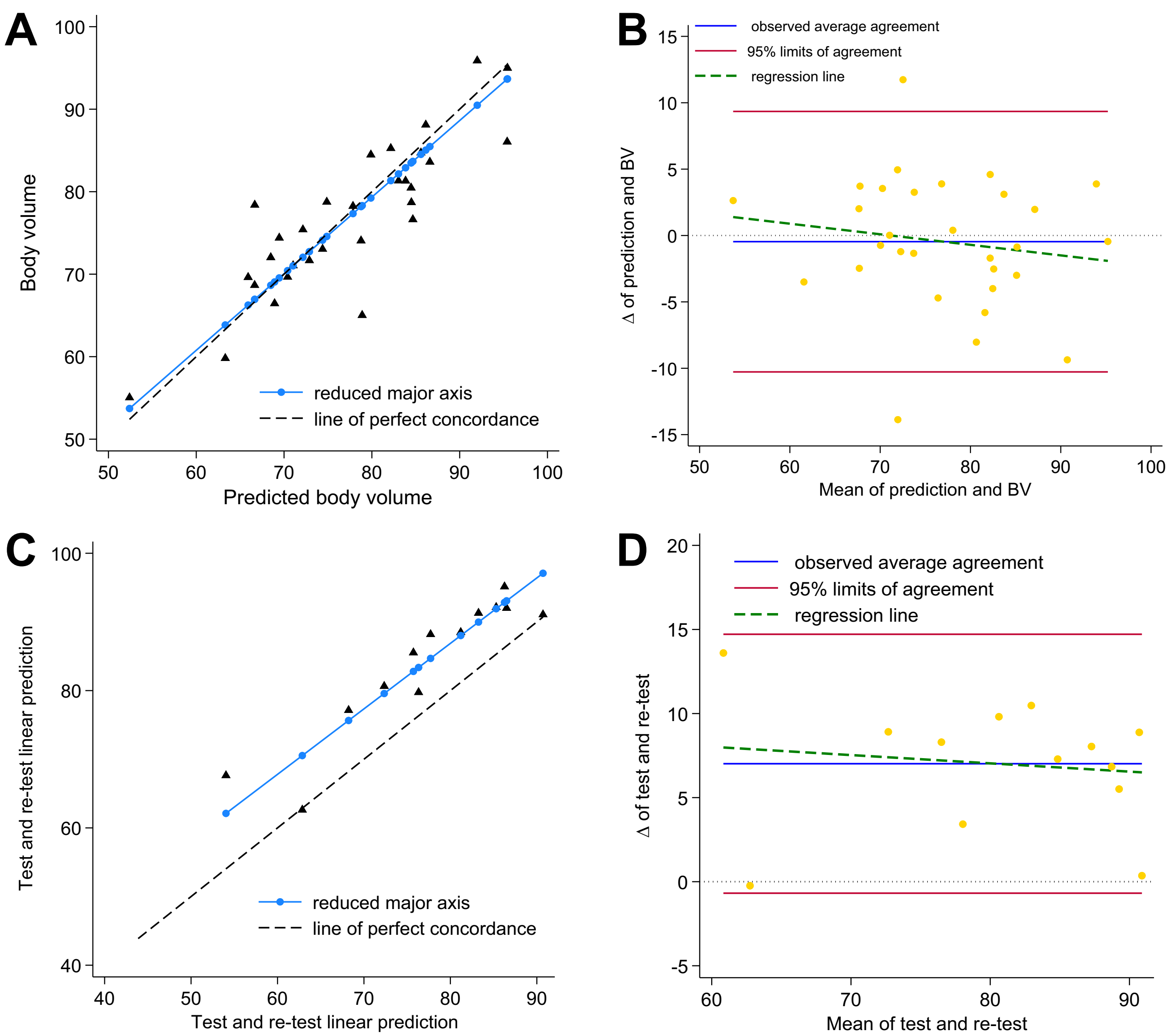

Fig. 5. Concordance line and Bland & Altman plots between observed and predicted body volume by BIA in developed (**A**, **B**) and cross-validated models (**C**, **D**). Note: BV, body volume; Δ, difference.

our theory. Research involving wider samples and many assessments could validate our models, embrace ethical issues and define new horizons in the body composition field.

Methods

Study design and sampling

This study was a cross-sectional design, assessed at the University of Bologna Sports Sciences laboratory in a room with 19.5 °C and 56% humidity. All the participants were players of the Virtus Bologna basketball Club, divided into two age categories: Under 17, composed of 16 players with 8.99 ± 2.62 years of experience (56.44% of life) and 12 h of training per week; Under 19, consisted of 14 players with 12.174 ± 3.07 years of experience (68.06% of life) and 14 h of training per week. A parent or legal guardian and adult players were informed of all experimental scopes, risks and privacy policies, and provided a written informed consent for both study participation and publication of identifying information in an online open-access publication. However, with respect to participant privacy, investigators provided data and results with no information that could lead to participants identification, deleting sensitive data such as name, surname, birthdate and/or personal images. The experiment was assessed in accordance with Helsinki ethical guidelines and approved by the bio-ethical University of Bologna committee (25,027, March 13, 2017).

The sample size was estimated a Priori to reach a statistical power of 0.8 with a type I error of 5% for a multiple Linear regression F test for partial correlation, with 12 covariates (number of measured parameters), with the effect size (squared partial correlation) equals to 0.5. The cross-validation was performed under the same conditions after 30 days.

Variable	TEM	Relative TEM (%)	Reliability (%)
arm circumference	0.064	0.21	99.93
thigh circumference	0.061	0.11	99.98
calf circumference	0.058	0.15	99.94
biceps SK	0.589	6.13	96.05
triceps SK	0.187	4.19	98.29
subscapular SK	0.348	3.98	97.30
suprailiac SK	0.341	3.29	98.83
supraspinal SK	0.365	5.03	97.99
thigh SK	0.404	3.50	98.51
medial calf SK	0.347	3.90	98.70

Table 4. Technical error and reliability of measurements.

Anthropometry

Stature was measured with a validated stadiometer (Health o Meter PORTROD, 9500 West 55th Street, McCook, IL, USA) by 1 mm of precision, according to Lohman[27]. Circumferences and skinfold thicknesses were detected on the right-body at standardized body sites[41–44]. Circumferences were measured twice at each body site with an elastic tape (Seca 201, Hammer Steindamm, Hamburg, Germany) for arm (95% CI ICC: 0.998, 0.999), thigh (95% CI ICC: 0.999, 0.999) and calf (95% CI ICC: 0.998, 0.999), whereas skinfold thicknesses were detected twice with a validated calliper (Lange, Beta Technology, Santa Cruz, CA, USA) at biceps (95% CI ICC: 0.917, 0.982), triceps (95% CI ICC: 0.965, 992), subscapular (95% CI ICC: 0.941, 0.988), sopra-iliac (95% CI ICC: 0.976, 0.995), sopra-spinal (95% CI ICC: 0.959, 0.991), thigh (95% CI ICC: 0.967, 0.993), medial calf (95% CI ICC: 0.973, 0.994), and the mean values were used for analysis. Table 4 shows the technical error of measurement (TEM) and coefficient of reliability for all anthropometrical variables.

Bio-impedance analysis (BIA)

Total body tissue resistance (R) and reactance (Xc) were detected by a BIA analyser (BIVA PRO, Akern, Florence, Italy) according to validated standards[45], at the right side of the body, with the upper-body proximal electrode placed at wrist joint mid-point and distal electrode five centimetres farer (close to metacarpal bones), while the lower-body proximal electrode placed at ankle joint mid-point and distal electrode five centimetres farer (close to metatarsal bones). The analyser was calibrated before the evaluation according to reference: R desired 383 ± 10 Ω and observed 384.2 Ω (Δ<1%), while Xc desired 45 ± 5 Ω and observed 44.5 Ω (Δ=1%). Participants were asked to respect experimental conditions such as 4-hour fasting, 12 h of resting, and at least 24 h of no alcohol assumption. Each assessment has been taken twice and the relative technical error of measurement (TEM) for R and Xc is ~ 5%.

The total body water (TBW) and intracellular body water (ICW) were estimated by Matias and colleagues' method[31], and the extracellular body water was computed as TBW – ICW.

Air displacement plethysmography (ADP)

Both body mass (BM) and body volume (BV) were measured using the Bod Pod GS-X (Cosmed, Rome, Italy). The ADP was calibrated before the evaluation day, in accordance with the manufacturer's instructions. The weight balance system worked with a precision of 0.01 kg and an error of less than 0.1%. An auto-calibration with six runs was assessed, with an average value of 45.025 ± 0.011 (error ~ 0.1%). Finally, the volume of the participant chamber was calibrated with an average value of 48.506 ± 0.008 (error ~ 0.01%). Each participant was tested twice, and if the system spotted a difference greater than 150 mL, an additional evaluation was required (95% CI ICC: 0.996, 0.999; relative TEM = 0.35%, reliability = 99.94%). All participants were instructed to wear a stretch nylon swimsuit and a Cosmed swimming cup and maintain a standardized posture during the evaluation. The volume thoracic has (VTG) was measured using standard pulmonary plethysmography or estimated by Crapo and collaborators method if it was not successfully obtained[46]. The surface area artefact (SAA) was calculated by Du Bois and Du Bois[47]. The body volume was finally computed by Dempster and Aitkens[30] as follows:

$$BV\ [L] = BV_{measured} + (0.4{*}VTG) - SAA \tag{1}$$

where $SAA = BM^{0.425} * stature^{0.725} * 71.84$.

The body density (d) was then obtained as $BM \Big/ BV\ \left[\frac{kg}{L}\right]$.

Body composition

Many models were used to estimate Body fat (BF) and fat-free mass (FFM), according to previous results:

$$BF = \left(\frac{4.57}{d} - 4.142\right){*}100 \tag{2}$$

Brozek[48]:

$$BF = \left(\frac{4.95}{d} - 4.5\right)*100 \quad (3)$$

2-C Siri 44:

$$BF = (2.118*BV) - (0.78*TBW) - (1.351*BM) \quad (4)$$

3-C Siri 44:

$$BF = \left(\frac{C_1}{d} - C_2\right)*100 \quad (5)$$

Lohman 3636:
where C_1 and C_2 are constant based on age.

According to Wang and colleagues[8], the 3-C Siri model has been considered as the reference for its high level of concordance with the atomical 6-C model (relative TEM = 3.43%, reliability = 99.54%). However, the higher level of BF (f_1) and FFM (f_0) and their relative densities (d_1 and d_0) have been recorded and then applied to customize standards for adolescent basketball players, into the general formula:

$$BF = \frac{d_1 d_0}{d}\left(\frac{f_1 - f_0}{d_0 - d_1}\right) - \frac{d_1 f_1 - d_0 f_0}{d_0 - d_1} \quad (6)$$

Where d_0 (density of FFM) has been computed by removing from BV the volume associated with fat mass, obtained as BM/ d_1 where density was constant at 0.9 kg/L, and by dividing the FFM by fat-free volume, obtained as BV-fat volume.

In addition, the uncertainty of propagation has been computed as follows:

$$\sigma_f = \sqrt{a^2\sigma_{BV}^2 + b^2\sigma_{BM}^2 - 2ab\sigma_{BV\,BM}} \quad (7)$$

Where a and b are scalars, σ is the standard deviation of the parameter and $\sigma_{BV\,BM}$ is the covariance of measured parameters. The error obtained is then divided by BM to obtain the desired percentage.

Statistical analysis

Central tendency and dispersion of variables have been quantified by mean and standard deviation. The technical error of repeated measurements (TEM) has been computed as $\sqrt{\sum \Delta^2 / 2n}$ and its relative effect as (TEM/mean) *100, while the coefficient of reliability as 1-(TEM^2/std^2). Linear correlation has been measured by the Pearson product-moment coefficient (ρ). Variables and residuals' distributions have been checked graphically and by Kolmogorov-Smirnov, Cramer-von Miles and Anderson-Darlin tests. The stepwise procedure has been performed to select the best regressors at 5% type I error probability(both for entry and removal level), with Bonferroni adjustment method. For meeting general linear model assumptions, the error sphericity has been tested by the White method, whereas tests on residuals such as Cook distance (with cut-off settled at 4/n), DFBETAS and DFFITS have been assessed for excluding outliers and leverage points. The variance inflation factor (VIF) was computed to account for multicollinearity, and a value lower than 10 was considered acceptable. To evaluate the goodness of fit, many indexes such as the adjusted-R^2, Akaike and Bayesian information criteria, and Bland and Altman's[49] limit of agreement have been implemented. Also, Lin's concordance correlation coefficient[50] given by the ratio of the Pearson correlation coefficient (a measure of precision) and the bias correction factor (a measure of accuracy) have been used. To compare variables between age categories, the one-way ANOVA has been assessed. To assess cross-validation, a paired sample t-test compared the mean values between the reference technique and new method, within cross-validated sample. Then, Lin's method was applied to measure precision, accuracy and bias. The alpha level was settled at 0.05 for each hypothesis test. The Microsoft Excel (version 2024, Windows edition) software was used to collect and gather data, while both SAS (version 9.4, Windows edition) and STATA (version SE 18, Windows edition) performed the statistical analysis.

Data availability

The data presented in this study are available upon request from the corresponding author. Additionally, the dataset can be accessed through the following DOI: https://doi.org/10.17605/OSF.IO/BUE65.

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Author contributions

M. M., F. M. and S. T. conceived and assessed the investigation. F. M. managed data. M. M. analysed data and prepared figures and tables. M. M. and S. T. wrote the main manuscript. All authors reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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