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Generalized Bioimpedance Equations Underestimate Fat-Free Mass in Elite Male Soccer Players: Development and Validation of Soccer-Specific Predictive Models

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Abstract

Bioelectrical impedance analysis (BIA) represents a quick and practical approach for evaluating body composition in sport environments. However, sport-tailored prediction equations are currently unavailable, and applying generic formulas may generate consistent estimation errors. Therefore, this study aimed to: (i) design and validate novel prediction equations for fat-free mass (FFM) components in male elite soccer players; and (ii) determine the validity of previously published predictive models. A sample of 102 male elite soccer players (mean age 24.7 ± 5.7 years), competing in the Italian first division, was assessed during the initial half of the in-season period. Participants were randomly assigned to either a development group or a validation group. Bioimpedance measurements, including resistance (R) and reactance (Xc), were obtained using a foot-to-hand BIA device operating at a single frequency of 50 kHz. Dual-energy X-ray absorptiometry was used as the criterion method to determine FFM, lean soft tissue (LST), and appendicular lean soft tissue (ALST). The newly generated equations were validated through regression analyses, Bland–Altman agreement tests, and evaluation of the area under the curve (AUC) derived from regression receiver operating characteristic (RROC) curves.

The resulting prediction equations were: FFM = − 7.729 + (bodymass × 0.686) + (stature²/R × 0.227) + (Xc × 0.086) + (age × 0.058), $R^2 = 0.97$, standard error of estimation (SEE) = 1.0 kg; LST = − 8.929 + (body mass × 0.635) + (stature²/R × 0.244) + (Xc × 0.093) + (age × 0.048), $R^2 = 0.96$, SEE = 0.9 kg; ALST = − 24.068 + (body mass × 0.347) + (stature²/R × 0.308) + (Xc × 0.152), $R^2 = 0.88$, SEE = 1.4 kg. Train–test validation conducted in the validation sample showed that commonly used athlete equations significantly underestimated all FFM-derived variables ($p < 0.01$). In contrast, the newly proposed models demonstrated no significant mean bias ($p > 0.05$), exhibited R^2 values between 0.83 and 0.91, and showed no proportional bias ($p > 0.05$). The RROC curve analysis yielded AUC values of 0.92 for FFM, 0.92 for LST, and 0.74 for ALST. Use of generalized prediction equations leads to systematic underestimation of FFM and ALST in elite soccer players. The soccer-specific equations introduced in this study provide accurate estimates of body composition while retaining the advantages of a portable, field-based assessment method.

Keywords: Bioelectrical impedance analysis, BIA, BIVA, Body composition, Lean soft tissue, Somatotype

Introduction

Body composition assessment is routinely implemented in soccer. Determination of body mass components enables clinicians and coaching staff to evaluate nutritional condition, estimate energy demands, customize dietary strategies, and monitor adaptations to training or detraining throughout the competitive calendar [1, 2]. Although body composition is often simplified as the combination of fat mass and fat-free mass (FFM), a more refined evaluation of individual FFM compartments improves measurement precision [3]. Specifically, FFM may be subdivided based on molecular (e.g., total body water and bone mineral content), cellular (e.g., intracellular and extracellular water, body cell mass), or tissue-level structures (e.g.,

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skeletal muscle, whole-body and appendicular lean soft tissue) [4].

Dual-energy X-ray absorptiometry (DXA) is widely recognized as a reference technique for both total and regional assessment of FFM components, including lean soft tissue (LST) and appendicular lean soft tissue (ALST). Nonetheless, its application is restricted by high operational costs and exposure to ionizing radiation, prompting the routine use of alternative approaches such as bioelectrical impedance analysis (BIA) [5]. Over recent decades, numerous BIA devices have been developed using different electrode configurations (hand-to-hand, leg-to-leg, foot-to-hand, and segmental) and a broad range of operating frequencies [6]. Additionally, bioelectrical impedance spectroscopy (BIS), a specialized form of BIA, applies multiple frequencies and nonlinear modeling to estimate intra- and extracellular resistance, potentially addressing several limitations associated with conventional BIA prediction equations [7].

BIA provides an estimate of body impedance, which is composed of resistance (R) and reactance (Xc) [impedance = $(R^2 + Xc^2)^{0.5}$] [8]. Resistance reflects the opposition encountered by an alternating electrical current as it passes through conductive tissues and is inversely associated with tissue hydration and electrolyte concentration [8]. Reactance, measurable only with phase-sensitive BIA instruments, is linked to the capacitive behavior of cell membranes and is influenced by membrane integrity, cellular function, and measurement frequency [8]. On the basis of established relationships between bioelectrical variables and FFM compartments [9, 10], numerous BIA-derived prediction equations have been proposed [6].

BIA-based prediction models typically incorporate anthropometric variables (e.g., stature and body mass), demographic factors (e.g., age), and bioelectrical parameters to estimate specific body compartments. These equations are developed by comparing BIA measurements collected in a defined population with reference values obtained using more precise techniques such as DXA. Regression analyses are then applied to model these associations. Once validated, the equations can be used to estimate body composition in comparable individuals without the need for invasive or time-consuming procedures [11].

In modern soccer practice, BIA is extensively used to individualize nutritional prescriptions, particularly for estimating protein requirements [12], based on FFM, or to assist in calculations of energy expenditure [13]. Furthermore, because LST and ALST predominantly represent muscle tissue and associated structures [14], their evaluation is especially relevant for soccer players due to their close association with strength and power performance [15, 16]. Additionally, FFM estimates derived from BIA allow fat mass to be calculated as the difference between total body mass and FFM, in accordance with the two-compartment body composition model [17]. Monitoring fat mass, particularly during the preparatory phase, is standard practice in soccer, as excess adiposity may impair aerobic performance and agility during repeated sprint activities [18, 19]. Collectively, these factors have contributed to the widespread adoption of BIA in sports settings as an economical, practical, and user-friendly method for body composition assessment [5].

Recent evidence has highlighted the importance of applying BIA-derived prediction equations that have been specifically developed and validated in populations comparable to those being evaluated [20, 21]. In particular, equations created using data from the general population tend to systematically underestimate fat-free mass (FFM) components when applied to athletic cohorts [22]. Such inaccuracies may arise when discrepancies exist between the anthropometric profiles of individuals included in the equation-development samples and those in whom the formulas are subsequently used [11]. From a body composition perspective, each sport is characterized by distinct morphological traits driven by sport-specific performance demands [14, 23].

For instance, soccer players generally exhibit lower stature and body mass compared with volleyball or basketball athletes, which translates into reduced FFM values and different body morphology [24, 25]. Indeed, height is not a decisive determinant of performance in soccer, unlike volleyball or basketball, where reaching over a net or scoring into a basket confers a competitive advantage. Given the contribution of FFM components to physical performance, soccer players may particularly benefit from elevated lower-limb lean soft tissue (LST), as repeated high-speed accelerations, decelerations, and changes of direction require frequent lifting of body mass against gravity [15, 26]. Owing to these sport-specific characteristics, previous investigations [24, 27] have demonstrated that soccer players exhibit bioelectrical properties distinct from those observed in other athletic populations [28], suggesting the need for dedicated prediction equations. Accordingly, bioelectrical

reference data for soccer players have been reported over the years [29, 30]. However, these references are based on a qualitative BIA approach known as bioelectrical impedance vector analysis (BIVA), which evaluates raw bioelectrical parameters as a vector plotted on a graph and compared with sport-specific tolerance ellipses [5, 31].

At present, the literature provides only BIA-based predictive equations developed using heterogeneous samples comprising athletes from multiple sports disciplines [32, 33], and no study has specifically validated BIA prediction models for estimating FFM components in soccer players. As previously noted, because each sport is associated with unique bioelectrical and body composition profiles [14, 18], we hypothesized that sport-specific equations would yield more precise estimates of FFM, lean soft tissue (LST), and appendicular lean soft tissue (ALST) in elite soccer players compared with generalized models. Therefore, the purpose of this study was to develop new soccer-specific BIA prediction equations and to evaluate their accuracy relative to existing generalized equations derived from mixed athletic populations.

Materials and Methods

Participants and study design

This cross-sectional investigation included 102 male soccer players (age 24.7 ± 5.7 yrs) competing in the Italian top division (Serie A). A priori sample size estimation indicated that 77 participants were required to achieve a type I error of 5% and a statistical power of 80%; thus, the final sample size was adequate to ensure sufficient power for model development. Inclusion criteria were as follows: (i) age ≥ 18 years; (ii) absence of performance-enhancing substances and any pharmacological treatment; and (iii) abstention from alcohol and caffeinated drinks for at least 15 h before testing. Players were excluded if they were injured or engaged in less than 10 h of training per week. Data collection took place during the first half of the competitive season, with measurements conducted in the morning between 9:00 and 11:00 AM. All participants provided written informed consent, and the study protocol received approval from the local University Ethics Committee (approval number 1052019), in accordance with the principles of the Declaration of Helsinki.

Procedures

Body mass and stature were assessed to the nearest 0.1 kg and 0.1 cm, respectively, using a calibrated scale with an integrated stadiometer (Seca, Hamburg, Germany). Body mass index (BMI) was computed as body mass (kg) divided by stature squared (m²). Somatotype components were determined using the Heath–Carter method [34], following procedures described previously [25].

Foot-to-hand BIA measurements were obtained using a single-frequency device operating at 50 kHz (BIA 101 BIVA®PRO, Akern Systems, Firenze, Italy). Participants were instructed to remove all metallic objects and to lie in a supine position during assessment, isolated from conductive surfaces, with legs abducted at 45°, shoulders abducted at 30° relative to the midline, and hands placed in pronation [17]. After skin preparation with isopropyl alcohol, two adhesive electrodes (Biatrodes Akern Srl, Firenze, Italy) were positioned on the right hand and two on the right foot, following athlete-specific guidelines [17, 35]. Device reliability was verified before each testing session; test–retest coefficients of variation (CV% = standard deviation/mean × 100%) for duplicate measurements were 0.3% for resistance (R) and 0.9% for reactance (Xc).

Hydration status was assessed through urine-specific gravity to confirm adequate hydration, defined as a value ≤ 1.020 [36]. First-morning urine samples were analyzed within 30 min using a handheld clinical refractometer (ATAGO Co., Tokyo, Japan). Generalized BIA-based equations for estimating FFM [33] and ALST [32] were included in the train–test validation procedures. Fat mass percentage was derived from BIA-predicted FFM using a two-compartment body composition model, whereby fat mass equals the difference between body mass and FFM [17]. To further characterize participants' body composition, bioelectrical R and Xc values were normalized to stature and plotted as vectors on the R–Xc graph according to BIVA methodology. This approach enabled comparison of bioelectrical characteristics between development and validation groups and relative to established soccer reference populations [29].

All participants also underwent whole-body dual-energy X-ray absorptiometry (DXA) scanning using a Lunar Prodigy system (General Electric, Boston, MA, USA), with body composition analyses performed using Lunar Encore software (2003 Version 157 7.0). The scanner was calibrated daily in accordance with manufacturer

guidelines using a standardized calibration block. DXA measurements were used to obtain whole-body estimates of FFM, fat mass, lean soft tissue (LST), and appendicular lean soft tissue (ALST).

Statistical analysis

Data processing and analyses were carried out using IBM SPSS Statistics 24.0 (IBM, Chicago, Illinois, USA), BIVA software (Piccoli and Pastori, 2002), and MedCalc v.11.1.1.0 (Mariakerke, Belgium, 2009). All variables underwent normality assessment via the Kolmogorov–Smirnov test. A train–test validation framework was implemented to evaluate the predictive accuracy of the models developed in this study. Two-thirds of participants were randomly assigned to the training dataset, and the remaining one-third were used as a testing dataset (randomization performed through random.org). Descriptive statistics for both the development and validation cohorts are reported as mean ± standard deviation (SD). Between-group differences in general characteristics were analyzed using the independent-sample Student's t-test.

To examine differences in bioelectrical vectors between groups, the two-sample Hotelling's T^2 test was used, which extends the t-test to multivariate outcomes. Separate 95% confidence ellipses were plotted to highlight differences in bioelectrical properties. In the training group, backward stepwise linear regression was applied to evaluate the contribution of age, body mass, stature, somatotype, resistance (R), and reactance (Xc) in predicting FFM, LST, and ALST. Assumptions of residual normality and homogeneity of variance were checked during model construction. For models retaining more than one predictor, variance inflation factors (VIFs) were calculated to detect multicollinearity. No significant interactions were identified, allowing the full dataset to be used for model development.

Cross-validation of both the newly developed and previously reported predictive equations was performed on the test set. Paired-sample t-tests compared BIA-derived estimates with reference measurements. Accuracy of the models was quantified using the coefficient of determination (R^2) and pure error. Concordance correlation coefficients (CCC) were computed following Lin [37] and interpreted according to McBride [38]: almost perfect > 0.99, substantial 0.95–0.99, moderate 0.90–0.95, and poor <0.90. CCC accounts for both precision (ρ) and accuracy (Cb). Agreement between BIA-predicted and reference values was further examined using Bland–Altman plots [39], including assessment of correlation between the mean and difference values and estimation of 95% limits of agreement (LoA). Statistical significance was set at $P < 0.05$. Additionally, predictive validity of the new equations was assessed using the area under the curve (AUC) from regression receiver operating characteristic (RROC) curves [40], with interpretations as follows: <0.7, poor discrimination; 0.7–0.8, acceptable; 0.8–0.9, excellent; >0.9, outstanding [41].

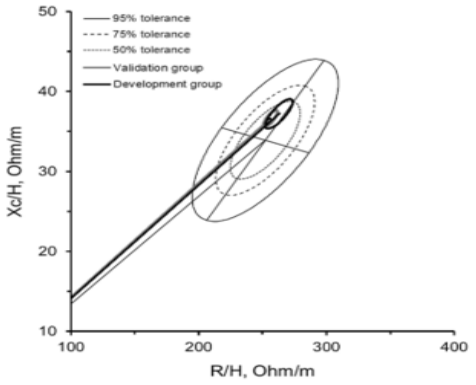
Results and Discussion

General descriptive data for development and validation groups are summarized in **Table 1** and illustrated in **Figure 1**. No statistically significant differences were observed for bioelectrical properties between groups ($T = 3.2$, $F = 1.6$, $P = 0.207$, Mahalanobis distance = 0.39). Mean bioelectrical vectors with 95% confidence ellipses were located within the 50% tolerance ellipses of the reference population of male elite soccer players **(Figure 1)**. Anthropometric analysis classified participants into three somatotype categories: balanced mesomorph, ectomorphic mesomorph, and mesomorph–ectomorph.

Table 1. Descriptive statistics and body composition variables for development and validation groups (mean ± SD)

	Validation group (N = 29)	Development group (N = 73)
Age (yrs)	25.9 ± 6.7	25.2 ± 5.2
Body mass (kg)	82.8 ± 5.9	80.3 ± 6.3
Stature (cm)	184.9 ± 4.8	184.8 ± 5.8
Body mass index (kg/m^2)	24.1 ± 1.2	23.6 ± 1.0
Endomorphy	2.0 ± 0.4	1.7 ± 0.3
Mesomorphy	4.5 ± 0.8	4.6 ± 0.6
Ectomorphy	2.5 ± 0.6	2.7 ± 0.5
Fat mass (kg)	10.2 ± 2.0	9.4 ± 1.6
Fat mass (%)	12.3 ± 2.3	11.6 ± 1.6
Fat-free mass (kg)	72.6 ± 5.8	71.5 ± 5.6
Lean soft tissue (kg)	68.7 ± 5.4	67.6 ± 5.3
Appendicular lean soft tissue (kg)	37.3 ± 3.3	36.6 ± 3.9
Resistance (ohm)	484.4 ± 35.8	471.5 ± 29.4
Reactance (ohm)	68.7 ± 5.9	67.4 ± 5.2

Phase angle (degree)	8.1 ± 0.7	8.2 ± 0.7



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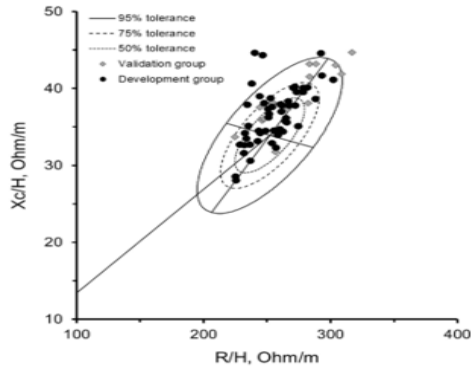

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Figure 1. The left-hand panel depicts the average impedance vectors for the development and validation groups, together with their 95% confidence ellipses, overlaid on the reference tolerance ellipses derived from elite male soccer players [29]. Results of the two-sample Hotelling's T^2 test are also reported. The right-hand panel shows the individual impedance vectors of all participants from both groups, plotted against the same reference ellipses of the elite soccer population.

Table 2 summarizes the predictive equations generated from the development sample using BIA measurements. Separate models were established for FFM, LST, and ALST. Only variables that contributed significantly in the backward stepwise regression procedure were incorporated into the final models. The derived prediction formulas were as follows:

1. FFM = − 7.729 + (body mass × 0.686) + (stature^2/R × 0.227) + (Xc × 0.086) + (age × 0.058), R^2 = 0.97, SEE = 1.0 kg;
2. LST = − 8.929 + (body mass × 0.635) + (stature^2/R × 0.244) + (Xc × 0.093) + (age × 0.048), R^2 = 0.96, SEE = 0.9 kg;
3. ALST = − 24.068 + (body mass × 0.347) + (stature^2/R × 0.308) + (Xc × 0.152), R^2 = 0.88, SEE = 1.4 kg.

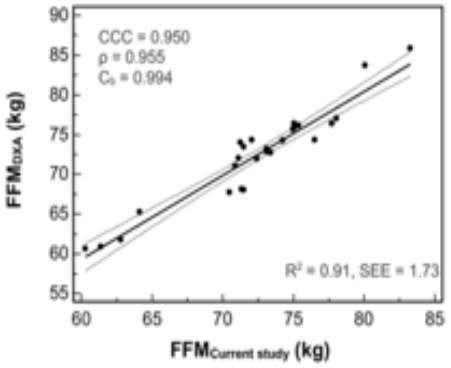
Table 2. Bioelectrical impedance-based prediction models were developed to estimate fat-free mass (FFM), total lean soft tissue (LST), and appendicular lean soft tissue (ALST).

	Standardized coefficient β	Unstandardized coefficient β	SEE (kg)	R^2	VIF
Fat-free mass (kg)			1.04	0.97	
Intercept		− 7.729			
BM (kg)	0.774	0.686			1.48
S^2/R (cm^2/Ω)	0.268	0.227			3.98
Xc (Ω)	0.080	0.086			1.56
Age (years)	0.054	0.058			1.09
Lean soft tissue (kg)			0.99	0.96	
Intercept		− 8.929			
BM (kg)	0.751	0.635			3.42
S^2/R (cm^2/Ω)	0.301	0.244			3.99
Xc (Ω)	0.091	0.093			1.52
Age (years)	0.046	0.048			1.00
Appendicular lean soft tissue (kg)			1.35	0.88	
Intercept		− 24.068			
BM (kg)	0.561	0.347			3.46

S^2/R (cm^2/Ω)	0.521	0.308	3.98
Xc (Ω)	0.203	0.152	1.52

Abbreviations: BM, body mass; S, stature (cm); R, resistance (Ω); Xc, reactance (Ω); R^2, coefficient of determination; SEE, standard error of the estimate; VIF, variance inflation factor.

A train–test validation approach was applied, and regression outcomes, concordance correlation coefficients (CCC), and agreement analyses are illustrated in **Figure 2**. For the newly derived soccer-specific models, no significant differences were detected between BIA predictions and reference measurements ($P > 0.01$). In contrast, conventional generalized athletic equations significantly underestimated FFM and ALST ($P < 0.01$; **(Figure 2)**). Within the sport-specific models, no significant correlation was observed between the differences and the mean values of BIA- and DXA-derived variables. However, generic equations showed significant negative trends across all predicted variables **(Figure 2)**. When using the soccer-specific FFM model, no mean differences were found between predicted and reference fat mass percentage (12.3% ± 0.8; $P = 0.954$). Conversely, application of the generalized athletic FFM equation [33] led to an overestimation of fat mass (15.6% ± 1.3; $P < 0.001$).



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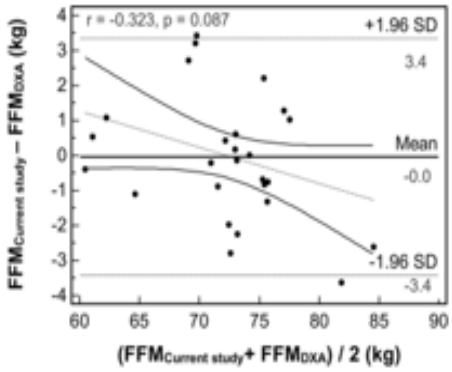

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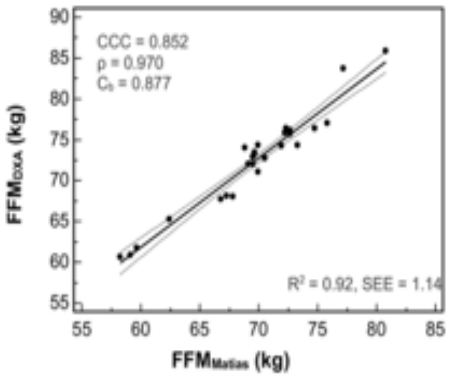

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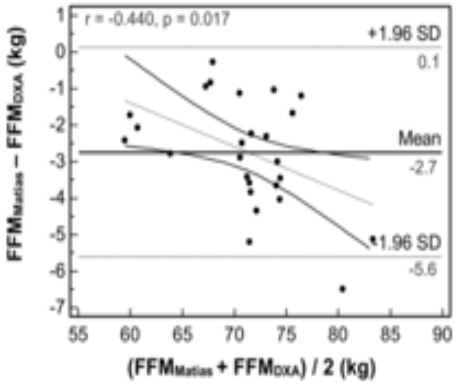

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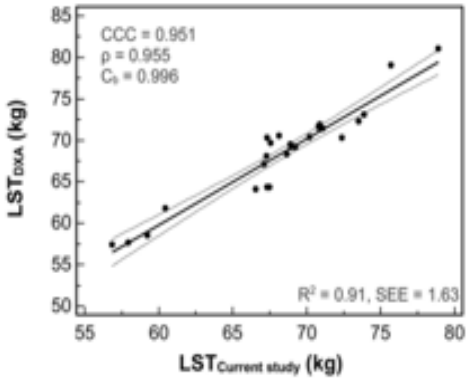

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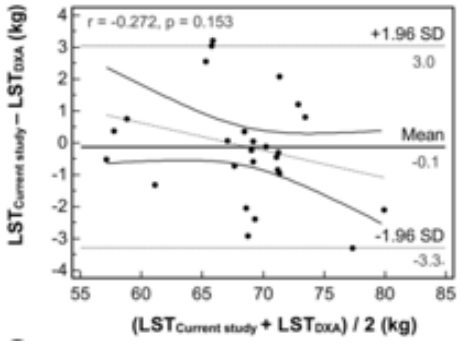

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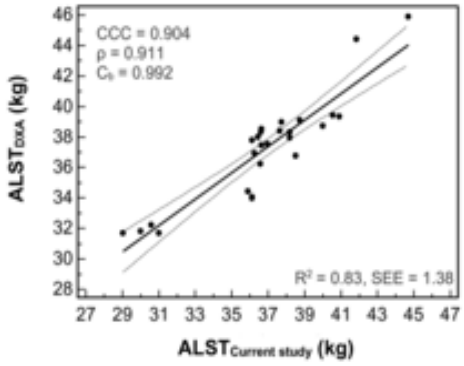

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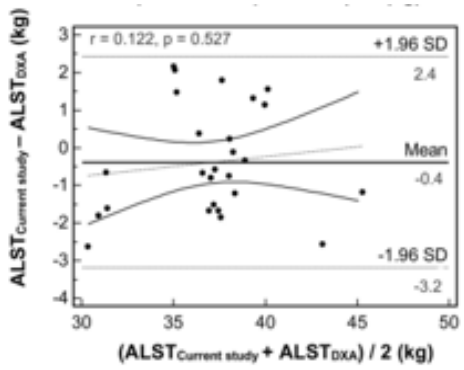

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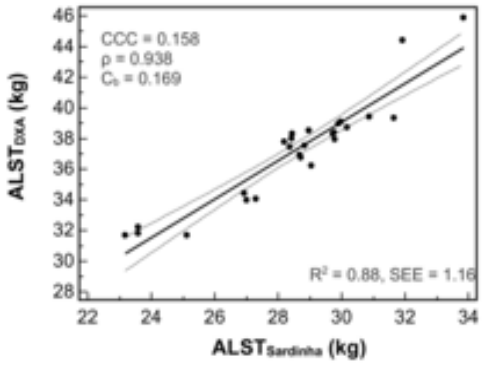

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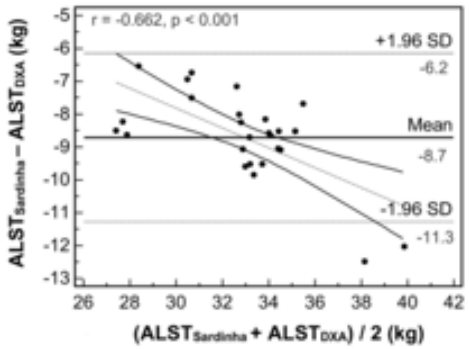

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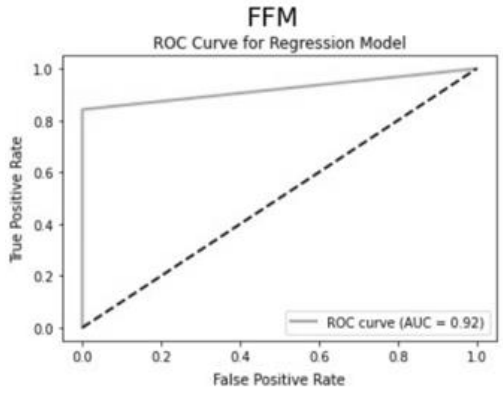
Figure 2. Left panel: scatterplots illustrating the relationships between BIA-predicted and reference values. Right panel: Bland–Altman plots depicting agreement analyses.

The RROC AUC analysis indicated outstanding predictive performance for FFM (0.92) and LST (0.92) and acceptable performance for ALST (0.74) **(Figure 3)**. Based on these results, all models can be considered valid for their intended predictive purposes.



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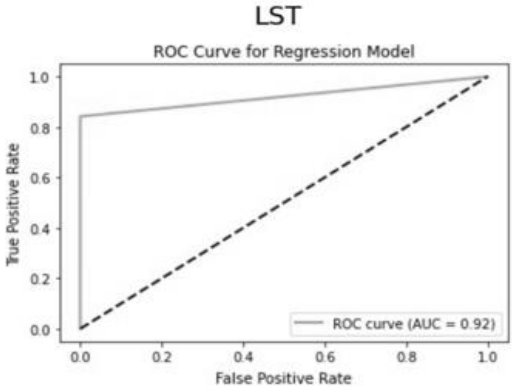

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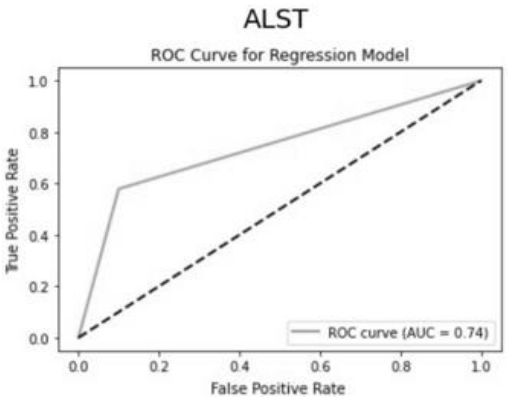

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Figure 3. Areas under the curve (AUC) from regression receiver operating characteristic (RROC) analyses for FFM, LST, and ALST.

This study was based on the premise that generalized BIA-based prediction equations would be less precise than sport-specific models when applied to a homogeneous athletic population. Therefore, elite soccer players were recruited to develop and validate new predictive equations while also evaluating the performance of previously published generalized formulas. Application of generic equations led to underestimation of FFM and ALST, whereas the newly developed soccer-specific equations provided more accurate estimations of body composition. These models allow, for the first time, valid BIA-based body composition assessment specifically tailored for elite soccer players.

Three sets of models were constructed to predict FFM, LST, and ALST using bioelectrical parameters (R and Xc), anthropometric measures (body mass and stature), and age. Across all models, body mass emerged as the strongest predictor, consistent with the fact that roughly 90% of a soccer player's body mass is composed of FFM. The resistance index (stature²/R) was the second most influential predictor in all models, reflecting the well-established conductive properties of soft tissues [5]. Using the new models, BIA-derived FFM, LST, and ALST were strongly correlated with DXA reference values (R^2 ranging from 0.83 to 0.91). In comparison, previously published generalized equations [32, 33] explained 88–91% of the variance. The standard error of estimation was lower for all newly developed equations (1.38–1.73 kg) compared with generalized models. Moderate to substantial agreement (CCC > 0.90) was observed between BIA-derived and reference values for the new equations, while generalized formulas showed poor agreement. Bland–Altman analyses revealed trends between mean and difference values with wide limits of agreement for the generic athletic equations [32, 33].

Underestimation of FFM by generalized equations has been previously reported when models developed in the general population are applied to athletes [22]. Differences in body composition, such as lower FFM values in the general population, contribute to these discrepancies [42]. Inclusion of athletes from multiple sports in previous development studies [32, 33] may have satisfied the need for broadly applicable predictive equations [20], but this approach compromises accuracy for sport-specific populations. Participants in prior studies included athletes from disciplines such as basketball, handball, swimming, triathlon, judo, pentathlon, athletics, tennis, rowing, sailing, karate/taekwondo, boxing, hockey, climbing, rugby, soccer, fencing, motorsports, powerlifting, padel, futsal, trail running, korfball, surfing, and gymnastics, with mean FFM and ALST values of 47.7 kg and 29.4 kg, respectively [33, 32]. In contrast, the soccer players in the present study exhibited higher FFM and ALST values, consistent with previous soccer-specific data [29, 43]. These differences highlight how predictive bias can occur when applying BIA-based models to populations with body composition characteristics that diverge from the development sample.

Bioelectrical characteristics and somatotype

The bioelectrical profiles of the soccer players in this study were initially compared with the reference data for elite players published in 2014 [29]. This comparison indicated that body composition patterns have remained stable over the last decade, as both individual and mean bioimpedance vectors fell within the 50% tolerance ellipse of the reference population. Most individual vectors aligned with the BIVA soccer-specific references [29], though a few extended beyond the 95% tolerance ellipse. According to BIVA principles, elongated vectors may reflect a lower total body water relative to the average soccer population. However, long vectors do not necessarily indicate hypohydration, as they may also be influenced by lower overall body mass. A key feature of BIVA is its ability to classify soft tissue status (under, normal, or over) and track changes over time by comparing individual vectors against a reference population [5].

Participants' somatotypes were also determined, revealing three morphologies: balanced mesomorph, ectomorphic mesomorph, and mesomorph–ectomorph, according to the Heath and Carter method [34]. Consistent with prior research, elite soccer players showed anthropometric profiles characterized by high musculoskeletal and linearity components with low body fat percentages [25, 44]. While somatotype was considered for inclusion in the new predictive models to account for potential positional differences, no correlation between morphology and playing position was observed. This finding reflects the modern soccer player, whose body dimensions are relatively uniform across roles. Recent evidence suggests that body composition in soccer is influenced more by gender, competitive level, and age than by positional role [44, 45]. Although somatotype was not included as an independent variable in the predictive models, future studies may explore the relationship between morphology and body composition in other sports [18, 46, 47], such as rugby (where higher body fat may be advantageous for defenders) or volleyball and basketball (where shorter stature may be observed in liberos or playmakers) [47–49].

Practical implications

When applying generalized athletic equations to individual soccer players, caution is warranted. For players with lower FFM, these equations produced overestimations (lower 95% LoA: −5.6 kg for FFM and −11.3 kg for ALST), whereas for players with higher FFM and ALST, systematic underestimations were observed (higher 95% LoA: 0.1 kg for FFM and −6.1 kg for ALST). During the preparatory phase, athletes are generally advised to consume protein at ~2.3–3.1 g per kg of FFM; underestimating FFM could therefore lead to inadequate protein intake and compromised maintenance of skeletal muscle [12]. Similarly, ALST tends to decrease during transition periods, making accurate monitoring essential [50]. Although the new predictive models improve ALST estimation, the acceptability of their standard errors and limits of agreement for practical coaching and nutritional decisions remains to be established.

Fat mass, another component quantified via BIA, negatively affects performance [44] and is closely monitored during transition periods [51]. Professional players typically display fat mass between 11–14%, depending on the assessment method [19]. Accurate FFM estimation allows for precise fat mass calculation as the difference between body mass and FFM, preventing overestimation. Using generalized equations [33] resulted in FFM underestimation and consequent fat mass overestimation. Smaller FFM components, such as LST and ALST, are closely linked to skeletal muscle and provide insight into strength and power performance in elite players [43]. Though specific reference values for elite soccer players are lacking, lean soft tissue is highly sensitive to changes during detraining, emphasizing the importance of accurate LST and ALST estimation [50]. Therefore, sport-specific BIA equations are recommended for monitoring training responses, seasonal variations, and return-to-play after injury [52].

Limitations

Despite positive outcomes, several limitations should be noted. DXA, although precise for lean soft tissue, is not considered the gold standard for assessing fat and total FFM, which ideally should involve a four-compartment model combining air plethysmography and dilution techniques [14]. The cross-sectional design also precludes tracking FFM changes over time, highlighting the need for longitudinal and interventional studies to validate these new equations. Additionally, findings cannot be generalized to other sports, female athletes, sub-elite or youth players, or BIA devices using different technologies or frequencies due to inter-device variability [53, 54]. These considerations underscore the population- and technology-specific nature of BIA equations. Nevertheless, the diversity of participants' origins suggests that the new equations may be applicable to elite soccer players worldwide.

Conclusion

Generalized BIA equations for athletes underestimate FFM components when applied to elite soccer players. The newly developed soccer-specific predictive models provide practitioners with highly accurate BIA-based assessments, enabling improved management of training and nutrition strategies to optimize body composition and performance while retaining the portability and practicality of BIA.

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