European Journal of Applied Physiology (2025) 125:595–610
https://doi.org/10.1007/s00421-024-05672-3

INVITED REVIEW

Anthropometric-based predictive equations developed with multi-component models for estimating body composition in athletes

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Received: 30 October 2024 / Accepted: 18 November 2024 / Published online: 6 December 2024

Abstract

Purpose Body composition can be estimated using anthropometric-based regression models, which are population-specific and should not be used interchangeably. However, the widespread availability of predictive equations in the literature makes selecting the most valid equations challenging. This systematic review compiles anthropometric-based predictive equations for estimating body mass components, focusing on those developed specifically for athletes using multicomponent models (i.e. separation of body mass into ≥ 3 components).

Methods Twenty-nine studies published between 2000 and 2024 were identified through a systematic search of international electronic databases (PubMed and Scopus). Studies using substandard procedures or developing predictive equations for non-athletic populations were excluded.

Results A total of 40 equations were identified from the 29 studies. Of these, 36 were applicable to males and 17 to females. Twenty-six equations were developed to estimate fat mass, 10 for fat-free mass, three for appendicular lean soft tissue, and one for skeletal muscle mass. Thirteen equations were designed for mixed athletes, while others focused on specific contexts: soccer ($n=8$); handball and rugby ($n=3$ each); jockeys, swimming, and Gaelic football ($n=2$ each); and futsal, padel, basketball, volleyball, American football, karate, and wheelchair athletes ($n=1$ each).

Conclusions This review presented high-standards anthropometric-based predictive equations for assessing body composition in athletes and encourages the development of new equations for underrepresented sports in the current literature.

Keywords Anthropometry · Girths · Fat mass · Fat-free mass · Skeletal muscle mass · Skinfolds

Abbreviations

ALSM	Appendicular lean soft mass
DXA	Dual X-ray absorptiometry
FM	Fat mass
FFM	Fat-free mass

Communicated by Michael I Lindinger.

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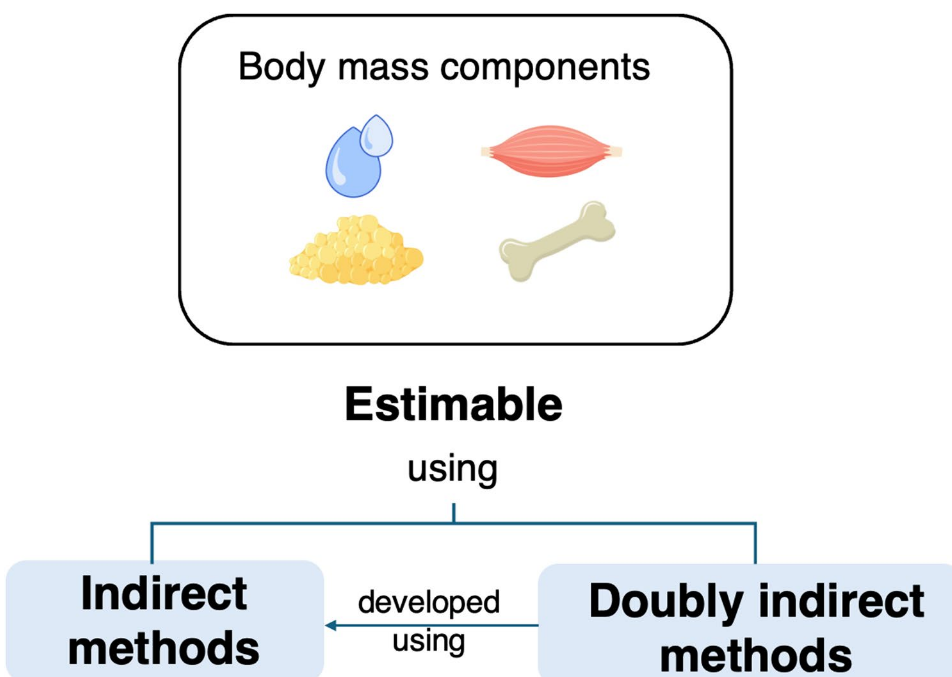
ISAK International Society for the Advancement of Kinanthropometry
SMM Skeletal muscle mass
4C Four-compartmental model

Introduction

Quantifying body composition is essential for assessing health status and monitoring the effects of training or nutritional interventions (Paoli and Campa 2024). As a result, research increasingly focuses on developing and applying methods to determine body composition with greater accuracy (Lohman and Milliken 2020). Typically, this process involves measuring physical dimensions (e.g., height, girths, skinfolds, body volume) or estimating the proportions of body mass components, such as fat, muscle, and bone (Paoli and Campa 2024). Since these components cannot be directly measured in living individuals, they are quantified using indirect or doubly indirect methods (Lohman and Milliken 2020). Indirect methods include imaging [e.g., dual X-ray absorptiometry (DXA), magnetic resonance imaging, and computed tomography] and dilution techniques. These methods rely on theoretical assumptions, such as those related to water or density, and are considered criterion or "gold-standard" procedures for the in vivo body composition assessment (Heymsfield et al. 2005). However, these basic assumptions have been questioned and their application for the estimation of body composition is uncertain (Martin et al. 1985). Moreover, their high cost and limited portability significantly constrain their applicability beyond laboratory settings (Lohman and Milliken 2020). Doubly indirect methods use regression models developed against indirect methods as reference and include bioelectrical impedance analysis and surface anthropometry (Campa et al. 2024). The paradigm of in vivo assessment of body mass components is depicted in Fig. 1.

Surface anthropometry allows for the direct measurement of heights, girths, skinfolds, and other dimensional characteristics. These parameters can then be used in predictive equations to estimate molecular and tissue components of body mass (Paoli and Campa 2024). The literature is rich in anthropometric equations, each developed using different reference methods and populations (Marano et al. 2020; Cerqueira et al. 2022; Abdalla et al. 2023; Duarte et al. 2023). The variety of equations exists because they are not interchangeable among populations (e.g., athletes and non-athletes or males and females) (Vaquero-Cristóbal et al. 2020; Baglietto et al. 2024) and should be selected with care, much like choosing the right outfit for a specific occasion. Indeed, there are predictive equations tailored for specific age groups, such as children, adults, or the elderly, whose validity depends on factors like sex, geographical origin, physical activity level, or sports discipline (Marano et al. 2020; Cerqueira et al. 2022; Abdalla et al. 2023; Duarte et al. 2023). A key advantage of anthropometry is that it offers a more portable, non-invasive, and cost-effective alternative to indirect methods. In this regard, it is important to note that, due to the lack of agreement among these laboratory techniques (Heard-Lipsmeyer et al. 2020; Cabre et al. 2021), two different equations for estimating fat mass may yield different results, primarily depending on the reference

Fig. 1 In-vivo assessment of body mass components



procedure involved in their development (Petri et al. 2020). Furthermore, even equations developed using the same indirect methods can yield different outputs depending on the characteristics of the subjects involved in the development procedures (Campa et al. 2023).

Although predictive equations enable an ecological quantification of body mass components, they still present estimation errors, which can become more pronounced when applied to populations different from those used in the original studies (Campa et al. 2023). Among those populations with specific body composition features that require ongoing monitoring and optimization are athletes (Silva 2019). An athlete is an individual engaged in competitive sports, either individually or as part of a team, who demonstrates high physical performance and follows a specific training regimen (Campa and Coratella 2021) Athletes, in particular, benefit from muscle mass in terms of strength and power production, while excessive fat can sometimes act as a mechanical obstacle, limiting movement efficiency (Brocherie et al. 2014). The secular trend is leading athletes to become distinct populations, not only compared to the general population but also due to a high degree of phenotypic variation between different sports (Holway et al. 2024; Petri et al. 2024). Indeed, endurance sports typically feature athletes who are particularly lean but have less muscle mass compared to velocity/power athletes (Silva 2019). Furthermore, certain playing positions require specific physical attributes that set them apart from teammates within the same sport (Holway et al. 2024; Petri et al. 2024). These factors make the study of body composition a crucial aspect that is monitored throughout the season, as well as during transitional periods of the competition (Silva et al. 2016).

Advances in body composition research have led to the development of models that allow the division of body mass it into multiple compartments, thus enabling greater accuracy in quantifying each individual component (Lohman and Milliken 2020). These approaches have helped overcome the limitations of two-compartment models, which may not account for the variability of key components of fat-free mass, such as water and bone, among individuals (Wang et al. 2002). In this context, appropriate equations are those developed using multicomponent models (i.e., separation of body mass into ≥ 3 components), with a preference for approaches that account for all relevant moderating factors (e.g., physical activity level, sport discipline, age, and sex) (Umapathysivam et al. 2017; Campa et al. 2024). The widespread use of these predictive equations in the literature makes it difficult for researchers and practitioners to identify the most appropriate formula for quantifying the variable of interest. In fact, many studies apply generalized equations to athlete samples, which may result in inaccuracies when predicting body composition (Campa et al. 2021; Coratella et al. 2021). Systematic reviews that summarize predictive models developed using doubly indirect methods provide valuable support for researchers and practitioners engaged in body composition assessment. In this regard, a recent systematic review has analysed the predictive equations for estimating body composition through bioelectrical impedance analysis, providing a list of appropriate equations for different populations (Campa et al. 2024).

Despite the widespread use of anthropometry, no study has systematically reviewed and summarized all the available equations. Consequently, the present scoping review aimed to analyze the relevant literature to identify anthropometric-based predictive equations developed using multicomponent models specifically for athletes. Additionally, summarizing the current state of body composition prediction will aid in improving the development of new equations by addressing gaps in the existing literature.

Methods

Search strategy and eligibility criteria

The present study was carried out following the Preferred Reporting Items for Systematic reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines (Tricco et al. 2018). The two independent researchers (SS and PI) conducted systematic searches in Scopus, and PubMed on October 1st, 2024, identifying potential eligible studies from 1990 to 2024. The time frame from 1990 to 2024 was selected to capture the most relevant advancements in body composition assessment, particularly the development of multi-compartment models, which gained popularity and refinement during this period (Lohman 1992). The search query was applied to the source title, abstract, and keywords, and included combinations of at least one of the terms identifying body composition, with at least one of the terms identifying the methods, and a term on the field of application. The resulting search query was:

("body composition" OR "fat mass" OR "fat free mass" OR "lean mass" OR "lean body mass" OR "skeletal muscle mass") AND (anthropometry OR skinfolds OR DXA OR densitometry OR MRI OR "BOD POD" OR "air-displacement plethysmography") AND (predictive* OR regression*) AND (sport OR athletes OR "athletic performance") AND YEAR > 1989 AND YEAR < 2024. To identify additional studies, a manual search was also conducted within the databases of the included studies.

The inclusion criteria were:

- Studies involving athletes.
- Peer-reviewed articles that developed at least one predictive equation for estimating body mass components using anthropometry.

- Developed using multicomponent models of body composition.
- Accessible in English full text.
- Year of publication since 1990.

For this review, DXA was considered a multicomponent model due to its generation of separate fat mass, lean soft mass, and bone mineral content variables.

The exclusion criteria were:

- Research protocols, thesis/dissertations, abstracts, letters to the editor, case reports, book chapters, guidelines, position papers, and unpublished works.
- Articles that aimed to develop predictive equations without use of a recognized reference technique.
- Articles presenting predictive models for estimating body density.
- Articles aimed to validate, rather than develop, predictive equations.
- Articles where predictive equations were developed on non-athletic populations.

Study selection and data processing

Based on the initial titles retrieved, duplicates were removed. After concluding the search, all records were compiled into the Endnote for Windows version X9, 2018 (Clarivate, Philadelphia, USA) software to delete all duplicates showing the same: (a) title, authors and year of publication and (b) title, authors and journal title. The records remaining after the deletion of duplicates were exported to an Excel file for Windows version 16.75.2 (Microsoft, Washington, USA) organized based on essential information for screening, such as authors' names, publication year, journal title, digital object identification (DOI), article title and abstract. Abstracts identified from the literature searches were screened for potential inclusion by two authors (SS and PI) and a third author (DC) when there was a disagreement between the first two. Data extraction included information about each article, such as: authors, year, anthropometric protocols, reference methods, predictive equations, participants' information (e.g., sex, age, sports), and statistical outputs related to development (e.g., coefficient of determination and standard error of estimation) and validation (e.g., bias, 95% limits of agreement, and trend) procedures.

Results

The procedures of the systematic search are reported in Fig. 2.

From the 29 eligible studies, a total of 2194 individuals (participants involved in the development procedures) were included in the present systematic review. Out of 40 equations, 13 included both male and female participants (Evans et al. 2005; Quiterio et al. 2009; Lozano-Berges et al. 2019; Cavedon et al. 2020; Sesbreno et al. 2020; Mitchell et al. 2020; Bonilla et al. 2022; Huang et al. 2023; Mauro et al. 2023; De Almeida-Neto et al. 2024), 23 included only males (Stewart and Hannan 2000; Bell et al. 2000; Reilly et al. 2009; Oliver et al. 2012; Novack et al. 2014; Santi-Maria et al. 2015; Goosey-Tolfrey et al. 2016; Muniz et al. 2017; Abdalla et al. 2017; Zemski et al. 2018; Suarez-Arrones et al. 2018; Munguía-Izquierdo et al. 2019; Nuñez et al. 2019; Dunne et al. 2020, 2022a, b; Giro et al. 2022; Cavedon et al. 2023; de Moraes et al. 2024) and four included only females (Warner et al. 2004; Cavedon et al. 2018).

The selected studies with all the extracted information are reported in Table 1.

Discussion

Valid procedures for estimating body mass components require the use of appropriate predictive equations. This scoping review aimed to compile a comprehensive list of all anthropometric equations developed using multicomponent models specifically for athletes.

Body composition prediction

The selected study reported predictive equations that allow the quantification of four body mass components, as depicted in Fig. 3.

Particularly, twenty-six equations were developed to estimate fat mass (Stewart and Hannan 2000; Evans et al. 2005; Reilly et al. 2009; Oliver et al. 2012; Novack et al. 2014; Santi-Maria et al. 2015; Goosey-Tolfrey et al. 2016; Muniz et al. 2017; Cavedon et al. 2018, 2020, 2023; Zemski et al. 2018; Suarez-Arrones et al. 2018; Lozano-Berges et al. 2019; Dunne et al. 2020, 2022a, b; Mitchell et al. 2020; Giro et al. 2022; Bonilla et al. 2022; Huang et al. 2023; Mauro et al. 2023), 10 for fat-free mass (Stewart and Hannan 2000; Warner et al. 2004; Munguía-Izquierdo et al. 2019; Nuñez et al. 2019; Sesbreno et al. 2020; Mitchell et al. 2020; de Moraes et al. 2024) of which one provided a model for predicting lower limb fat-free mass (Bell et al. 2000), three for appendicular lean soft tissue (Quiterio et al. 2009; Abdalla et al. 2017; Cavedon et al. 2018), and one for skeletal muscle mass (Sesbreno et al. 2020). Interesting, the equations that estimate fat mass also allow the calculation of fat-free mass by difference from total body mass, and vice versa. Importantly, equations that examine the different components of fat-free mass, such as skeletal muscle mass and appendicular lean soft tissue, provide a more specific evaluation. This is because fat-free

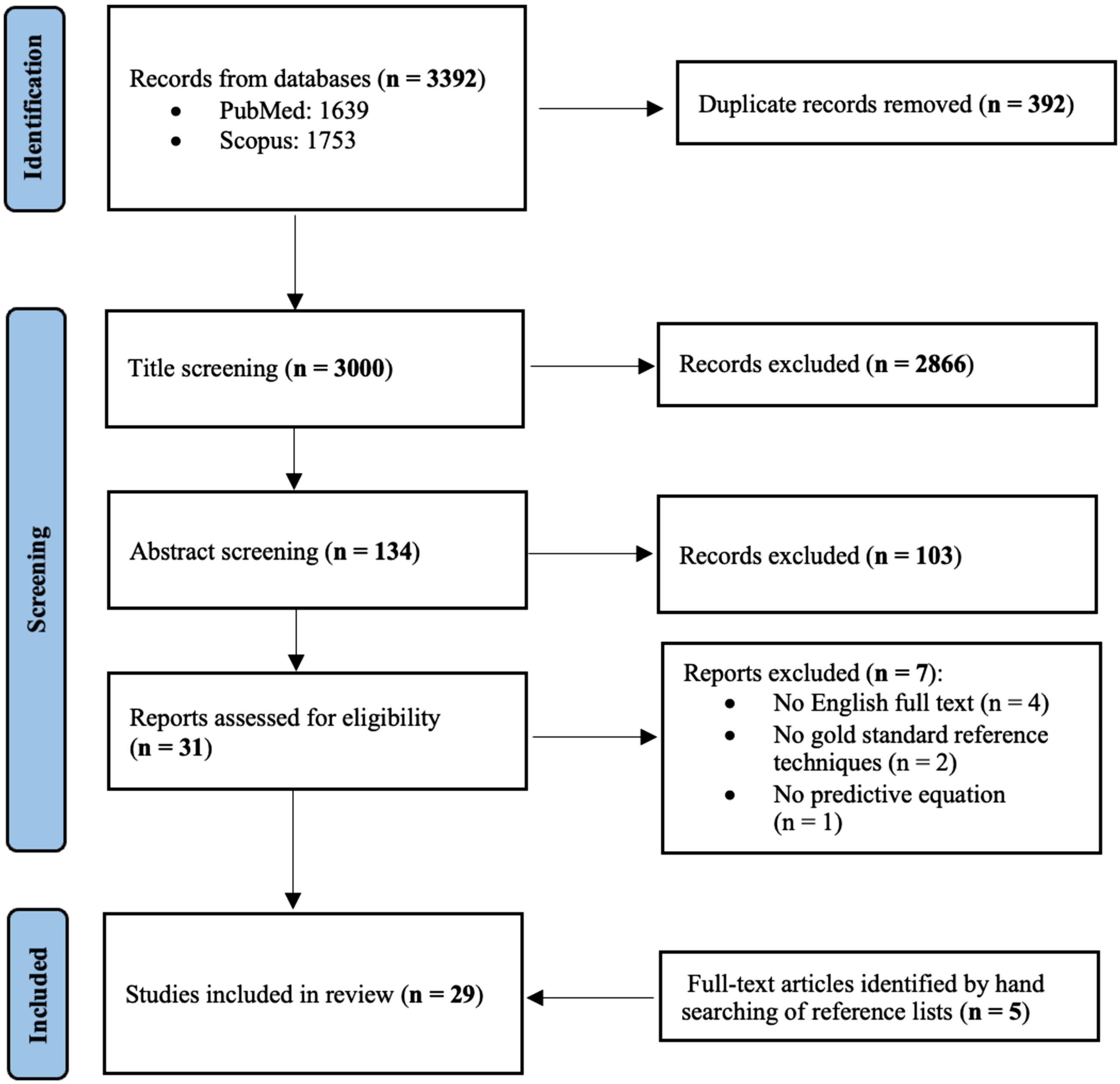


Fig. 2 Flow-chart of the included studies

mass includes the non-fat molecules from multiple tissues or organs that are significantly different from each other, some of which are particularly metabolically active, like the high-metabolic-rate organs (i.e., brain, heart, kidneys, and liver), while others have intermediate metabolic rates (e.g., skeletal muscle mass), and others have lower energy expenditure (e.g., bone) (Dittmar and Reber 2004). This suggests that, when possible, it is recommended to quantify the individual components of frat-free mass for a more accurate assessment of body composition.

Sports

The identified equations were developed by including athletes participating in various sports. Some of these models included mixed participants, considering only sex as an independent variable and without accounting for potential differences due to sports practice (Stewart and Hannan 2000; Warner et al. 2004; Evans et al. 2005; Quiterio et al. 2009; Abdalla et al. 2017; Cavedon et al. 2020; Sesbreno et al. 2020; Bonilla et al. 2022; Huang et al. 2023; De

Table 1 Anthropometric-based predictive equations ($N = 40$) developed using multi-component models from studies ($N = 29$) on athletes

Author	Variable	Procedures	Reference	Equation	Participants	R^2	SEE	Note	Validation	Bias	95% LoA	Trend
Bell et al. (2000)	Lower limb FFM (%)	Cameron et al. (1984)	DXA (Hologic)	−24.6 + (0.0201 × leg length) + (0.511 × calf girth)	15 male rugby athletes from Welsh National League aged 21.1 ± 2.1 y	0.90	0.6%		Yes	0.2	−1.0; 1.02	N.A
Stewart and Hannan (2000)	FFM (g)	Lohman et al. (1988)	DXA (Hologic)	(890 × body mass) − (261 × abdominal skinfold) − (244 × thigh skinfold) − (342 × suprailiac skinfold) − (237 × thigh patellar skinfold) + 9966	82 male mixed athletes aged 28.1 ± 7.5 y	0.96	1694.0g		Yes	1.3	−4.2; 6.7	N.A
Stewart and Hannan (2000)	FM (g)	Lohman et al. (1988)	DXA (Hologic)	(105.2 × body mass) + (189.5 × abdominal skinfold) + (345.2 × pectoral skinfold) − (521 × forearm radial skinfold) + (215.9 × medial calf skinfold) + (258.3 × thigh skinfold) + (293 × suprailiac skinfold) − 8334. 4	82 male mixed athletes aged 28.1 ± 7.5 y	0.85	1679.0g		Yes	−0.8	−5.9; 4.2	N.A
Warner et al. (2004)	FFM (kg)	Keys and Committee on Nutritional Anthropometry National Research Council (1956)	DXA (Hologic)	8.51 + (0.809 × body mass) − (0.178 × abdominal skinfold) − (0.225 × thigh skinfold)	101 female mixed athletes aged 20.3 ± 1.4 y	0.98	1.1 kg		No	–	–	–
Evans et al. (2005)	FM (%)	Lohman et al. (1988)	Loman's equation using a 4C model	10.566 + (0.12077 × sum of 7 skinfolds) – (8.057 × sex) – (2.545 × race)	102 mixed athletes (63 males and 39 female) aged 20.6 ± 2 y	0.76	4.5%	Sum of 7 skinfolds = subscapular, triceps, chest, midaxillary, suprailiac, abdominal and thigh skinfolds Sex: Male = 1, Female = 0 Race: white = 0 black = 1	Yes	0	−6.9;6.9	N.A
Evans et al. (2005)	FM (%)	Lohman et al. (1988)	Loman's equation using a 4C model	8.997 + (0.24658 × sum of 3 skinfolds) – (6.343 × sex) – (1.998 × race)	102 mixed athletes (63 males and 39 female) aged 20.6 ± 2 y	0.85	3.7%	Sum of 3 skinfolds = abdomen, thigh and triceps skinfolds Sex: Male = 1, Female 0 Race: white = 0 black = 1	No	–	–	–

Table 1 (continued)

Author	Variable	Procedures	Reference	Equation	Participants	R^2	SEE	Note	Validation	Bias	95% LoA	Trend
Quinterio et al. (2009)	ALST (kg)	ISAK	DXA (Hologic)	− 20.338 + (0.199 × body mass) + (3.294 × sex) + (14.230 × stretch stature) + 0.192 × age)	176 male and 92 female mixed athletes aged 15.0 ± 2.8 and 14.6 ± 2.8 y, respectively	0.91	2.1 kg	Sex: male = 1, female = 0 Stretch stature in m	Yes			
Reilly et al. (2009)	FM (%)	ISAK	DXA (Hologic)	5.174 + (0.124 × thigh skinfold) + (0.147 × abdominal skinfold) + (0.196 × triceps skinfold) + (0.130 × calf skinfold)	45 male professional soccer players aged 24.2 ± 5 y	0.73	N.A		No	–		
Oliver et al. (2012)	FM (%)	Lohman et al. (1988)	DXA (Lunar)	(0.178 × hip girth) + (0.097 × umbilical girth) + (0.089 × sum of 7 skinfolds) – 19.641	157 male collegiate soccer players aged 20 ± 1 y	0.94	2.4%	Sum of 7 skinfolds: chest, triceps, subscapular, midaxillary, suprailiac, and abdominal skinfolds	No	–	–	–
Novack et al. (2014)	FM (%)	Lohman et al. (1988)	DXA (Lunar)	(0.83196071 × midaxillary skinfold) + (0.16367624 × abdominal skinfold) + (0.75492553 × anterior thigh skinfold) – 2.33295828	31 male professional soccer players aged 21.5 ± 3.4 y	0.84	1.69%		No	–	–	–
Santi Maria et al. (2015)	FM (%)	ISAK	DXA (Lunar)	20.38 – (0.695 × age) + (0.298 × iliac crest skinfold) + (0.344 × abdominal skinfold) + (0.595 × calf skinfold)	22 male soccer goalkeepers aged 14.7 ± 2.5 y	0.94	1.89%		No	–	–	–
Santi Maria et al. (2015)	FM (%)	ISAK	DXA (Lunar)	22.46 – (0.866 × age) + (0.642 × iliac crest skinfold) – (0.055 × abdominal skinfold) + (0.464 × thigh skinfold)	141 male soccer camp players aged 15.2 ± 2.4 y	0.75	2.28%		No	–	–	–
Goosey-Tolfrey et al. (2016)	FM (%)	ISAK	DXA (Lunar)	− 3.04 + (0.41 × sum of 7 skinfolds) – (0.001 × (sum of 7 skinfolds) ^{2}) + (0.03 × calf girth)	30 male wheelchair games players from basketball n = 19 (aged 29 ± 7 y) and rugby n = 11 (aged 32 ± 5 y)	0.84	N.A	Sum 7 skinfolds: triceps, subscapular, biceps, supraspinal, abdominal, front thigh, and medial calf skinfolds	No	–	–	–
Abdalla et al. (2017)	ALST (kg)	N.A	DXA (Lunar)	(0.427 × body mass) – (0.197 × triceps skinfold) – (0.115 × thigh skinfold) + 1.620	174 male mixed athletes aged between 8 and 18 y	0.98	0.9 kg		No	–	–	–
Muniz et al. (2017)	FM (%)	ISAK	DXA (Lunar)	8.26 + (0.57 × triceps skinfold) – (0.42 × subscapular skinfold) + (0.40 × iliac crest skinfold) – (0.15 × calf skinfold)	29 male volleyball players aged between 16.0 to 20.9 y	0.80	1.8%		No	–	–	–

Table 1 (continued)

Author	Variable	Procedures	Reference	Equation	Participants	R^2	SEE	Note	Validation	Bias	95% LoA	Trend
Cavedon et al. (2018)	FM (%)	Lohman et al. (1988)	DXA (Hologic)	10.01 + (0.17 × sum of 8 skinfolds) + (0.30 × hip girth) – (0.44 × arm girth) – (0.17 × waist girth) – (0.29 × calf girth)	60 female handball players aged 22.1 ± 5.7 y	0.88	2.0%	Sum of 8 skinfolds: triceps, subscapular, thorax, axillary, abdominal, suprailiac, thigh, and calf	Yes	−0.2	−6.1;5.7	N.A
Cavedon et al. (2018)	ALST (g)	Lohman et al. (1988)	DXA (Hologic)	− 49,295.84 + (271.79 × body mass) + (2123.80 × elbow breadth) + (380.84 × stretch stature)	60 female handball players aged 22.1 ± 5.7 y	0.83	2412.2 g	Stretch stature in cm	Yes	485.5	−3790.6;4761.7	N.A
Cavedon et al. (2018)	FFM (g)	Lohman et al. (1988)	DXA (Hologic)	− 53,156.59 + (278.27 × body mass) + (2294.04 × elbow breadth) + (409.64 × heigh)	60 female handball players aged 22.1 ± 5.7 y	0.82	2579.32 g		Yes	518.7	−4068.8;5106.2	N.A
Zemski et al. (2018)	FM (%)	ISAK	DXA (Hologic)	5.896 + (0.265 × triceps skinfold) + (0.251 × supraspinal skinfold) + (0.394 × calf skinfold)	26 Caucasian male rugby players aged 25.5 ± 3.1 y	0.75	N.A		No	–	–	–
Zemski et al. (2018)	FM (%)	ISAK	DXA (Hologic)	5.577 + (0.170 × abdominal skinfold) + (0.749 × calf skinfold)	17 Polynesians male rugby players aged 25.5 ± 3.1 y	0.90	N.A		No	–	–	–
Lozano-Berges et al. (2019)	FM (%)	ISAK	DXA (Hologic)	11.115 + (0.775 × triceps skinfold) + (0.193 × iliac crest skinfold) – (1.606 × sex)	98 American football players (65 males and 33 females) aged 13.4 ± 0.6 y 13.4 ± 0.6 y, respectively	0.85	0.36%	Sex: male = 1, female = 0	Yes	0.57	−3.14;4.29	0.36
Munguía-Izquierdo et al. (2019)	FFM (kg)	ISAK	DXA (Hologic)	− 84.470 + (0.692 × hips girth) + (0.532 × waist girth) + (− 0.090 × sum of 8 skinfolds) + (0.629 × arm flexed and tensed girth) + (1.681 × humerus breadth) + (0.420 × calf girth)	42 youth male soccer players aged 17.1 ± 0.6 y	0.89	1.47%	Sum of 8 skinfold: triceps, biceps, subscapular, iliac crest, supraspinal, abdominal, anterior thigh and medial calf skinfolds	No	–	–	–
Suarez-Arrones et al. (2018)	FM (%)	ISAK	DXA (Hologic)	8.047 + (0.616 × iliac crest skinfold) + (0.189 × triceps skinfold)	18 Serie A male soccer players aged 27.6 ± 2.9 y	0.75	N.A		No	–	–	–

Table 1 (continued)

Author	Variable	Procedures	Reference	Equation	Participants	R^2	SEE	Note	Validation	Bias	95% LoA	Trend
Nunez et al. (2019)	FFM (kg)	ISAK	DXA (Hologic)	− 66.388 + (1.121 × arm relaxed girth) + (1.029 × hips girth)	17 international male soccer players aged 29.3 ± 3.1 y	0.65	N.A		No			
Sesbreno et al. (2020)	SMM (kg)	ISAK	DXA (Lunar)	− 2.485 + (1.058 × fractionated skeletal muscle mass) – (0.235 × fractionated fat mass)	65 male and female mixed athletes aged 17 y or older	0.92	1.3 kg		No	–	–	–
Sesbreno et al. (2020)	FFM (kg)	ISAK	DXA (Lunar)	3.397 + (0.975 × fractionated fat-free mass) – (0.576 × fractionated fat mass)	65 mixed athletes aged 17 y or older	0.94	1.6 kg	Fractionated body composition was calculated from Drinkwater and Ross (1980)	No	–	–	–
Cavedon et al. (2020)	FM (%)	Lohman et al. (1988)	DXA (Hologic)	(0.241 × anterior thigh skinfold) + (0.418 × abdominal skinfold) + (0.329 × subscapular skinfold) + (0.259 × axillary skinfold) – 1.689	29 mixed athletes with unilateral lower limb amputation aged 35.8 ± 9.1 y	0.94	1.05%	Anterior thigh and calf skinfolds of the non-impaired leg	No	–	–	–
Dunne et al. (2020)	FM (%)	ISAK	DXA (Lunar)	5.561 + (0.035 × age) + (0.394 × triceps skinfold) + (−0.121 × subscapular skinfold) + (0.184 × biceps skinfold) + (0.413 × iliac crest skinfold) + (0.257 × supraspinal skinfold) + (0.285 × abdominal skinfold) + (0.168 × thigh skinfold) + (−0.265 × calf skinfold)	35 professional male flat jockeys aged 27.5 ± 5 y	0.84	N.A		Yes	0.0	−2.2;2.3	N.A
Dunne et al. (2020)	FM (%)	ISAK	DXA (Lunar)	8.012 + (0.26 × age) + (−0.497 × triceps skinfold) + (−0.103 × subscapular skinfold) + (0.083 × biceps skinfold) + (0.376 × iliac crest skinfold) + (−1.073 × supraspinal skinfold) + (0.647 × abdominal skinfold) + (0.318 × thigh skinfold) + (0.967 × calf skinfold)	37 professional male hunt jockeys aged 27.5 ± 5.4 y	0.83	N.A		Yes	0.0	−1.7;1.7	N.A
Mitchell et al. (2020)	FM (kg)	ISAK	DXA (Hologic)	(0.16 × body mass) + (8.78 × logarithm (sum of 7 skinfolds) – (1.83 × sex) – 32.77	44 swimmers (18 males, 26 females) aged 21.6 ± 3.3 y	0.91	1 kg	Sum of 7 skinfolds: triceps, subscapular, biceps, supraspinal, abdomen, front thigh, and medial calf); Sex: male = 1, female = 0	No	–	–	–

Table 1 (continued)

Author	Variable	Procedures	Reference	Equation	Participants	R^2	SEE	Note	Validation	Bias	95% LoA	Trend
Mitchell et al. (2020)	FFM (kg)	ISAK	DXA (Hologic)	(0.79 × body mass) – (8.46 × log (sum of 7 skinfolds) + (1.80 × sex) + 30.94)	44 swimmers (18 male, 26 females) aged 21.6 ± 3.3 y	0.99	1 kg	Sum of 7 skinfolds: triceps, subscapular, biceps, supraspinal, abdomen, front thigh, and medial calf; sex: male = 1, female = 0	No	–	–	–
Bonilla et al. (2022)	FM (kg)	ISAK	DXA (Lunar)	(5.46 × sex) + (0.21 × (body mass/waist girth)) + (81.7 × (waist girth/stretch stature)) – 41.8	114 mixed athletes from Columbia (58 females, 56 males) aged 14.85 ± 2.38 y	0.68	2.4 kg	Sex: male = 0, female = 1 Stretch stature in cm	Yes	1.02	−3.7;5.8	N.A
Dunne et al. (2022a, b)	FM (%)	ISAK	DXA (Lunar)	4.270 + (age × 0.154) + (body mass × (− 0.040) + (sum of 7 skinfolds × 0.207)	32 elite male Gaelic football player aged 23.4 ± 3.3 y	0.83	N.A	Sum of 7 skinfolds: triceps, subscapular, biceps, supraspinal, abdominal, mid-thigh and medial calf	No	–	–	–
Dunne et al. (2022a, b)	FM (kg)	ISAK	DXA (Lunar)	− 9.098 + (age × 0.147) + (body mass × 0.110) + (sum of 7 skinfolds × 0.165)	32 elite male Gaelic football player aged 23.4 ± 3.3 y	0.87	N.A	Sum of 7 skinfolds: triceps, subscapular, biceps, supraspinal, abdominal, mid-thigh and medial calf	No	–	–	–
Giro et al. (2022)	FM (%)	ISAK	DXA (Hologic)	− 0.620 + (0.159 × (sum of 4 skinfolds) + (0.120 × waist girth)	78 adult male futsal players aged 23 y	0.85	1.32%	Sum of 4 skinfolds: triceps, abdominal, iliac crest, and front thigh skinfolds	Yes	0.05	−2.7;2.0	−0.19
Cavedon et al. (2023)	FM (%)	Lohman et al. (1988)	DXA (Hologic)	(0.383 × abdominal skinfold) + (0.319 × triceps skinfold) + (0.240 × calf skinfold) – (0.750 × biceps skinfold) + 6.499	45 male karate athletes aged 21.7 ± 3.8 y	0.88	1.3%		Yes	1.2	−0.97;0.52	N. A
Mauro et al. (2023)	logarithm FM	Lohman et al. (1988)	DXA (Hologic)	(0.016 × body mass) + (0.180 × log biceps skinfold) + (0.255 × log supra-iliac skinfold) + (0.012 × thigh skinfold) + 0.658	15 mixed padel players aged 26.6 ± 11 y	0.95	N.A		No	–		

Table 1 (continued)

Author	Variable	Procedures	Reference	Equation	Participants	R^2	SEE	Note	Validation	Bias	95% LoA	Trend
Huang et al. (2023)	FM (%)	ISAK	DXA (Lunar)	$-8.304+(0.239\times$ triceps skinfold$)+(0.230\times$ subscapular skinfold$)+(4.199\times$ logarithm (abdominal skinfold)$)+(0.517\times$ thigh skinfold$)+(0.001\times$ waist girth$^2)-(4.106\times$ male$)$	95 elite mixed Asian athletes (46 male and 49 female) aged 24.0 ± 4.3 y	0.64	N.A	Sex: male = 1, female = 0	Yes	N.A	N.A	N.A
De Almeida-Neto et al. (2024)	FFM (kg)	N.A	DXA (Lunar)	$-16.679+(0.615\times$ body mass$)-(2.601\times$ sex$)+(0.618\times$ age$)-(0.332\times$ hips girth$)+(0.278\times$ stretch stature$)$	154 mixed (39 males and 115 females) athletes aged 13 ± 2.6 y	N/A	N.A	Sex: male = 0, female = 1 Stretch stature in cm	Yes	0.5	−5.7;4.6	–
De Moraes et al. (2024)	FFM (kg)	ISAK	DXA (Lunar)	$-30.059+(2.926\times$ age$)+(0.625\times$ body mass$)$	105 male basketball players aged 11–15 y	0.92	3.6 kg		No	–	–	–

LoA Limits of Agreement, R^2 coefficient of determination, *SEE* standard error of estimation, *FFM* fat-free mass, *DXA* dual-energy X-ray absorptiometry, *FM* fat mass, *4C* four-compart model using DXA Hologic, underwater weighing, dilution techniques, *ALST* appendicular lean soft tissue, *ISAK* International Society for the Advancement of Kinanthropometry, *SMM* skeletal muscle mass

Body mass expressed in kg; girth expressed in cm; skinfolds expressed in mm

Almeida-Neto et al. 2024). This could be an advantage when sport-specific equations to estimate body mass components are not available. On the other hand, 27 out of 40 included studies provided predictive equations for individual sports. In some cases, athletes within the same sport, such as goalkeepers and field players in soccer (Santi-Maria et al. 2015) and hunt and flat jockeys (Dunne et al. 2020) were also differentiated. When applied appropriately, these sport-specific models can offer significantly more accurate solutions compared to generalized equations (Campa et al. 2023) and are, therefore, preferred for assessing body composition.

Anthropometric protocols

Various anthropometric protocols were used in the selected studies. Twenty-four (Quiterio et al. 2009; Reilly et al. 2009; Santi-Maria et al. 2015; Goosey-Tolfrey et al. 2016; Muniz et al. 2017; Zemski et al. 2018; Suarez-Arrones et al. 2018; Lozano-Berges et al. 2019; Munguía-Izquierdo et al. 2019; Nuñez et al. 2019; Dunne et al. 2020, 2022a, b; Sesbreno et al. 2020; Mitchell et al. 2020; Giro et al. 2022; Bonilla et al. 2022; Huang et al. 2023; de Moraes et al. 2024) out of 40 equations were developed following the protocol defined by the International Society for the Advancement of Kinanthropometry (ISAK) (International Society for Advancement of Kinanthropometry. 2001), while 10 (Stewart and Hannan 2000; Evans et al. 2005; Oliver et al. 2012; Novack et al. 2014; Cavedon et al. 2018, 2020, 2023) followed the procedures suggested by Lohman et al. (1988), one (Warner et al. 2004) those by Keys and Committee on Nutritional Anthropometry National Research Council (1956), one those by (Cameron 2022), while two (Abdalla et al. 2017; De Almeida-Neto et al. 2024) did not report any information about the measurement protocol. Some of these protocols differ in aspects such as the side of the body measured and anatomical landmarks. However, no studies have investigated the potential differences in body composition estimates due to the use of different anthropometric procedures. Researchers and practitioners should follow the measurement protocols established in the studies that developed the equations they are using.

Reference methods

The reference methods used in the selected studies all allowed for a multicomponent analysis of body mass. Most of the equations were developed using DXA as a reference, with differences between types of scanners. In fact, 21 used Hologic DXA (Stewart and Hannan 2000; Bell et al. 2000; Warner et al. 2004; Quiterio et al. 2009; Reilly et al. 2009; Cavedon et al. 2018, 2020, 2023; Zemski et al. 2018; Suarez-Arrones et al. 2018; Lozano-Berges et al. 2019; Munguía-Izquierdo et al. 2019; Nuñez et al. 2019; Mitchell et al. 2020;

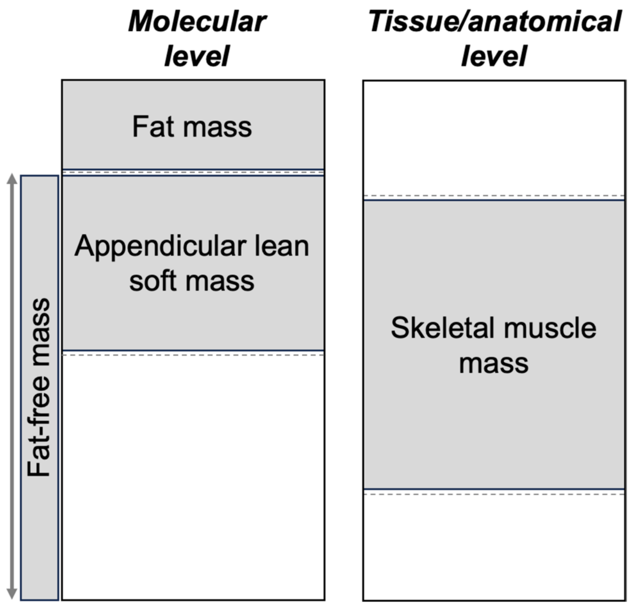


Fig. 3 Body mass components predicted by the selected studies

Giro et al. 2022; Mauro et al. 2023), while 17 used Lunar DXA (Oliver et al. 2012; Novack et al. 2014; Santi-Maria et al. 2015; Goosey-Tolfrey et al. 2016; Muniz et al. 2017; Abdalla et al. 2017; Dunne et al. 2020, 2022a, b; Sesbreno et al. 2020; Bonilla et al. 2022). This aspect should be considered by practitioners who want to obtain data comparable to those produced by other studies in the literature or other teams, given the lack of agreement between DXA models (Vendrami et al. 2024). Additionally, since the research described here spans several decades, software modifications and improvements over time could also influence results, even within a specific DXA manufacturer. The difference in body composition outputs due to the use of different indirect methods is one of the topics of study in body composition research. In this regard, some studies showed that DXA-derived fat mass, regardless of the model, is systematically higher compared to other methods, such as those based on the use of multiple techniques and four-compartment (4C) analysis (Santos et al. 2010; Cabre et al. 2021). This approach, which is currently considered the state-of-the-art method for assessing fat mass, was used in one (Evans et al. 2005) of the selected studies in this review and provided an equation for athletes from different sports. Therefore, practitioners should choose to compare anthropometric-derived outputs only with data quantified using indirect methods similar to those employed in the equations considered.

Limitations and future perspectives

A limitation of this review, intrinsic to the scoping review design, is that it did not assess the quality of the included studies. In this regard, it should be noted that some studies did not include a validation group and accuracy at the individual level remains uncertain. Additionally, the quality of the equations was not assessed based on sample size or the performance of the developed predictive models. Considering the limited number of predictive equations in relation to the wide variety of sports currently practiced, as well as the differences within each sport, future studies will need to develop increasingly specific models based on sport, sex, and playing position. The geographic origin of the athletes included in the studies has not been extensively discussed in the text. In our view, especially when considering elite athletes, participants often come from diverse regions, making geographic factors less relevant in selecting equations for athletes than they would be for the general population. Additionally, the characteristics of the anthropometric tools have not been thoroughly discussed. However, high-quality skinfold calipers produce comparable results (Fernandes Filho et al. 2017), and their reproducibility is generally less compromised than that of bioelectrical technologies (Stratton et al. 2021). While the limitation of not assessing the quality of the listed equations has been acknowledged, some key points are suggested below for the development of future predictive models. The first step is to identify the target body composition variables (e.g., fat or muscle mass) that the equation will predict. Next, it is important to use a gold-standard body composition method for obtaining reference data. This ensures the accuracy of the body composition values that the predictive equation will be compared against. In this regard, 4C-based evaluation models (e.g., Wang's equation (Wang et al. 2002)) should be preferred for estimating fat mass, while magnetic resonance imaging is recommended for estimating whole body and regional muscle mass. Procedures based on the 4C model typically involve air displacement plethysmography to quantify body volume, DXA for measuring bone mineral content, and isotope dilution to estimate fluids. Recently, studies have demonstrated the validity of using DXA to derive body volume and bioimpedance to estimate total body water (Nickerson et al. 2023; Bongiovanni et al. 2024), offering a more cost-effective and simplified alternative to the regular 4C model procedures. Additionally, other studies have confirmed the validity of DXA for quantifying muscle mass through specific conversion models tailored to each scanning technology (McCarthy et al. 2023; Tinsley et al. 2023). The third step involves selecting a representative and sport-specific sample. It is essential to ensure that the sample represents the broader population being studied. This is particularly important in sports, as different disciplines have distinct body composition profiles. Additionally, variations in body composition can occur depending on an athlete's playing role within team sports. Once the sample is selected, the next step is to choose relevant anthropometric measurements. The measurements

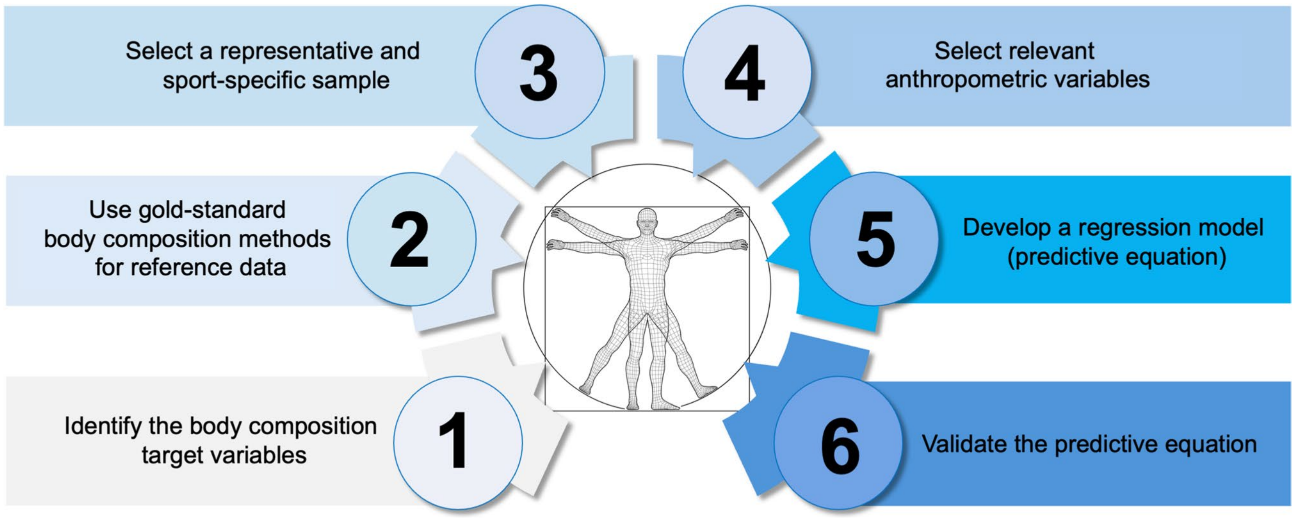


Fig. 4 Key steps for developing an anthropometric-based predictive equation for assessing body composition in athletes

selected should be those most strongly correlated with the body composition components being predicted. Commonly used anthropometric measures include body mass, height, girths, skinfold thickness, and bone breadths measurements. After selecting the relevant measurements, the next step is to develop a regression model or predictive equation. It is worth noting that models with smaller estimation errors and a greater explained variability should be preferred by researchers and practitioners. Finally, it is crucial to validate the predictive equation. This involves testing the equation on different subsets of the data to ensure that it is both accurate and reliable at both the group and individual levels. The aforementioned key points are outlined in Fig. 4.

Moreover, no study considered aspects related to biological maturity as a potential factor influencing body composition in youth athletes. Lastly, there is a clear need for more equations tailored specifically to female athletes, as they remain underrepresented in current research. Based on this evidence, it is recommended to monitor raw parameters (e.g., sum of skinfolds or girths) in addition to estimating body mass components for a more comprehensive assessment of body composition, especially when specific predictive models are not available. Based on these raw parameters, a future approach could involve identifying an indicator to determine when it is more appropriate to use an athlete-specific equation for individuals whose body composition characteristics resemble those of athletes more than those of the general population.

Conclusions

This scoping review provides a list of all anthropometric equations developed using multicomponent models in athletes. This allows for the selection of the most appropriate predictive equation, taking into account the sport, sex, and in some cases, the playing position. Researchers and practitioners can now easily identify the most suitable anthropometric equation based on the characteristics of the athlete being assessed. This helps avoid the use of inappropriate equations, which, if applied, can lead to inaccurate body composition data. Additionally, specific recommendations are provided for selecting the most appropriate equations from those available and for conducting new development studies.

Author contributions All authors worked collaboratively on the content and organization of this manuscript. FC and AP coordinated the author team, drafted the initial sections of the main text, and designed the figures. All authors participated in reviewing, editing the manuscript, and contributed to the abstract and conclusion. The final manuscript was read and approved by all authors.

Funding This research project received no external funding.

Availability of data and material Not applicable.

Declarations

Conflict of interest The authors declare no conflict of interest.

Ethics approval Not applicable.

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