Pediatric Exercise Science, (Ahead of Print)
https://doi.org/10.1123/pes.2017-0009

Human Kinetics
ORIGINAL RESEARCH

Improving the Prediction of Maturity From Anthropometric Variables Using a Maturity Ratio

Job Fransen, Stephen Bush, and Stephen Woodcock
University of Technology Sydney (UTS)

Andrew Novak
University of Newcastle

Dieter Deprez
Ghent University

Adam D.G. Baxter-Jones
University of Saskatchewan

Roel Vaeyens and Matthieu Lenoir
Ghent University

Purpose: This study aimed to improve the prediction accuracy of age at peak height velocity (APHV) from anthropometric assessment using nonlinear models and a maturity ratio rather than a maturity offset. ***Methods:*** The dataset used to develop the original prediction equations was used to test a new prediction model, utilizing the maturity ratio and a polynomial prediction equation. This model was then applied to a sample of male youth academy soccer players ($n = 1330$) to validate the new model in youth athletes. ***Results:*** A new equation was developed to estimate APHV more accurately than the original model (new model: Akaike information criterion: −6062.1, $R^2 = 90.82\%$; original model: Akaike information criterion = 3048.7, $R^2 = 88.88\%$) within a general population of boys, particularly with relatively high/low APHVs. This study has also highlighted the successful application of the new model to estimate APHV using anthropometric variables in youth athletes, thereby supporting the use of this model in sports talent identification and development. ***Conclusion:*** This study argues that this newly developed equation should become standard practice for the estimation of maturity from anthropometric variables in boys from both a general and an athletic population.

Keywords: sports, children, adolescence, growth, peak height velocity

Youth athletes are often grouped by their chronological age (CA) for training and competition purposes (1). However, large interindividual discrepancies between the CA (years from birth) and the biological age (BA; years from a maturation milestone) of individuals exist. During the period surrounding the adolescent growth spurt (±12 y in girls and ±14 y in boys), individuals' BA can differ by as much as 4 years (31). These differences are particularly apparent around the age at peak height velocity (APHV) and reflect the large variations in the timing and tempo of growth among individuals (15).

It is well known that physical dimensions influence motor performance (12) and play an important role in the success of individuals in sport (3,34). This is particularly prevalent during adolescence when biological maturation has been shown to affect physical performance in a range of sports. In such sports, early maturing individuals mostly outperform their later maturing counterparts, except in sports where the body dimensions associated with early maturation can be a disadvantage, such as figure skating, gymnastics, and dancing (14,15). This confounding influence of biological maturation on performance in youth sports is of particular interest in talent identification (21). Consequently, Vaeyens et al (33) reported that failing to control for maturation significantly confounds the identification of talented athletes, especially in sports where anthropometrical and physical fitness variables are strongly correlated with successful performance outcomes.

There are numerous ways to assess an individual's biological maturation. The traditional clinical methods

Fransen is with the Bachelor of Sport and Exercise Science, Faculty of Health, University of Technology Sydney (UTS), Sydney, New South Wales, Australia. Bush and Woodcock are with the School of Mathematical and Physical Sciences, University of Technology Sydney (UTS), Sydney, New South Wales, Australia. Novak is with the Bachelor of Exercise and Sport Science, Faculty of Science and IT, University of Newcastle, Ourimbah, New South Wales, Australia. Deprez, Vaeyens, and Lenoir are with Department of Movement and Sports Sciences,, Faculty of Medicine and Health Sciences, Ghent University, Ghent, Belgium. Baxter-Jones is with the College of Kinesiology, University of Saskatchewan, Saskatoon, Saskatchewan, Canada. Address author correspondence to Job Fransen at job.fransen@uts.edu.au.

consist of assessing skeletal age through X-ray of the wrist or the assessment of secondary sex characteristics (15). When assessing skeletal age using X-ray techniques, an X-ray image from the left wrist is used to compare an individual's bone and grades of skeletal maturity indicators are combined to estimate skeletal age that are then compared with reference data (4,10,30). The assessment of sexual maturation uses the onset and development of secondary sex characteristics (breasts, genitals, and pubic hair) compared with reference images. Both of these methods have been used extensively in youth populations to classify individuals according to their maturity status. However, these techniques involve considerable exposure to radiation or may be considered invasive in some cultures. Therefore, more recently dual-energy X-ray absorptiometry has been used as an alternative to the X-ray method (25) as it only exposes participants to one-tenth of the radiation dose (9) or about 0.001 mSv, with the average human dose from background radiation at sea level typically amounting to approximately 2.5 mSv per annum (32). Furthermore, a self-observation technique has been used as an alternative to the assessment of sexual maturation by a physician (7,28). Hence, it is clear that researchers have attempted to overcome some of the ethical, medical, and logistical limitations of traditional methods of assessing biological maturation.

One increasingly common method for assessing biological maturity is a noninvasive calculation of BA using anthropometric measures that incorporates the known proportionality in differences in leg and trunk length growth (19). The rationale behind this method is the known difference in timing between height, sitting height, and leg length. Therefore, these authors (19) argued that the changing relationship between these variables over time provides a good base for the prediction of APHV. This equation predicts the years from APHV and terms this BA a "maturity offset" (years from APHV) using measures of stature, body mass, leg length, sitting height, and CA to predict a maturity offset. Using this predicted BA and the CA at time of measurement, the APHV can be estimated. In the aforementioned study (19), sex-specific prediction equations were developed using a Canadian sample of 228 children (113 boys and 115 girls) between 4 years prior and three 3 years post APHV and cross-validated using Canadian and Belgian reference samples. The researchers emphasize that the accuracy of the prediction equation involves an error of 1 year 95% of the time. However, they suggest that the prediction of this maturity offset is only applicable in a sample of youths between 10 and 18 years. Malina and Koziel (16) attempted to validate this noninvasive method of predicting APHV in an external sample of Polish boys between 8 and 18 years, but showed that there was a systematic discrepancy between predicted and observed APHV, where this value was underestimated at younger ages and overestimated in the older age groups within the study. These findings were consistent with the limitations of the equation discussed in the original publication (19) and show a potential problematic application of the prediction equation in boys younger than 11 and older than 16 years. Furthermore, even when used within these age brackets, the prediction of APHV lacks validity, as demonstrated by Mills et al (18) who concluded that equation-based methods appear to overestimate the timing of peak height velocity (PHV) when they are applied in the year or stage immediately preceding PHV. Therefore, the original prediction equation by Mirwald et al (19) has considerable limitations, especially for individuals further removed from their APHV (16,20) and therefore warrants the cautious use of these prediction equations.

Despite these clear limitations, the use of the APHV prediction equation has been widespread in talent identification and talent development research within youth sports (5,17,34). This is not surprising given that a practical, noninvasive, and relatively accurate estimation of an athlete's maturity is of particular interest to talent identification and development as these processes require large numbers of youth athletes to be assessed in limited periods of time. However, the potential erroneous prediction of APHV embedded in the original prediction equation limits its usability and warrants an enhancement of the original equation. Indeed, Moore et al (20) developed new equations based on the original dataset (19) that would account for the overfitting (ie, the inclusion of artificially large coefficients or when covariance in the data is based on spurious associations) (20) generated by the original equations, and validated them in an external sample of British and Canadian children. The authors succeeded in simplifying the original equations by removing predictors and argued that these new equations should theoretically produce better fits across a range of external samples. However, they stated that the prediction error from these equations likely still increases to a greater degree the further away a child is from their actual APHV. Although commendable, these new equations do not produce more valid estimations for children who are further removed from their APHV. This increase in error in the tails of the distribution is potentially due to the linear estimation of an inherently nonlinear biological process, such as somatic growth during the adolescent growth spurt (24). Therefore, this study developed a new equation for the prediction of APHV from anthropometric variables in boys by fitting a nonlinear relationship between anthropometric predictors and a maturity ratio (CA/APHV) to the original data from Mirwald et al (19). Using a maturity ratio as a response variable might prove to be useful as adolescents move into adulthood and the rate of growth decreases. Therefore, it was hypothesized that this new model would yield similar prediction accuracy overall but a more valid prediction in the tails of the original data (boys relatively far removed from APHV). Moreover, it was expected that this new equation could be validated in an external sample of youth soccer players, thereby consolidating the use of the new prediction equation in a population of youth male athletes.

Methods

Participants

Dataset 1 [Mirwald and Baxter-Jones (MBJ)]: Developing a New Equation Using the Original Dataset (2). The University of Saskatchewan's Pediatric Bone Mineral Accrual Study (1991 to present) used a mixed longitudinal study design. Between 1991 and 1993, a total of 251 Canadian boys ($n = 115$) and girls ($n = 136$) were recruited from 2 elementary schools in Saskatoon, Saskatchewan (2). The study by Baxter-Jones et al (2) was designed to assess factors associated with bone acquisition in growing children. Participants were between 8 and 15 years of age at baseline, and ages ranged between 8 and 21 years across the initial 7 years of the study. Ninety-eight percent of the participants were white. All children were healthy with no conditions known to affect growth. Growth parameters were measured semiannually. Written informed consent was obtained from parents of participating children between 1991 and 1993. The University of Saskatchewan's Research Ethics Board approved all procedures.

Dataset 2 [Belgian Soccer Players (BSP)]: Validating the New Equation Using a New Dataset of BSP. This study involved 1330 high-level male youth soccer players who were recruited from Belgian soccer academies. Athletes were aged 8–17 years and from various ethnic backgrounds, with the majority of players of white descent. Due to the large number of participants, their ethnicity was not established. The data were collected longitudinally—testing was conducted during the same month each year across a period of 6 years, resulting in a total of 4829 observations, with each player having between 1 and 19 observations. The research was approved by the appropriate local university hospital ethical review panel, and written informed consent was received from all the participants and their parent(s) or guardian(s) prior to inclusion in the study.

Procedures

Dataset 1: Mirwald and Baxter-Jones. Anthropometric measures included stature and body mass, following the anthropometric standards outlined by Ross and Marfell-Jones (26). Stature was recorded without shoes to the nearest 0.1 cm against a wall-mounted stadiometer (Holtain, Crosswell, United Kingdom). Body mass was measured on a calibrated digital scale to the nearest 0.5 kg (model 1631; Tanita, Kewdale, Australia). A decimal CA (in years) was determined by identifying the numbers of days between an individual's date of birth and the date of the assessment. A measure of somatic maturation was defined by identifying the CA of attainment of peak linear growth during adolescence (PHV). To determine the CA at PHV, whole-year height velocities were calculated for each participant. A cubic spline fitting procedure was applied to each individual's whole-year velocity values, and the CA at the highest point was estimated (GraphPad Prism 5; GraphPad Software, San Diego, CA). A BA was then calculated by subtracting the CA at PHV from the CA at time of measurement for each individual. For this study, only male data were used.

Dataset 2: BSP. Stature (Harpenden portable stadiometer; Holtain) and sitting height (Harpenden sitting table; Holtain) were measured for all participants to the nearest 0.1 cm, with leg length calculated by subtracting sitting height from stature. Body mass was assessed to the nearest 0.1 kg (model BC-420SMA; Tanita), and from body mass, the ratio of body mass to stature was derived. All assessments were conducted according to the anthropometric standards outlined by Ross and Marfell-Jones (26). A decimal CA was obtained by calculating the number of days between an individual's date of birth and the date at the assessment occasion.

Statistical Analysis

The first phase of the analyses was to fit a variety of different models to the data used to develop the original equation (MBJ). The goal of these models was to predict the maturity offset, defined as the difference between a player's CA and his APHV. The second part of this analysis was to refit each of these models to predict APHV in a dataset consisting of Belgian high-level soccer players (BSP) (6). In the second phase of these analyses, the same fitting procedures were used to predict a maturity ratio (maturity ratio = CA/APHV) rather than a maturity offset (maturity offset = CA − APHV).

Phase 1: Predicting a Maturity Offset. In reanalyzing the data from Mirwald et al (19), several theoretically appropriate models were compared to identify the model with the most appropriate fit, assessed by how well the predicted values of the model match the observed data values. First, the linear model developed by these authors was evaluated; the model includes interactions between leg length and sitting height, CA and leg length, and CA and sitting height, as well as the body mass–to–stature ratio. Then the second model was implemented including these variables, as well as the main effects for leg length, sitting height, and age. However, as some nonlinearity was apparent in the data, polynomial terms were added to account for this. Given the presence of some nonlinearity in the residual analysis, generalized additive models were also considered (11). These involve fitting smooth relationships between the predictive and response variables. Because of the complexity of these relationships, only the main effects of each factor were considered. Cubic splines were used as the smoothing function.

Phase 2: Predicting a Maturity Ratio. In the final model, the maturity ratio rather than the maturity offset was used as the outcome variable. Using a maturity ratio as the response variable is particularly useful as adolescents move into adulthood and the rate of growth decreases. Similar to the procedure used in phase 1, linear, polynomial, and general additive models were fitted to the maturity ratio response.

All models were compared using the coefficient of determination (R^2) as a measure of how much of the variation in the offset could be explained by the anthropometric variables. Analysis of the residuals was also conducted to determine how well each of these models fit, especially for the youngest and oldest players in the dataset. All models were fitted in version 3.2.3 of the R statistical software system (R Core Team) (23), with plots constructed using the ggplot2 package (36) and linear mixed models fitted using the MASS package (35).

Results

Dataset 1: MBJ

Phase 1: Predicting a Maturity Offset. Figure 1 shows the relationship of CA, stature, body mass, and leg length with BA (years from PHV) for the data in Mirwald et al (19). The maturity offset measurements range from 4 years before APHV (BA = −4) and 3 years after APHV (BA = +3). The relationships between these variables and the BA were identified to be generally positive but nonlinear in some cases. This supports the further examination of the data using nonlinear models. Table 1 provides the model parameters for (a) the original model, (b) the model with main effects and interactions, (c) the model with main effects only, (d) the polynomial model, and (e) the generalized additive model when the maturity ratio is estimated. The Akaike information criterion (AIC) (27) and the adjusted R^2 values for each of the models are also included in Table 1. Both of these measures indicate that the polynomial model with interaction terms yields the best fit when predicting the offset. This is indicated by the smaller AIC and the larger adjusted R^2.

Phase 2: Predicting a Maturity Ratio. One of the issues with all of these models is that there is a small but systematic relationship between the model residuals and the fitted offsets. This relationship indicates that as the offset becomes larger in absolute value, the fit of the model to the data becomes poorer. The residual plots for each of these models are provided (Online Supplementary Figure 1, residuals vs fitted values scatterplots for the different models used to predict a maturity offset in the MBJ dataset). However, when using the maturity ratio as the outcome variable, an improved model fit was evident (see Online Supplementary Figure 2, residuals vs fitted values scatterplots for the different models used to predict a maturity ratio in the MBJ dataset). The model parameters, AIC and R^2 for the same set of models as in Table 1 but with a ratio response, are given in Table 2. The main-effects-only model was omitted as there are significant interactions. Like the maturity offset model, the best-fitting model appeared to be the polynomial model. Table 2 provides a thorough description of all models fitted and the various comparative measures related to goodness of fit. When performing a residual analysis on the models using the maturity ratio, the systematic pattern in the residuals observed in the prediction of the maturity offset is diminished. This is particularly true for the polynomial and generalized additive models and, to a lesser degree, true for the main effects and interaction model. This suggests that a ratio response fit provides a better fit when the difference between the APHV and the observed CA is large. The polynomial prediction equation that yielded the best model fit for the estimation of a maturity ratio can be found below:

$$
\begin{aligned}
\text{Maturity ratio} = {} & 6.986547255416 \\
& + (0.115802846632 \times \text{Chronological age}) \\
& + (0.001450825199 \times \text{Chronological age } (2)) \\
& + (0.004518400406 \times \text{Body mass}) \\
& - (0.000034086447 \times \text{Body mass } (2)) \\
& - (0.151951447289 \times \text{Stature}) \\
& + (0.000932836659 \times \text{Stature } (2)) \\
& - (0.000001656585 \times \text{Stature } (3)) \\
& + (0.032198263733 \times \text{Leg length}) \\
& - (0.000269025264 \times \text{Leg length } (2)) \\
& - (0.000760897942 \times [\text{Stature} \\
& \quad \times \text{Chronological age}]).
\end{aligned}
$$

Dataset 2: BSP

In contrast to the MBJ dataset, an assessment of APHV based on whole-year height velocities derived from longitudinal follow-up was not provided in the BSP dataset, so the estimates from each model provided a best guess of maturity. When using the model from Mirwald et al (19), the relationships between each of the variables and the maturity offset estimates did not seem to be smooth (Figure 2). An improved fit is obtained when the maturity offset is defined as a ratio rather than a difference (Figure 3). In particular, the variation of the fitted values across different values of each of the factors was more uniform than when using maturity offset as the outcome variable (Figure 4), even for leg length that showed high variation for larger leg lengths.

Discussion

The aim of this study was to improve the accuracy of the maturity offset and APHV prediction previously proposed by Mirwald et al (19). These sex-specific prediction equations have been critically reviewed, widely accepted, and frequently applied by researchers

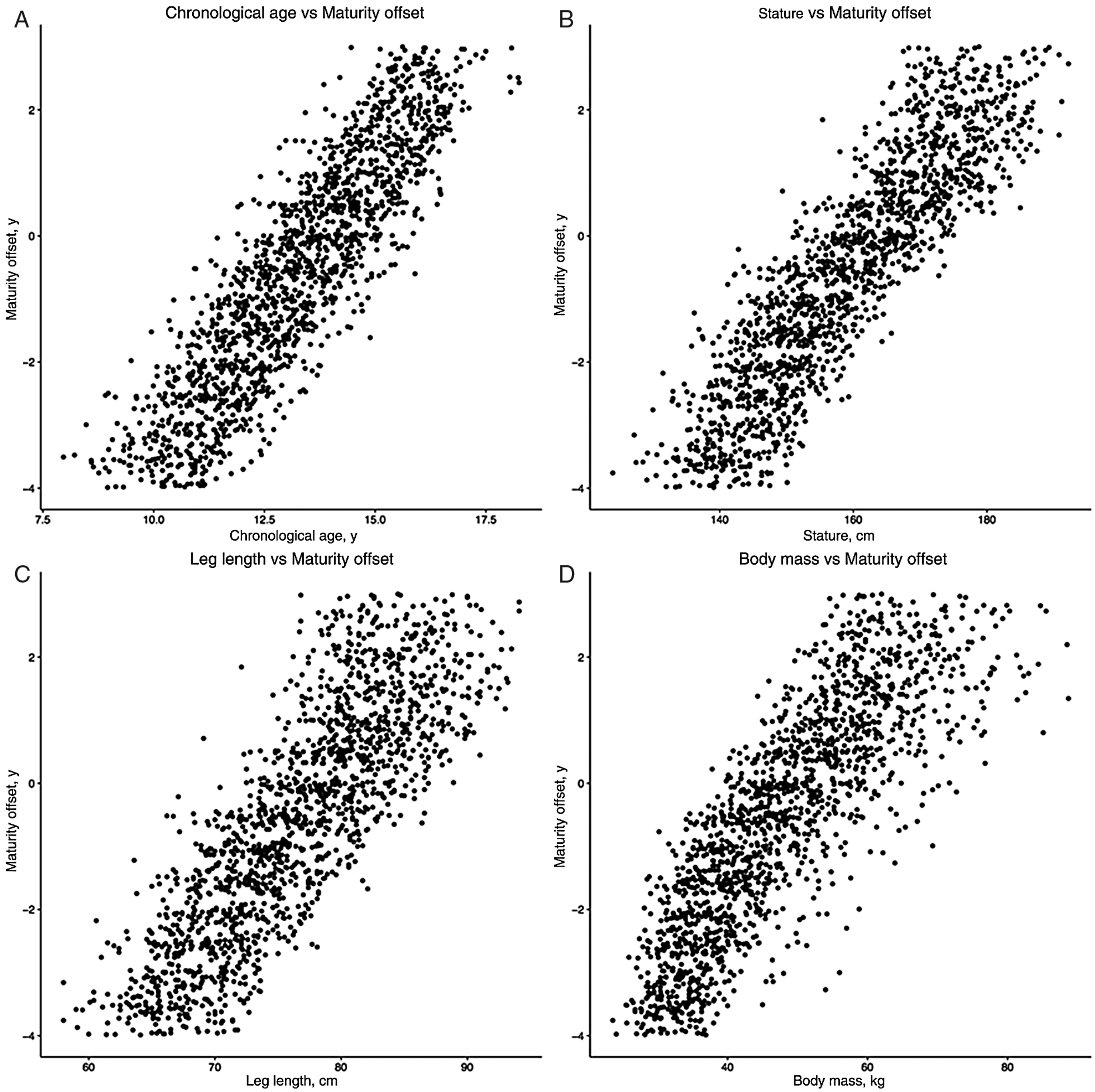

Figure 1 — Scatterplots of measured maturity offsets against (A) chronological age, (B) stature, (C) leg length, and (D) body mass using the data in Mirwald et al (19).

(569 citations of the original study, according to Scopus, January 6, 2016). However, both the original publication and a subsequent validation study (16) identified a systematic error when predicting APHV from anthropometric variables whereby the prediction of maturity offset was increasingly inaccurate at the upper and lower classification limits. In fact, both studies concluded that the equation for boys in particular could be used only in individuals of an average maturity range between the ages of 12 and 16 years. Also, the most accurate predictions were found to occur around the APHV of the individual (13.8 ± 0.8 y in averagely maturing boys). These findings indicate that perhaps there is a viable alternative to the original equations that allows for a more accurate estimation of APHV throughout the 12- to 16-year age span. Although Moore et al (20) proposed simplified versions of the original equations that do not require the assessment of sitting height, the same consistent errors seemed to be apparent when using these enhanced equations. The results of the present study, however, have resulted in an updated equation that better accounts for the systematic prediction error as individuals are further removed from their APHV.

Table 1 Fitted Models for Models With Maturity Offset Defined as the Difference Between Actual Age and Age at Peak Velocity

Model	Variable	Estimate	*SE*	*t*	*P* value	AIC	R^2
(a) Original model	Intercept	−9.206	0.095	−97.066	.000	3048.7	88.88%
	Body mass/stature ratio	0.023	0.004	5.046	.000		
	Leg length × sitting height	0.000	0.000	6.790	.000		
	Leg length × chronological age	−0.002	0.000	−4.935	.000		
	Sitting height × chronological age	0.007	0.000	22.248	.000		
(b) Main effects and interactions	Intercept	−21.290	1.962	−10.851	.000	3000.1	89.22%
	Leg length	−0.052	0.070	−.745	.456		
	Stature	0.127	0.039	3.286	.001		
	Chronological age	0.597	0.168	3.555	.000		
	Body mass/stature ratio	0.020	0.004	4.416	.000		
	Leg length × height	0.000	0.000	−.776	.438		
	Leg length × chronological age	−0.004	0.005	−.799	.424		
	Stature × chronological age	0.001	0.003	.387	.699		
(c) Main effects only	Intercept	−16.796	0.298	−56.399	.000	3006.6	89.16%
	Leg length	−0.130	0.009	−14.961	.000		
	Stature	0.122	0.006	21.726	.000		
	Chronological age	0.474	0.013	35.384	.000		
	Body mass	0.011	0.003	4.132	.000		
(d) Polynomial model	Intercept	82.63104	18.684	4.423	.000	2923.6	89.72%
	Chronological age (1)	1.03482	0.181	5.711	.000		
	Chronological age (2)	0.04002	0.008	4.709	.000		
	Body mass (1)	−0.04496	0.039	−1.143	.253		
	Body mass (2)	−0.00101	0.000	−5.255	.000		
	Stature (1)	−2.05143	0.364	−5.633	.000		
	Stature (2)	0.01329	0.002	5.898	.000		
	Stature (3)	−0.00003	0.000	−5.44	.000		
	Leg length (1)	0.39035	0.110	3.56	.000		
	Leg length (2)	−0.00404	0.001	−5.092	.000		
	Leg length × chronological age	−0.01043	0.002	−4.836	.000		
	Body mass × leg length	0.00215	0.001	3.106	.002		
(e) Generalized additive model	Intercept	−3.700	0.189	−19.531	.000	2930.7	89.71%
	Chronological age (1)	1.542	0.176	8.750	.000		
	Chronological age (2)	1.962	0.204	9.608	.000		
	Chronological age (3)	2.646	0.142	18.698	.000		
	Chronological age (4)	3.668	0.404	9.090	.000		
	Chronological age (5)	3.950	0.201	19.700	.000		
	Leg length (1)	−2.124	0.226	−9.382	.000		
	Leg length (2)	−4.743	0.528	−8.989	.000		
	Leg length (3)	−4.091	0.262	−15.590	.000		
	Body mass (1)	13.286	0.701	18.948	.000		
	Body mass (2)	26.359	1.508	17.482	.000		
	Body mass (3)	21.294	0.912	23.349	.000		
	Body mass/stature ratio (1)	−6.161	0.591	−10.424	.000		
	Body mass/stature ratio (2)	−10.385	0.617	−16.833	.000		
	Body mass/stature ratio (3)	−18.780	1.169	−16.064	.000		
	Body mass/stature ratio (4)	−17.526	0.862	−20.339	.000		

Note. For each model, the AIC value (smaller is better) and adjusted R^2 (larger is better) are provided. (a) Model reported in Mirwald et al (19). (b) Model including effects of height, age, leg length, height/weight ratio, and interactions. (c) Main effects model containing height, weight, age, and leg length. (d) Linear model including interactions and polynomial terms: (1) linear term; (2) quadratic term; and (3) cubic term. (e) Generalized additive model with cubic splines. Knots were equally spaced across the range of the predictive variable, and AIC was used to determine the number of knots, that is, in the generalized additive model the number 1–5 indicates the number of cubic splines needed to fit the data.
Abbreviation: AIC, Akaike information criterion.

Table 2 Fitted Models for Models With Maturity Offset Defined as the Ratio of Actual Age to Age at Peak Velocity

Model	Variable	Estimate	*SE*	*t*	*P* value	AIC	R^2
(a) Original model	Intercept	0.332	0.007	50.103	.000	–5888.4	89.72%
	Body mass/stature ratio	0.001	0.000	4.778	.000		
	Leg length × sitting height	0.000	0.000	6.450	.000		
	Leg length × chronological age	0.000	0.000	–4.807	.000		
	Sitting height × chronological age	0.001	0.000	23.385	.000		
(b) Main effects and interactions	Intercept	–0.333	0.051	–6.539	.000	–5964.9	90.19%
	Chronological age × stature	0.035	0.001	36.735	.000		
	Body mass	0.003	0.001	2.933	.003		
	Stature	0.006	0.001	4.650	.000		
	Leg length	–0.002	0.003	–.901	.368		
	Body mass × stature	0.000	0.000	2.082	.038		
	Body mass × leg length	0.000	0.000	–2.922	.004		
(c) Polynomial model	Intercept	6.98655	1.287	5.431	.000	–6062.1	90.82%
	Chronological age (1)	0.11580	0.012	9.273	.000		
	Chronological age (2)	0.00145	0.001	2.477	.013		
	Body mass (1)	0.00452	0.001	5.027	.000		
	Body mass (2)	–0.00003	0.000	–4.272	.000		
	Stature (1)	–0.15195	0.025	–6.05	.000		
	Stature (2)	0.00093	0.000	6.004	.000		
	Stature (3)	0.00000	0.000	–5.191	.000		
	Leg length (1)	0.03220	0.007	4.449	.000		
	Leg length (2)	–0.00027	0.000	–5.852	.000		
	Stature × chronological age	–0.00076	0.000	–5.114	.000		
(d) Generalized additive model	Intercept	1.493	0.037	40.000	.000	–6038.6	90.64%
	Chronological age (1)	0.467	0.017	28.270	.000		
	Chronological age (2)	0.252	0.008	30.870	.000		
	Leg length (1)	–0.156	0.015	–10.280	.000		
	Leg length (2)	–0.201	0.015	–13.270	.000		
	Leg length (3)	–0.406	0.032	–12.780	.000		
	Leg length (4)	–0.314	0.019	–16.390	.000		
	Body mass (1)	0.986	0.038	26.260	.000		
	Body mass (2)	1.997	0.081	24.780	.000		
	Body mass (3)	1.580	0.062	25.410	.000		
	Body mass/stature ratio	–0.045	0.002	–23.190	.000		

Note. For each model, the AIC value (smaller is better) and adjusted R^2 (larger is better) are provided. (a) Model reported in Mirwald et al (19). (b) Model including effects of height, age, leg length, height/weight ratio, and interactions. (c) Linear model including interactions and polynomial terms: (1) linear term; (2) quadratic term; (3) cubic term. (d) Generalized additive model with cubic splines. Knots were equally spaced across the range of the predictive variable, and AIC was used to determine the number of knots, that is, in the generalized additive model the number 1–4 indicates the number of cubic splines needed to fit the data.
Abbreviation: AIC, Akaike information criterion.

Somatic growth is not a linear process. Research has frequently demonstrated growth peaks in early infancy and during the adolescent growth spurt (15). Therefore, this research modeled a nonlinear relationship between anthropometric measures and a novel response variable. Although the original prediction included only linear predictors, the use of a polynomial equation allows a more accurate representation of the nonlinear relationship between the anthropometric variables and maturity offset (Figure 1). Furthermore, the use of a maturity ratio (CA/APHV) rather than a maturity offset (CA – APHV) seems to yield a better model fit in both the general sample and the athletic sample, even when the difference between the APHV and the observed CA is large. Hence, the inclusion of polynomial terms and the prediction of a ratio rather than an offset

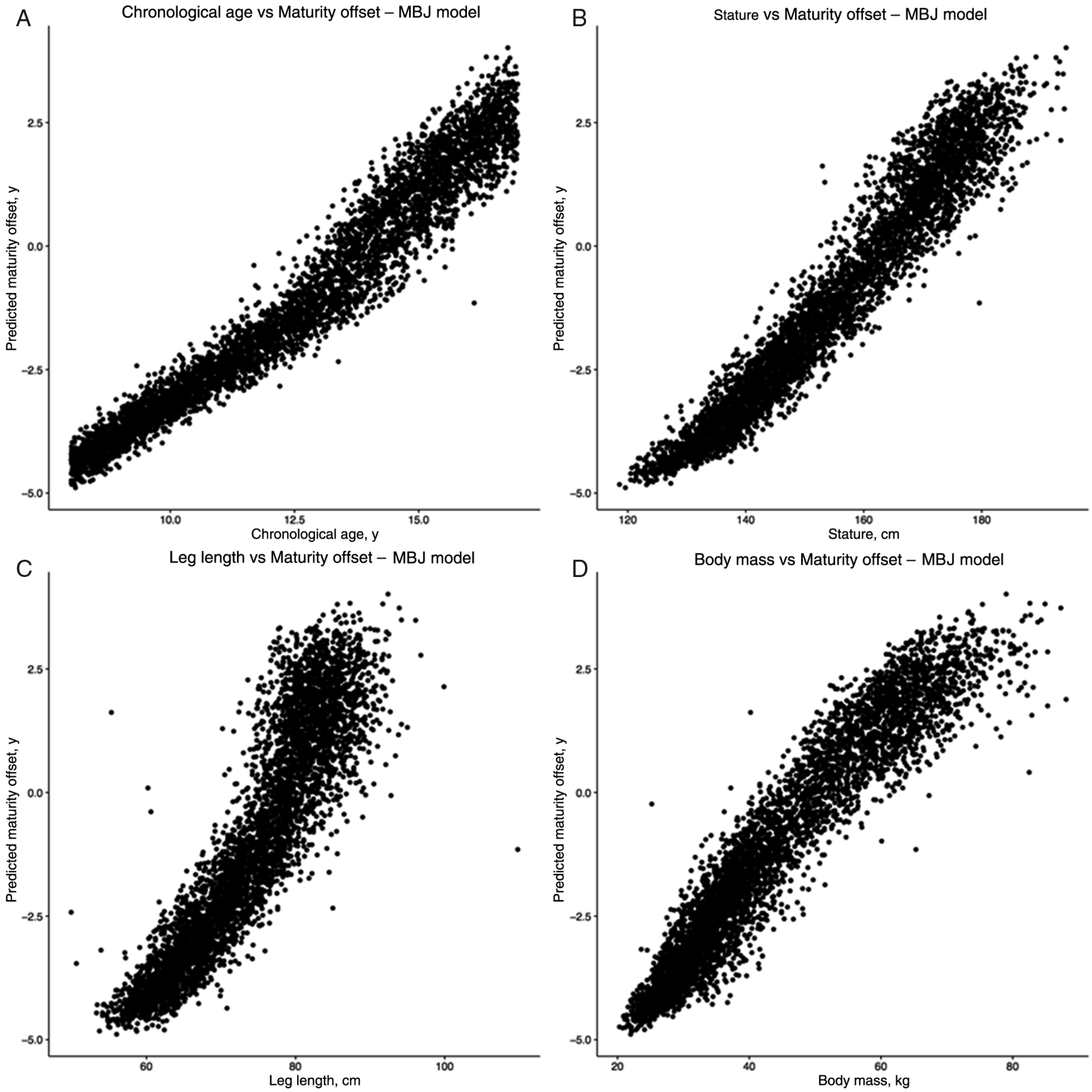

Figure 2 — Scatterplots of predicted maturity offsets against (A) chronological age, (B) stature, (C) leg length, and (D) body mass for the Belgian Soccer Players dataset when the model in Mirwald et al (19) is used. MBJ indicates Mirwald and Baxter-Jones.

resulted in a superior prediction of APHV over use of linear models in both the MBJ and the BSP datasets. However, this is not novel information as the original manuscript (19) already concluded that as the maturity offset increased, the prediction error increased as well. This was later confirmed to be the original equation's most significant limitation by Malina and Koziel (16). The new prediction equation has the same explained variance as the old equation, but there seems to be no systematic change in the prediction error as the predicted maturity ratio changes. This finding indicates that the current equation provides more reliable estimations of APHV than the original model (19), even when age is further removed from APHV. This increased accuracy of the new calculation will allow researchers and practitioners to determine APHV and maturity offset from anthropometric measures with greater confidence across a wide range of age and maturity status. This presents researchers with the opportunity to reliably collect maturity data noninvasively and with minimal cost and time required when compared with more traditional longitudinal measurements or estimations (dual-energy X-ray

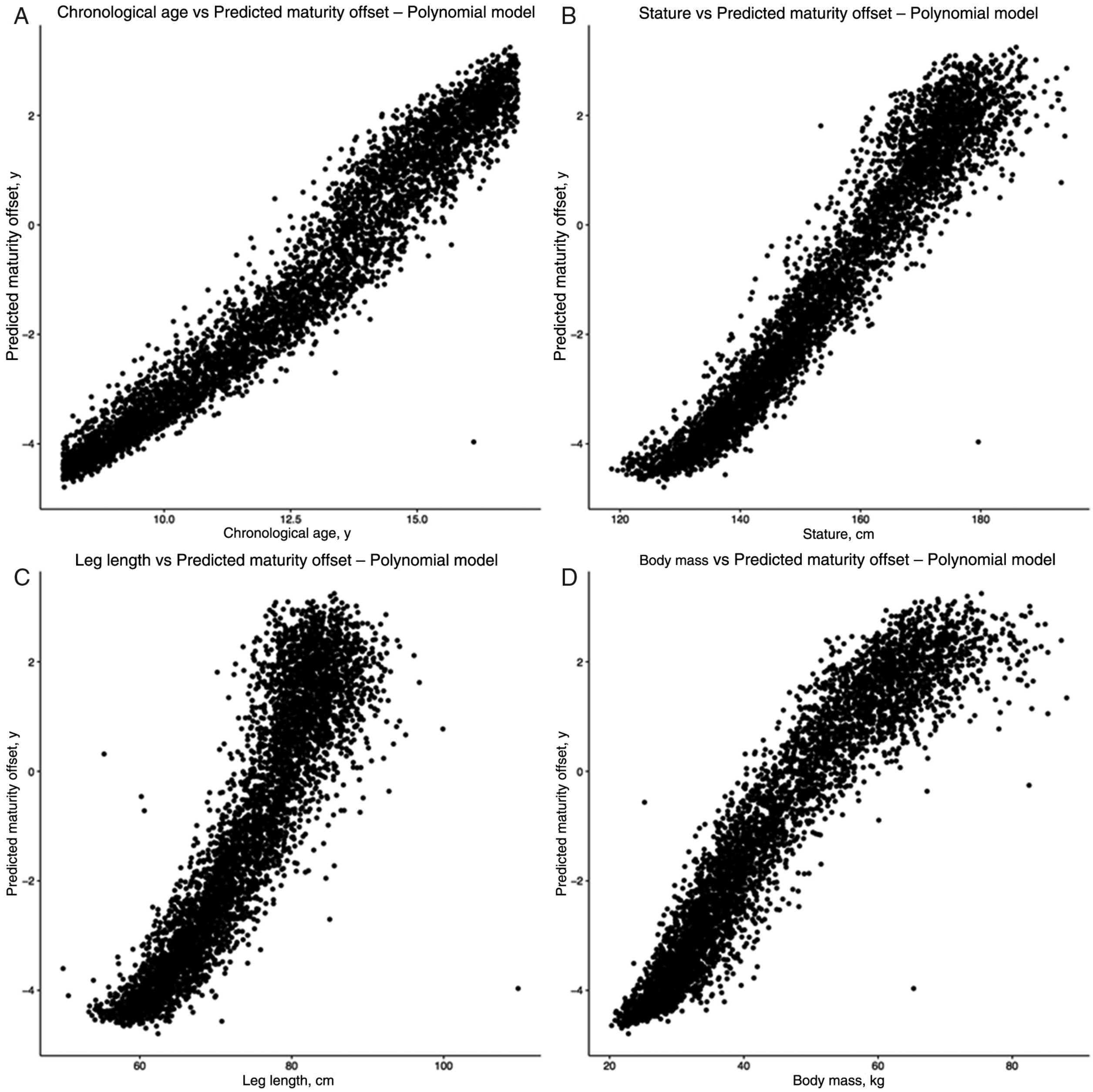

Figure 3 — Scatterplots of predicted maturity offsets against (A) chronological age, (B) stature, (C) leg length, and (D) body mass for the Belgian Soccer Player dataset when a polynomial model is used and the maturity offset is defined as the difference between age and age at peak velocity.

absorptiometry, X-ray, etc) of APHV. However, validating these new predictive models using longitudinal datasets should be the scope of future research.

One of the major strengths of this study is the successful application of the prediction equation to an external sample of high-level youth athletes. The validation of the new maturity ratio prediction in youth soccer players in this study is demonstrated by the fitted plots versus the residual plots (Online Supplementary Figures 1 and 2). Ideally, a good model fit is indicated by residuals that "bounce randomly" around the 0 line, forming a horizontal band around the 0 line and having no clear outliers. These criteria all seem to be met when a polynomial model is used to predict a maturity ratio. Furthermore, smaller AICs indicate a better model fit. As the AIC in the polynomial model yields ideal residual versus fitted plots and a low AIC, this model can be presumed to adequately fit the data. The validation of the newly developed prediction equation using "out-of-sample testing" is particularly important as the original

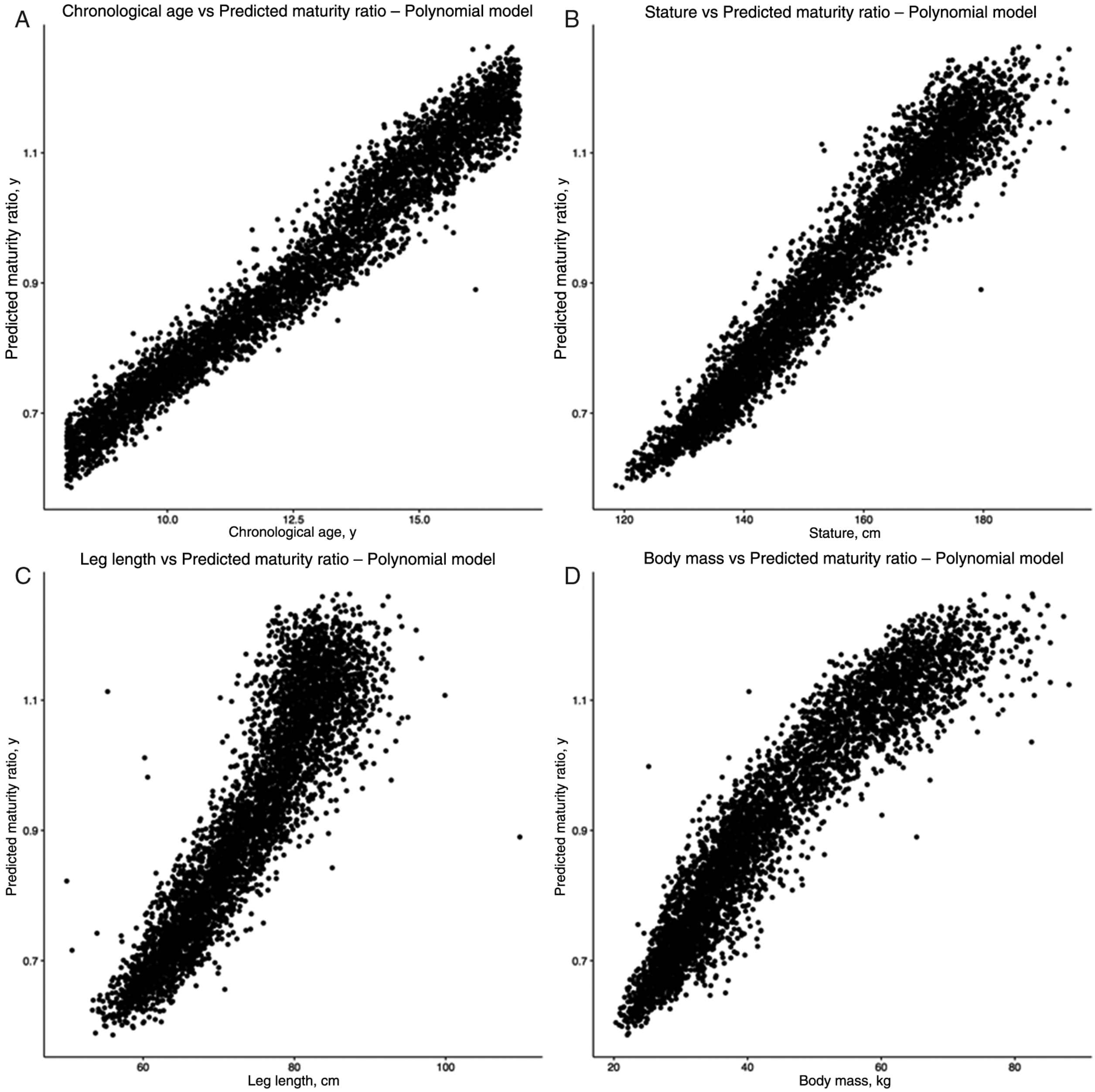

Figure 4 — Scatterplots of predicted maturity ratios against (A) chronological age, (B) stature, (C) leg length, and (D) body mass for the Belgian Soccer Players dataset when a polynomial model is used and the maturity offset is defined as the ratio between age and age at peak velocity.

equation was frequently used in samples that were distinctly different from the original sample (5,34). First of all, accurately determining maturation in youth athletes—both pre-APHV and post-APHV—is of great importance as it allows researchers and coaches to account for the confounding effect an advanced or delayed maturation might have on performance. Furthermore, accurately monitoring maturation via relatively quick and noninvasive anthropometric measures should aid in classifying youth athletes according to their biological maturity. This may ultimately result in a reduction in risk of physical injury (8), fairer match play, and decreased dropout from team sports (13,29). Finally, retrospective estimation of the APHV in athletes older than their predicted APHV might help map career progressions of successful athletes, a commonly used methodology in talent identification and development research. A second advantage of an accurate prediction of APHV in youth athletes is that training practice can be planned around the APHV of athletes. Philippaerts et al (22) showed that peak growth in physical performance in young soccer players coincides with peak growth in height and weight, and that differences in maturity status between players should therefore be taken into account when planning individualized training interventions.

Although this study has clearly identifiable strengths, there are also limitations to utilizing the prediction equations from this study in samples of general and athletic populations. First of all, it is important to note that despite the improvement in accuracy of the new maturity ratio estimation, longitudinal measurement of PHV provides much more accurate estimations of APHV. However, they are rarely viable alternatives for nonelite sporting academies or smaller sporting organizations, largely due to budget and time constraints. In circumstances such as these, the estimation of maturity ratio from anthropometric variables developed in this study might offer the best alternative. However, future studies should investigate the construct validity of these novel equations using dual-energy X-ray absorptiometry imaging, X-ray, or sexual maturation assessments. A second limitation is this study's inability to produce sex-specific prediction equations. Hence, the prediction equations derived from this study only refer to a male population. In the future, research should attempt to use similar models to describe the relationship between anthropometric variables and a maturity ratio in a sample of females.

Conclusion

This study overcomes some of the limitations of the prediction of APHV—as suggested by Mirwald et al (19)—by modeling a nonlinear relationship between anthropometric variables and a maturity ratio rather than a maturity offset. Furthermore, this study has established the practical validity of the novel equation in an external sample of high-level soccer players. This has significantly improved the applicability of this prediction equation within a population of 11- to 16-year-old boys. Hence, this newly developed method of estimating APHV should become standard practice for the noninvasive assessment of maturity from anthropometric variables.

Acknowledgments

No funding was received for this research, and there is no conflict of interest declared by any of the authors. The authors also declare that the results of this study are presented clearly and without falsification or inappropriate data manipulation.

References

1. Baxter-Jones ADG. Growth and development of young athletes: should competition levels be aged related? *Sports Med*. 1995;20(2):59–64. PubMed doi:10.2165/00007256-199520020-00001
2. Baxter-Jones ADG, Faulkner RA, Forwood M, Mirwald RL, Bailey DA. Bone mineral accrual from 8 to 30 years of age: an estimation of peak bone mass. *J Bone Miner Res*. 2011;26(8):1729–39. PubMed doi:10.1002/jbmr.412
3. Baxter-Jones ADG, Helms PJ. Effects of training at a young age: a review of the training of young athletes (TOYA) study. *Pediatr Exerc Sci*. 1996;8:310–27. doi:10.1123/pes.8.4.310
4. Chumela WC, Roche AF, Thissen D. The FELS method of assessing the skeletal maturity of the hand-wrist. *Am J Hum Biol*. 1989;1(2):175–83. PubMed doi:10.1002/ajhb.1310010206
5. Deprez D, Coutts AJ, Fransen J, et al. Relative age, biological maturation and anaerobic characteristics in elite youth soccer players. *Int J Sports Med*. 2013;34(10):897–903. PubMed doi:10.1055/s-0032-1333262
6. Deprez D, Vaeyens R, Coutts AJ, Lenoir M, Philippaerts R. Relative age effect and Yo-Yo IR1 in youth soccer. *Int J Sports Med*. 2012;33(12):987–93. PubMed doi:10.1055/s-0032-1311654
7. Duke PM, Litt IF, Gross RT. Adolescents' self-assessment of sexual maturation. *Pediatrics*. 1980;66(6):918–20. PubMed
8. Fukunaga Y, Nishizono H. Longitudinal height velocity during adolescence and its relationship to sports injury. *Jpn J Phys Fit Sports Med*. 2010;59(5):521–28. doi:10.7600/jspfsm.59.521
9. Gordon CM, Bachrach LK, Carpenter TO, et al. Dual energy X-ray absorptiometry interpretation and reporting in children and adolescents: the 2007 ISCD Pediatric Official Positions. *J Clin Densitom*. 2008;11(1):43–58. PubMed doi:10.1016/j.jocd.2007.12.005
10. Greulich WW, Pyle SI. Radiographic atlas of skeletal development of the hand and wrist. *Am J Med Sci*. 1959;238(3):393. doi:10.1097/00000441-195909000-00030
11. Hastie TJ. Generalized additive models. In: Chambers JM, Hastie TJ, editors. *Statistical Models in S*. Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software; 1992, pp. 249–308.
12. Jones MA, Hitchen PJ, Stratton G. The importance of considering biological maturity when assessing physical fitness measures in girls and boys aged 10 to 16 years. *Ann Hum Biol*. 2000;27(1):57–65. PubMed doi:10.1080/030144600282389
13. Malina RM. Growth and maturity status of young soccer (football) players. In: Reilly T, Williams M, editors. *Science and Soccer*. 2nd ed. London, UK: Routledge; 2003, pp. 287–306.
14. Malina RM. Physical growth and biological maturation of young athletes. *Exerc Sport Sci Rev*. 1994;22(1):280–4. doi:10.1249/00003677-199401000-00012
15. Malina RM, Bouchard C, Bar-Or O. *Growth, Maturation, and Physical Activity*. 2nd ed. Champaign, IL: Human Kinetics; 2004, p. 728.
16. Malina RM, Koziel SM. Validation of maturity offset in a longitudinal sample of Polish boys. *J Sports Sci*. 2014;32(5):424–37. PubMed doi:10.1080/02640414.2013.828850
17. Matthys SP, Fransen J, Vaeyens R, Lenoir M, Philippaerts R. Differences in biological maturation, anthropometry and physical performance between playing positions in youth team handball. *J Sports Sci*. 2013;31(12):1344–52. PubMed doi:10.1080/02640414.2013.781663

18. Mills K, Baker D, Pacey V, Wollin M, Drew MK. What is the most accurate and reliable methodological approach for predicting peak height velocity in adolescents? A systematic review. *J Sci Med Sport*. 2017;20(6):572–7. PubMed doi:10.1016/j.jsams.2016.10.012
19. Mirwald RL, Baxter-Jones ADG, Bailey DA, Beunen GP. An assessment of maturity from anthropometric measurements. *Med Sci Sports Exerc*. 2002;34(4):689–94. PubMed
20. Moore SA, McKay HA, Macdonald H, et al. Enhancing a somatic maturity prediction model. *Med Sci Sports Exerc*. 2015;47(8):1755–64. PubMed doi:10.1249/MSS.0000000000000588
21. Pearson DT, Naughton GA, Torode M. Predictability of physiological testing and the role of maturation in talent identification for adolescent team sports. *J Sci Med Sport*. 2006;9(4):277–87. PubMed doi:10.1016/j.jsams.2006.05.020
22. Philippaerts RM, Vaeyens R, Janssens M, et al. The relationship between peak height velocity and physical performance in youth soccer players. *J Sports Sci*. 2006;24(3):221–30. PubMed doi:10.1080/02640410500189371
23. R Core Team. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing; 2015. Available from: https://www.R-project.org
24. Rogol AD, Clark PA, Roemmich JN. Growth and pubertal development in children and adolescents: effects of diet and physical activity. *Am J Clin Nutr*. 2000;72(2):521s–8s.
25. Romann M, Fuchslocher J. Assessment of skeletal age on the basis of DXA-derived hand scans in elite youth soccer. *Res Sports Med*. 2016;24(11):200–11.
26. Ross W, Marfell-Jones M. Kinanthropometry. In: Green H, editor. *Physiological Testing of the High Performance Athlete*. Champaign, IL: Human Kinetics; 1991, pp. 223–307.
27. Sakamoto Y, Ishiguro M, Kitagawa G. *Akaike Information Criterion Statistics*. Dordrecht, The Netherlands: D. Reidel Publishing Company; 1986, p. 290.
28. Schlossberger NM, Turner RA, Irwin CE. Validity of self-report of pubertal maturation in early adolescents. *J Adolesc Health*. 1992;13(2):109–13. PubMed doi:10.1016/1054-139X(92)90075-M
29. Simmons C, Paull GC. Season-of-birth bias in association football. *J Sports Sci*. 2001;19(9):677–86. PubMed doi:10.1080/02640410152475801
30. Tanner JM. *Growth at Adolescence: With a General Consideration of the Effects of Hereditary and Environmental Factors Upon Growth and Maturation From Birth to Maturity*. 2nd ed. Oxford: Blackwell Scientific Publications; 1962, p. 325.
31. Tanner JM, Whitehouse RH, Marshall WA, Carter BS. Prediction of adult height from height, bone age, and occurrence of menarche, at ages 4 to 16 with allowance for midparent height. *Arch Dis Child*. 1975;50(1):14–26. PubMed doi:10.1136/adc.50.1.14
32. Baim S, Wilson CR, Lewiecki EM, Luckey MM, Downs RW, Lentle BC. Precision assessment and radiation safety for dual-energy X-ray absorptiometry: position paper of the International Society for Clinical Densitometry. *Journal of Clinical Densitometry*. 2005;8(4):371–78.
33. Vaeyens R, Lenoir M, Williams AM, Philippaerts RM. Talent identification and development programmes in sport. *Sports Med*. 2008;38(9):703–14. PubMed doi:10.2165/00007256-200838090-00001
34. Vandendriessche JB, Vaeyens R, Vandorpe B, Lenoir M, Lefevre J, Philippaerts RM. Biological maturation, morphology, fitness, and motor coordination as part of a selection strategy in the search for international youth soccer players (age 15–16 years). *J Sports Sci*. 2012;30(15):1695–703. PubMed doi:10.1080/02640414.2011.652654
35. Venables WN, Ripley BD. *Modern Applied Statistics With S*. 4th ed. New York: Springer-Verlag; 2002, p. 498.
36. Wickham H. *ggplot2: Elegant Graphics for Data Analysis*. New York: Springer-Verlag; 2009, p. 213.