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Improving longitudinal performance assessment of youth soccer players: 10 m sprint percentile curves adapted to biological age

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ABSTRACT
Monitoring athletic development in youth soccer is crucial for player evaluation, identifying training needs, and determining long-term progression. However, standard percentile assessments based on chronological age (CA) do not account for biological maturity or developmental variability. This study aimed to improve 10 m sprint performance assessment in youth soccer by integrating biological age (BA) into percentile modeling and applying linear mixed models (LMM) to capture individual development. The analysis was based on 10 m sprint data collected within the Swiss Football Association's talent development program between 2017 and 2024, comprising 9476 observations for the Lambda Mu Sigma (LMS) method and 3983 for LMMs. BA was calculated using the Mirwald method as an estimation for peak height velocity. Empirical percentile curves (LMS) were generated for both CA and BA, while LMMs established longitudinal reference curves and enabled individual performance predictions using bootstrap resampling. In males, BA explained more variance in sprint performance than CA ($R^2 = 0.22$ vs. 0.18), whereas no significant predictors were identified for females. Percentile curves based on BA elevated rankings of late-maturing players and lowered those of early-maturing players, suggesting better consideration of developmental differences. LMMs provided a more comprehensive modeling framework than LMS, by incorporating repeated measures and individual developmental trajectories. Integrating BA and LMMs longitudinal modeling could enhance the fair evaluation of youth soccer players. Findings support individualized, maturity-adjusted monitoring, offering practical value for longer-term performance diagnostic and evaluation. This statistical approach, applied to a large practice-oriented dataset, enables targeted and sustainable improvement of youth player development.

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KEYWORDS
Player evaluation; youth soccer; talent development; performance prediction; player development

Introduction

Monitoring athletic development is centrally important in sport contexts like soccer, where early talent identification and long-term development programming occur (Armstrong 2023). In soccer, short-distance acceleration and sprint performance under 20 m is a fundamental physical quality and key performance indicator (Haugen et al. 2014; Agudo-Ortega et al. 2024). They contribute to various soccer-specific tasks such as pressing, duels, and creating space (Bradley et al. 2009), while straight-line sprinting has been identified as the most frequent action immediately preceding goals, particularly for attacking players (Faude et al. 2012). Furthermore, acceleration over 10 m has been shown to correlate with performance-relevant actions, including agility, dribbling, and vertical jumping ability (Sun et al. 2025). However, despite its importance, higher linear acceleration may not directly translate into greater change-of-direction efficiency, potentially due to increased inertia at higher velocities (Loturco et al. 2019; Papla et al. 2020). As such, 10 m sprint times are commonly used to evaluate short-distance acceleration in soccer players and compared to percentile benchmarks to evaluate performance development of youth athletes.

Traditionally, percentile benchmarks have been constructed using the LMS (Lambda Mu Sigma) method based on chronological age (CA). This is an effective method for modelling performance data while accounting for both skewness and kurtosis (Cole and Green 1992; Bountziouka et al. 2023). However, this approach

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has two critical limitations: It fails to account for the biological maturity status of the player, and it does not capture individual developmental trajectories over time. As skeletal age (an indicator of biological maturity) of adolescents of the same CA can vary by −2.1 and +4.6 years (Ruf et al. 2024), performance evaluations using solely CA may not reflect the player's true physiological developmental stage (Cobley et al. 2009; Malina et al. 2015), resulting in potentially inaccurate or biased player evaluations (Owen et al. 2022; Ruf et al. 2024; Pinczon Du Sel et al. 2025). Studies have shown that biologically advanced players typically outperform their later-maturing peers in strength and speed tests – not due to their superior talent or technical competency, but due to earlier anthropometric and accompanying physiological development (Tønnessen et al. 2013). Thus, evaluations that neglect biological maturity assessment in youth risk reinforcing systematic biases in talent selection and retention.

The timing and tempo of maturation differ fundamentally between boys and girls. On average, girls reach peak height velocity (PHV) at 11.5–12 years of age, while boys reach PHV later at 13.5–14 years of age (Mirwald et al. 2002). These sex-specific differences affect musculoskeletal growth, strength acquisition, and subsequent performance progression (Malina 2010; Romann et al. 2024). As such, performance assessments must be analyzed independently for boys and girls to provide accurate developmental context.

Several recent publications advocate for the inclusion of biological age (BA) indicators to create more equitable performance assessments (Born et al. 2022; Ruf et al. 2024; Pinczon Du Sel et al. 2025). Ruf et al. (2024), for instance, demonstrated that when 5 m and 30 m sprint reference centiles were indexed to skeletal age instead of CA, performance assessments changed significantly for both early- and late-maturing soccer players. Another noteworthy approach is the Percentile Comparison Method (PCM) developed by Abbott, Cobley & colleagues (Abbott et al. 2024) which uses maturity- and relative age-adjusted distributions to classify players into developmental profiles. These approaches provide a more accurate assessment framework, as they account for individual variation not captured in models based solely on CA.

The LMS method has also remained as the standard procedure for constructing smoothed percentile curves (Waterlow et al. 1977; Flegal and Cole 2013). However, LMS is designed to produce cross-sectional percentiles, modeling variance and skewness as age-dependent (time-varying) functions. It does not model longitudinal change (Cole and Green 1992). LMS does not incorporate repeated measures or make individual-level performance predictions. To address these limitations, this study employed linear mixed models (LMM), a statistical framework well-suited for longitudinal data. LMMs can both accommodate fixed effects (e.g., age) and random effects (e.g., individual growth trajectories), enabling performance modeling that reflects the real-world, unbalanced nature of player data (Fransen et al. 2017; Weippert et al. 2021). Critically, LMMs incorporate player development in model structure, creating more accurate, individualized, and predictive percentile curves. As such, LMMs offer a more appropriate framework for player performance and development evaluation, addressing longstanding limitations.

In the soccer context, the Swiss Football Association (SFA) has initiated a longitudinal performance monitoring project across its elite youth development system. Within the project, the influence of biological maturation on performance is recognized via BA assessment and tracking. The aim is to develop more individualized, maturity-adjusted tools for tracking performance, enabling more homogeneous match scheduling and offering late-maturing players tailored developmental opportunities.

To address the risk of systematic bias from ignoring biological maturity in player evaluation, the main aims of this study were to: (1) examine sprint performance percentiles in youth soccer players by incorporating biological age as a key variable and comparing these with percentiles based on chronological age; and (2) implement LMM as an advanced method for generating longitudinal reference curves, as well as identifying developmental patterns, and predicting longer-term trends.

Methods

Participants

All participants were officially licensed SFA soccer players and were part of the national talent development framework (Footeco). Between 2017 and 2024, SFA trained staff collected 10 m sprint performance data twice a year according to standardized protocols (Schweizerischer Fussballverband 2016). A total of 34,428 anonymized 10 m sprint data from male and female players aged 9–32 years ($N = 11{,}882$) were collected for analysis. Additionally, in a sub-sample ($N = 8{,}674$), anthropometric measurements (22,362 observations) were collected, permitting calculation of BA. For the present study purposes, participants were screened to include males and females with anthropometric and performance measures between the ages of 10.5–21 years, timepoints aligning with maturational growth. A detailed description of data retrieval procedures, inclusion steps, and sample selection is provided in the

Supplementary Material (Figure S1). The study protocol was approved by the institutional review board of the Swiss Federal Institute of Sport Magglingen (Reg.-Nr. 252–2025) and was conducted in accordance with the Declaration of Helsinki. All players and their guardians provided general consent for the use of anonymized performance and anthropometric data for scientific analysis within the SFA framework.

Procedure and data analysis

Anthropometric measures, i.e., height, weight, and sitting height, were collected according to the WHO guidelines (Sellen 1998) within an average of 1.3 (±0.88) months (maximum 3 months) of sprint performance assessment. Anthropometric measures were used to calculate participants' BA. BA can be described as a mean-centered maturity timing value, which is transformed to permit plotting along a scale to more closely resemble CA, helping simplify interpretation for practitioners. To determine BA, participants' CA (decimal), height, weight, and sitting height measures were entered into sex-specific predictive equations established by Mirwald et al. (2002), to estimate maturity offset in years from PHV. Then, maturity offset values were added to the average age at PHV (13.8 years for males and 11.8 years for females) (Malina et al. 1997; Kozieł and Malina 2018). Sprint performance was measured using photocell timing systems (TCi System, Brower Timing Systems, Draper, UT, USA). The 10 m sprint test has been shown to be a valid and reliable measure of short-distance acceleration in soccer players (Haugen et al. 2012; Buchheit and Mendez-Villanueva 2013). Prior to the assessment, players completed a sprint-specific warm-up. The front foot was placed at the start line, aligning with the first timing gate. Starts were performed without a command and a backward arm swing was allowed if the feet remained on the ground. A rest interval of 3–4 min was ensured between attempts to minimize fatigue effects. Each player performed two 10 m sprints from a standing start, with the better time used for data analysis. Sprint trials were repeated if they were initiated by a flying start, if timing gates were triggered early, if a foot lifted prior to the start, or if players reached their hand through the final gate to improve their time (Schweizerischer Fussballverband 2016).

For the LMS-based percentile modeling, player sprint observations with both valid 10 m sprint times and BA estimates were included. To focus specifically on youth player development, the dataset was filtered to include only players within the U21 age group. Single and repeated measurements were both considered, as the LMS method models age-dependent distributions rather than individual trajectories (Cole and Green 1992); for the LMM dataset, only players with at least three such measurements were retained to enable longitudinal analysis (see Table 1 for subject characteristics and Supplementary Material Figure S2 for repeated measure distribution). To ensure data quality for subsequent modeling, outliers were identified and removed using the Locally Estimated Scatterplot Smoothing (LOESS) method (Cleveland and Devlin 1988), which applies localized weighted regressions to fit a smooth curve through the data (see Figure S3 in Supplementary Material). This step allowed for the detection of sprint times deviating significantly from the underlying performance trend. All data analyses were completed using R statistical software (R Core Team, 2024; version 4.4.1) and RStudio version 2024.12.1 + 563.

Empirical percentile curves; chronological age vs. biological age

The first aim of the study was to examine 10 m sprint percentiles by incorporating BA using LMS and comparing these with percentiles based on CA. LMS models were fitted using the Generalized Additive Models for Location, Scale, and Shape (GAMLSS) method and gamlss function (v5.4.22) in R. The Box–Cox t (BCT) distribution family was applied, which is an extension of the Box–Cox Cole–Green (BCCG) distribution and provides additional flexibility by modeling both skewness and heavy tails in the data.

Table 1. Subject characteristics for the LMS and LMM dataset.

Dataset	Sex	N (obs.)	N (players)	Repeated measures* (n)	Chronological Age (years) Mean ± SD (Range)	Biological Age (years) Mean ± SD (Range)	Weight (kg) Mean ± SD (Min – max)	Height (cm) Mean ± SD (Min – max)
Lambda Mu Sigma	F	391	211	1–8	14.2 ± 0.90 (12.0–16.0)	13.6 ± 0.87 (11.3–16.2)	51.5 ± 8.06 (31.4–80.6)	160.8 ± 6.58 (142.9–176.7)
Lambda Mu Sigma	M	9,085	4,896	1–6	13.5 ± 0.88 (11.0–16.5)	13.2 ± 1.05 (10.4–17.2)	47.7 ± 9.58 (26.7–94.0)	160.6 ± 9.91 (132.2–198.5)
Linear Mixed Models	F	185	46	3–8	14.1 ± 0.85 (12.0–15.9)	13.5 ± 0.81 (11.3–15.7)	50.6 ± 7.99 (31.8–80.6)	160.2 ± 6.56 (143.3–176.7)
Linear Mixed Models	M	3,798	1,101	3–6	13.6 ± 0.89 (11.3–16.8)	13.3 ± 1.05 (10.5–17.2)	47.8 ± 9.49 (26.7–82.8)	161.1 ± 9.62 (132.2–189.5)

*Repeated measures refer to multiple observations collected from the same player.

Compared with the BCCG distribution, the BCT model includes an additional parameter (tau) that controls kurtosis and allows the tails of the distribution to vary, providing a better fit for data with heavier or lighter tails (Rigby and Stasinopoulos 2006). Age (CA/BA) was used as the independent variable and was not transformed. To capture the nonlinear relationship between age and sprint performance, a penalized B-spline smoother (pb(age)) was used for the modeled parameter mu, sigma, nu, allowing smooth age-dependent curves to be fitted rather than simple linear trends, while tau was kept constant across age. The GAMLSS model was fitted using the formula *gamlss(Sprint_10m ~ pb(age), sigma.formula = ~ pb(age), nu.formula = ~ pb(age), data = na.omit(data), family = 'BCT')*, with *age* referring to chronological or biological age. This provided the required flexibility for capturing complex variations in athletic performance across ages.

Normal distribution of the 10 m sprinting times was visually assessed using Q–Q Plots (see Supplements, Figure S4), which is preferable to the highly sensitive formal tests when interpreting large datasets (Field et al. 2012). Percentile curves of the 3rd, 10th, 25th, 50th, 75th, 90th, and 97th percentiles were generated for visual representation. This procedure was performed twice – once for CA and once for BA – using the identical data to enable direct comparison. Percentile ranks were calculated for each measurement to analyze differences in percentile ranks between the CA and BA reference curves. The dataset was divided into three maturity groups: (1) early developers (BA – CA > 1), (2) normative developers (–1 ≤ BA - CA ≤ 1), and (3) late developers (BA – CA < –1). Within-group differences between CA and BA percentile ranks were assessed using a paired t-test, while between-group differences were evaluated using ANOVA. Effect-sizes were reported using Cohen's d (d) and eta-squared (η^2).

Linear mixed model (LMM) approach

The second aim of the study was to use LMM to enable the analysis of longitudinal measures without excluding data. In this framework, sprint performance was modelled as a linear function of age (on the log-transformed scale), while accounting for repeated observations within players. Random intercepts were included to allow individuals to differ in baseline sprint performance, and random slopes were used to capture individual differences in the rate of performance change with age. The LMM framework was well suited to the structure of the available data, as it allowed for the integration of all repeated measures per player, providing a more accurate representation of individual developmental trajectories than cross-sectional approaches. This approach also appropriately accounted for within-player dependence while avoiding overfitting given the limited number of repeated observations (McElreath 2018; Newans et al. 2022).

Accordingly, sprint times were log-transformed to reflect the natural performance improvements with age, as opposed to absolute changes (Hopkins 2000). In addition, age was modeled on the logarithmic scale, such that the LMM specifies a linear relationship between log(sprint performance) and log(age). This transformation is appropriate when an approximately exponential age–performance relationship is expected, as it linearizes the association and satisfies the assumptions of linear mixed modeling (Atkinson and Nevill 1998). A predictive model showing the relationship between 10 m sprint performance and CA and BA was created to generate reference values. To allow log transformation of age and to ensure that model estimation was restricted to the observed age range, new variables were created by subtracting the minimum observed age and adding 1 (chron_age_mindiff = CA – min(CA) + 1; bio_age_mindiff = BA – min(BA) + 1). This step avoids undefined logarithms at zero and does not affect the interpretation of age-related effects.

The first step of the LMM analysis was to identify the best fitting mixed effect model. Models were created using the Linear Mixed-Effects Regression (LMER) model function from the lme4 package (v1.1.37) in R Studio. The models were constructed following literature guidelines (Bates 2016), starting with a baseline model, then progressively increasing model complexity to account for both fixed effects of age (CA resp. BA) and individual developmental trajectories. An overview of the model specifications is presented in Table 2. To identify the best-fitting model, the following parameters were first assessed using the ANOVA

Table 2. Overview of linear mixed models used to analyze the relationship between 10 m sprint time and age (males, CA). Identical modeling procedures were applied separately for BA as well as for the female dataset.

Model Name and Description	Model Formula
Baseline Model *Baseline model that captures between-player variability only*	lmer(log(Sprint_10m) ~ 1 + (1 | PersonID)
CA Model *Models sprint performance as a function of CA with player-specific intercepts*	lmer(log(Sprint_10m) ~ log(chron_age_mindiff) + (1 | PersonID)
CA Random Slope Model *Models sprint performance as a function of CA with player-specific intercepts and slopes*	lmer(log(Sprint_10m) ~ log(chron_age_mindiff) + (log(chron_age_mindiff) |PersonID)

function and then compared: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and likelihood ratio. Linearity was examined using a Tukey-Anscombe plot, while the normality of random effects and residuals was assessed by Q–Q plots (Buchheit and Mendez-Villanueva 2013).

The next step involved creating reference values based on the best-fitting linear mixed-model. To facilitate practical interpretation, model predictions were back-transformed from the log scale to the original units of measurement (seconds and years). Using the model's estimated parameters, typical development trajectories were generated, representing the mean trajectory as well as trajectories corresponding to ±0.67, ±1.28, and ±1.88 standard deviations from the intercept. In a normal distribution (Gaussian distribution) and based on the fixed proportions of data captured by the standard normal cumulative distribution function (Wilks 2011), these standard deviations correspond to the 25th and 75th, 10th and 90th, and finally 3rd and 97th percentiles, respectively. These trajectories were plotted to visually illustrate the relationship between CA/BA and 10 m sprint performance.

Individual forecasting model

The developed linear mixed-effects model was used as a reference framework for individual player forecasting. New 10 m sprint performance data were incorporated by extracting the individual-specific coefficients (random intercept and random slope) from the fitted model, which were combined with the population-level fixed effect. These personalized coefficients were used to construct an individualized predictive equation and generate player-specific sprint performance trajectories across CA/BA. Percentile ranks were calculated to evaluate individual player's standing within the reference population. Specifically, the player's individual intercept (baseline performance) and individual slope (performance development over time) were each compared to the distribution of corresponding coefficients in the model. This approach, based on the LMM framework, allows for the assessment of longitudinal performance development.

Bootstrapping for prediction uncertainty

To account for uncertainty in the individualized 10 m sprint performance forecast, a non-parametric bootstrapping approach was applied (Efron and Tibshirani 1994). Accordingly, 1000 bootstrap samples were drawn from the original dataset, and a linear mixed-effects model was refitted to each sample. For each bootstrap iteration, individual-specific coefficients (random intercept and random slope) were extracted, and predicted sprint times were computed across the target age range. This generated a distribution of predicted outcomes at each age point, from which mean predictions and 95% confidence intervals were calculated. The resulting prediction intervals reflect both the variability in model estimation and the uncertainty inherent in the player's future performance trajectory.

Results

Aligned to study objectives, the following results are presented. (1) examining sprint performance percentiles in youth soccer players by incorporating biological age as a key variable and comparing these with percentiles based on chronological age; and (2) implement LMM as an advanced method for generating longitudinal reference curves, as well as identifying developmental patterns, and predicting longer-term trends.

LMS percentile curves

Figure 1 shows the empirical percentile curves across CA and BA for 10 m sprints in male soccer players. Percentile curves for female players are presented in Supplementary Figure S5. Detailed model results for both sexes are available in Supplementary Table S1, and additional GAMLSS parameter curves (mu, sigma, nu, tau) can be seen in Supplementary Figure S6.

Comparison LMS chronological vs. biological age

Percentile ranks shifted significantly in male and female soccer players when performance was evaluated by BA compared to CA. Among males, late-maturing players improved their ranks ($M = +13.49 \pm 8.0$ SD, $p < .001$, d = 0.46), while those of early-maturing players declined markedly ($M = -20.84 \pm 10.7$ SD, $p < .001$, d = −0.71); normative-maturing players ranks showed a small decrease ($M = -1.32 \pm 7.4$ SD, $p < .001$, d = −0.05). Female soccer players showed the same pattern but with smaller effect sizes: late maturing players' ranks improved slightly ($M = +2.51 \pm 1.9$ SD, $p < .001$, d = 0.09), early maturing players' ranks declined ($M = -7.76 \pm 3.1$ SD, $p < .001$, d = −0.30), and normative maturing players' ranks declined minimally ($M = -0.24 \pm 2.0$ SD, $p = .046$, d = −0.01). One-way ANOVAs confirmed significant differences across all maturity groups for both sexes (male: $F(2, 9082) = 2588$, $p < .001$, $\eta^2 = 0.36$; female: $F(2, 388) = 185.4$, $p < .001$, $\eta^2 = 0.49$).

Longitudinal modeling using LMM

Model comparison

LMM was fitted separately for male and female players using both CA and BA to predict 10 m sprint

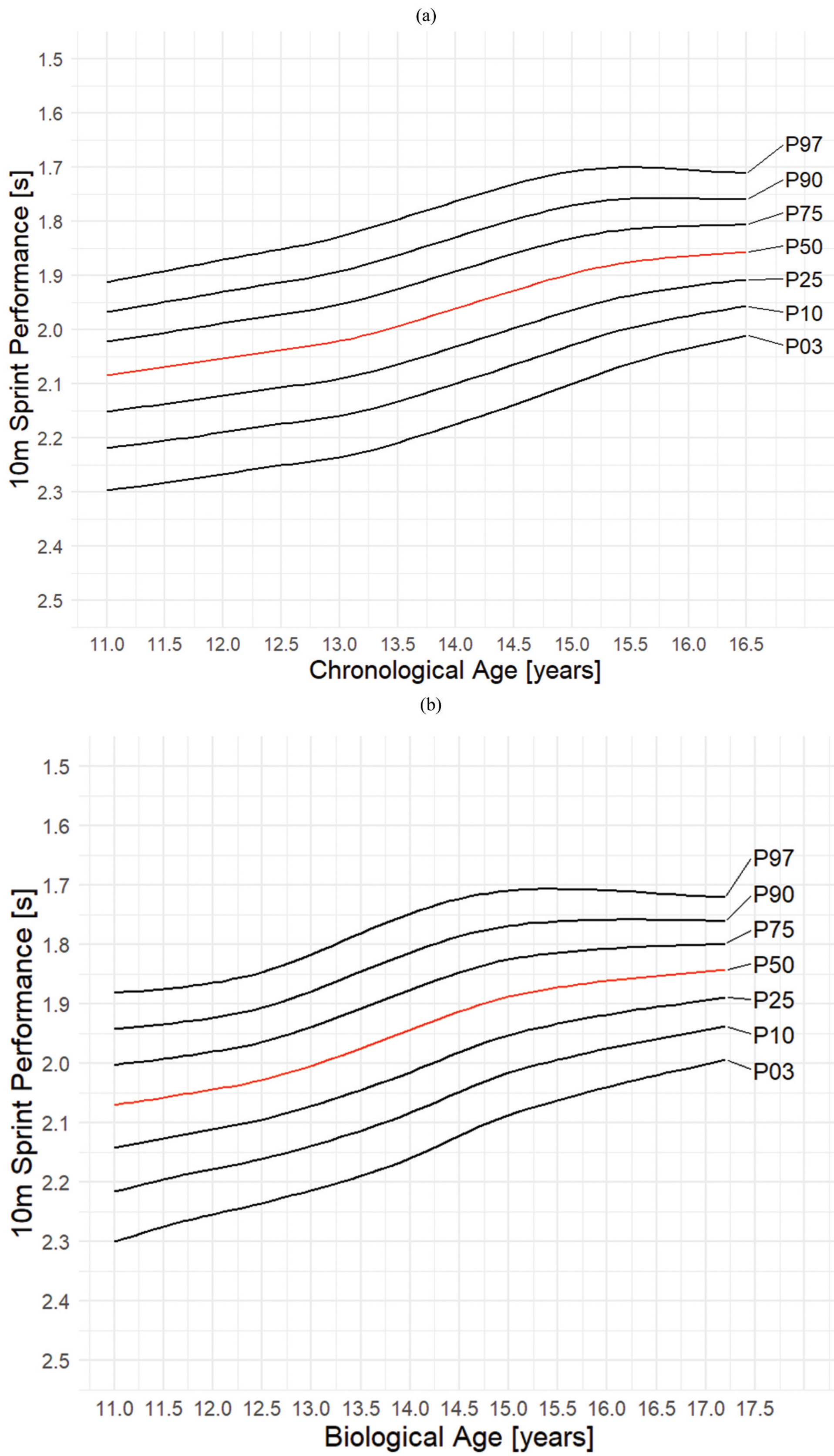

Figure 1. LMS percentile curves for 10 m sprint performance across (a) chronological age and (b) biological age in male youth soccer players. The red line indicates the 50th percentile (P50). Percentiles shown include the 3rd, 10th, 25th, 50th, 75th, 90th, and 97th (P03, P10, P25, P50, P75, P90, and P97, respectively). To aid interpretation, the y-axis was reversed so that faster sprint times appear higher on the plot, representing performance improvement as an upward trend.

performance across the developmental period. Linear mixed-model comparison by AIC, BIC, and likelihood ratio tests consistently indicated that the random slope model provided the best fit for all combinations (see Supplements Table S2). Accordingly, the final models included both random intercepts and random slopes, thus, capturing individual-specific deviations in baseline sprint performance and rate of change over time. The Tukey-Anscombe plot residuals showed no major deviations, and the Q–Q plots indicated approximate normality, with points closely following the diagonal reference line (see Supplements Figure S7).

For male players, both CA and BA models revealed significant negative relationships between age and sprint time. In the CA model, log-transformed age was a significant predictor of sprint times (β = –0.14, 95% CI [–0.15, –0.13], $p < .001$, d = –0.50). The model explained 18% of the variance through fixed effects (marginal $R^2 = 0.18$) and 60% when including random effects (conditional $R^2 = 0.60$). In the BA model, performance also improved significantly with increasing age (β = –0.10, 95% CI [–0.11, –0.09], $p < .001$; Std. β = –0.39), with slightly higher marginal explanatory power ($R^2 = 0.22$) and similar conditional power ($R^2 = 0.58$). The marginal R^2 was higher in the BA (0.22) compared to the CA model (0.18), representing a relevant increase in variance explained by the fixed effects. For females, neither CA nor BA showed statistically significant effects on sprint performance within the LMM framework. In the CA model, the effect of age was negative but not significant (β = –0.02, 95% CI [–0.04, 0.006], $p = 0.137$; Std. β = –0.12), with marginal ($R^2 = 0.01$) and conditional power ($R^2 = 0.68$). Similarly, in the BA model, the effect of age on performance was non-significant (β = –0.02, 95% CI [–0.04, 0.006], $p = 0.155$; Std. β = –0.08), with marginal ($R^2 < 0.01$) and conditional power ($R^2 = 0.60$). Detailed results for the best-fitting model (e.g., Model CA/BA for males) are described in Table 3, with the remaining models for females reported in Supplements' Table S3.

Benchmarks and performance prediction of individual trajectories

Typical developmental trajectories in 10 m sprint performance of male soccer players were modelled based on the best-fitting LMMs using BA as it explained more variance than the CA model (see Results Model comparison). Performance trajectories were projected based on at least three prior observations and model parameters. Since predictive precision is influenced by both the number of available measurements per player and the complexity of the model, uncertainty estimates were generated by the bootstrapping procedure. An example of such a prediction is presented in Figure 2, where the red dots and solid line represent an example of an individual's sprinting times, and the blue area indicates the 95% confidence interval around the predicted trajectory (blue dashed line). A corresponding figure for female players can be found in Supplements Figure S8.

Analysis of individual trajectories indicated that players starting with lower sprint performance tended to show greater improvements over time, whereas those with initially higher performance improved less, independent of whether chronological or biological age. This pattern was supported by a strong negative correlation between random intercepts and slopes ($r = -0.79$) in the male BA model. Figure 2 presents one player's predicted (blue dashed line) and observed (solid red line) actual sprint progression over time. Based on his model-derived intercept and slope, percentile ranks can be calculated to assess his relative standing in the overall cohort. Notably, the figure also illustrates the considerable variation that can be expected in both baseline

Table 3. Summary of best fitting random intercept, random slope model considering CA/BA of male players.

Predictors	Estimates (CA)	Estimates (BA)	CI (CA)	CI (BA)	*p* (CA)	*p* (BA)
(Intercept)	0.8948	0.8150	0.8807–0.9089	0.8064–0.8236	<0.001*	<0.001*
Chron age mindiff [log]	–0.1368	–0.1012	–0.1458––0.1278	–0.1075––0.0948	<0.001*	<0.001*
Random Effects	**(CA)**	**(BA)**				
σ^2	0.0015	0.0015				
$\tau_{00\ \mathrm{PersonID}}$	0.0106	0.0033				
$\tau_{11\ \mathrm{PersonID.log(chron\_age\_mindiff)}}$	0.0039	0.0012				
$\rho_{01\ \mathrm{PersonID}}$	–0.9317	–0.7931				
ICC	0.51	0.46				
N_{PersonID}	1101	1101				
Observations	3798	3795**				
Marginal R^2/Conditional R^2	0.179/0.599	0.217/0.579				

**Three observations were excluded from the biological age model, as one individual lacked sufficient within-subject variability to support random slope estimation.

CI = 95% confidence interval; σ2: Residual variance; τ00 PersonID: variance of the random intercepts across individuals; τ11 PersonID.log(chron_age_mindiff): variance of the random slopes for log(chron_age_mindiff) across individuals (PersonID); ρ01 PersonID: correlation between the random intercepts and random slopes; ICC: Intraclass Correlation Coefficient; N PersonID : ID-Number. Significance level is evaluated at α = .05 and marked with an asterisk (*).

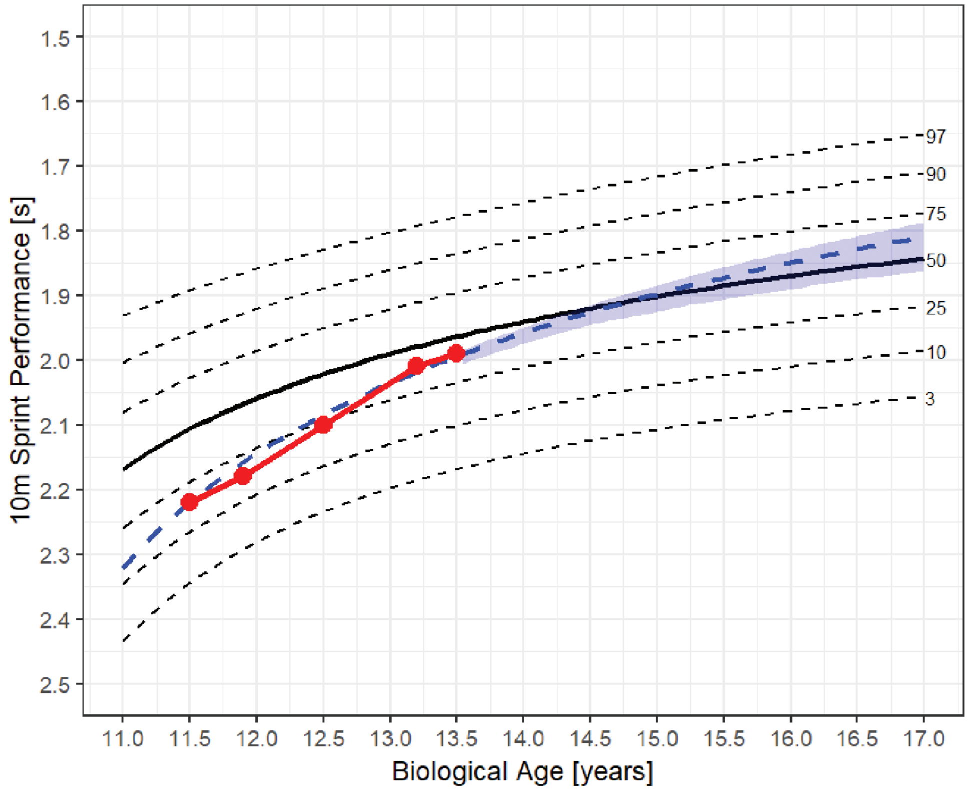

Figure 2. Percentile curves of 10 m sprint performance based on the best-fitting LMM using biological age in male youth soccer players. Red line and dots represent the observed sprint times of one individual. The blue dashed line shows the bootstrapped predicted trajectory, with the blue area indicating the 95% confidence interval. Black dashed lines correspond to standard deviation intervals (±0.67, ±1.28, ±1.88 SD), approximating the 3rd to 97th percentiles. Sprint times are shown in seconds on the y-axis, with lower values indicating better performance.

performance and in developmental trajectories over time. This case (along with others) illustrates how relative standing can traverse across percentile curves, demonstrating the potential for substantial change in cohort standing over time.

Discussion

This study aimed to improve the assessment of sprint performance in youth soccer by including BA within percentile curve modeling and applying LMM to account for longitudinal data and permitting the capability to assess individual developmental trajectories. Findings demonstrated that incorporating BA provides a more accurate reflection of performance relative to CA, and that LMM-based curves provide a more comprehensive modeling framework than traditional LMS percentile modeling.

Consistent with previous research, results indicate that using BA rather than CA significantly altered players rankings. Specifically, late-maturing players' rankings increased within performance curve distributions, while inflated rankings for early-maturing players decreased. Thus, a more appropriate, biological developmental stage considered evaluation of performance was achieved (Abbott et al. 2024; Ruf et al. 2024). This supports longstanding concerns that CA-based evaluations may misclassify players, favoring those with advanced maturation (Cobley et al. 2009; Pinczon Du Sel et al. 2025). The magnitude of rank shifts observed is in line with the findings by Ruf et al. (2024), who reported similar effects when indexing sprint performance to skeletal age. Furthermore, our findings extend the Percentile Comparison Method (PCM) introduced by Abbott, Cobley & colleagues (Abbott et al. 2024) by incorporating not only maturity adjustments but also developmental trajectories using LMMs.

LMM application enabled the modeling of both fixed age effects and random individual growth patterns, offering a nuanced view of performance development. For male players, both CA and BA were significant predictors of sprint time, with BA explaining more 10 m sprint performance variance, as evidenced by higher marginal R^2. This suggests that BA is more closely aligned with the physiological processes influencing sprint performance across youth. Notably, a strong negative correlation between random intercepts and slopes in the BA model ($r = -0.79$) was observed, indicating players with initially lower performance levels tended to improve more over time. This finding also highlights the importance of accounting for individual development rather than making individual performance judgments. A large longitudinal study of players within the English talent development system also identified that those who became professionals were consistently faster over 20 m than their non-professional peer; but interestingly, observed sprint development over time was non-linear with substantial individual variation, highlighting the complexity of physical development in youth football (Saward et al. 2020). While the study focused on 20-m sprints, it did not account for BA. Still, it provided initial evidence as to the importance of sprint speed on subsequent success. Whether similar patterns between professionals and non-professionals will emerge in this dataset remains to be confirmed.

By contrast, neither CA nor BA metrics significantly predicted performance in the female cohort. While the conditional R^2 values were high, indicating high player-level variance, the marginal R^2 was close to zero. This may reflect higher variability in female maturation timing, fewer repeated measures (only 4.9% in relation to male data), or different developmental patterns not fully captured by current models. Importantly, female biological development is driven by different hormonal mechanisms than males, with lower testosterone and higher estrogen leading to increased fat mass and reduced muscle and tendon adaptations. Consequently, maturation has a less pronounced impact on sprint performance in females, making sprint speed development less biologically driven than in males (Talukdar et al. 2022). This further highlights a broader issue: research on female players, particularly in soccer, remains limited. As emphasized in recent literature, there is an urgent need for sex-specific research frameworks that consider the unique physiological, hormonal, and developmental trajectories of female players (Kelly and Ackerman 2023). Our findings reinforce this need, supporting calls for increased representation and methodological investment in research on girls and women in sport.

From a practical perspective, the integration of BA and longitudinal modeling has direct applications for player evaluation and development. Maturity-adjusted percentile curves derived from LMMs allow practitioners to evaluate players not only in relation to peers of the same BA, but also across time according to their own individual development. By incorporating maturity status and accounting for individual growth trajectories through repeated measures, the LMM approach is expected to outperform the LMS-based percentile curves presented in LMS percentile curves, which do not consider longitudinal development or within-player variance. As a result, differences in centile shape between the two approaches are expected, reflecting the contrast between a longitudinal, model-based trajectory and a cross-sectional, spline-smoothed representation of the data. Such methods are particularly relevant in federated development systems, such as that of the SFA, which aims to create equitable performance environments and better support of late developing players (Lüdin L S D, et al. 2022; Lüdin L S M 2022). Thus, the development of an interactive application would further enhance utility for coaches and performance staff in real-world settings.

Methodologically, the study benefits from a large, real-world dataset spanning multiple years, the inclusion of both sexes, and the use of robust statistical techniques such as LOESS smoothing for outlier detection and bootstrapping to estimate prediction uncertainty. The use of a longitudinal design and repeated measures adds ecological validity and reflects real-world player monitoring practices (Armstrong 2023).

The study is not without limitations. While BA was estimated using the widely applied Mirwald method (Mirwald et al. 2002), it is a prediction, not a direct measure of skeletal maturity (Bountziouka et al. 2023). Although we explored applying the SITAR growth curve model (Cole et al. 2010), the dataset's age coverage (11–17 years, with most data between 12 and 15 years), short observation window, and a limited number of repeated and evenly spaced measurements per player were insufficient to capture the full and detailed trajectory of individual and whole-cohort growth spurt trends. While a log-transformed biological age–performance relationship provided an accurate and concise fit. For future research and monitoring practices, we are transitioning in collaboration with the SFA to a nationwide BA assessment by systematically measuring height and weight at earlier ages (prior to U12), enabling the use of the validated SITAR growth curve model. However, at the time of this study, the available longitudinal height data were insufficient for a reliable SITAR-based estimation of APHV, and we therefore relied on the Mirwald method (Cole 2018). Moreover, the female longitudinal sample size was limited, which may have reduced statistical power and model sensitivity. Further, no external validation cohort was available to test prediction accuracy across independent datasets. It is also valuable to remind that sprint performance is influenced by non-biological parameters (biomechanics and skills), and can be enhanced through targeted training interventions (Pardos et al. 2024). These factors could not be considered or controlled in this study. Present participants were also part of a national talent development framework, representing a pre-selected, high-performing subgroup. While this may limit the generalizability of the findings to broader player populations, it also strengthens the study's relevance by directly informing talent development practices within the Swiss soccer system. These limitations highlight the importance of subsequent research aimed at validating and extending analytical models in broader populations and sport contexts.

In summary, this study provides a novel, practical, and advanced evaluation of sprint performance in youth soccer by combining BA-based assessments with longitudinal modeling. These approaches allow a more individualized and equitable performance monitoring, with implications for both player evaluation and long-term player development. The present study highlights differences between male and female soccer players, thereby showing the necessity of further research, and in this case, a larger representation of female players. However, while present analytical models offer valuable insights, they should not be used as standalone tools for early selection or deselection. As previously highlighted, there are clear dangers in relying on one-off performance measures for early (de)selection of players, particularly given the variability in maturation and development trajectories (Vaeyens et al. 2008). Instead, such tools are best used to support individualized, long-term development pathways. The aim is to foster fair evaluations and to retain potential talent within the development system. Practitioners should focus on each player's longitudinal trend, treating isolated test scores with caution. This study provides a foundation for exploring additional key performance indicators and ultimately improving player evaluation, talent identification and selection processes.

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Author contributions

CRediT: **Julia Hernandez:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing; **Chantal Widmer:** Conceptualization, Methodology, Writing – review & editing; **Shaun Abbott:** Conceptualization, Methodology, Writing – review & editing; **Stephen Cobley:** Conceptualization, Methodology, Supervision, Writing – review & editing; **Dennis-Peter Born:** Conceptualization, Methodology, Supervision, Writing – review & editing; **Raphael Kern:** Conceptualization, Funding acquisition; **Markus Tschopp:** Conceptualization, Writing – review & editing; **Wolfgang Taube:** Conceptualization, Methodology, Supervision, Writing – review & editing; **Michael Romann:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing.

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Abbreviations

BA	Biological Age
CA	Chronological Age
LMM	Linear Mixed Models
LMS	Lambda Mu Sigma
LOESS	Locally Estimated Scatterplot Smoothing
PHV	Peak Height Velocity
SFA	Swiss Football Association

Code availability statement

The R code used for statistical analysis presented in the paper can be accessed online at https://doi.org/10.5281/zenodo.18257250.

Data availability statement

The datasets presented in this article are not readily available because they are the property of the Swiss Football Association and contain sensitive performance data that are not authorized for public sharing. Requests to the corresponding author.

Informed consent statement

Within the framework of the Swiss Football Association, all players and their guardians had provided general consent for the use of anonymized performance and anthropometric data for scientific analysis.

Institutional review board statement

The study protocol was approved by the institutional review board of the Swiss Federal Institute of Sport Magglingen (Reg.-Nr. 252–2025) and was conducted in accordance with the Declaration of Helsinki.

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