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Interactions between chronological age, relative age, and maturation on training load, recovery, and technical– tactical performance in pre-pubertal sub-elite football players

Pedro Afonso[1,2,3,4], Pedro Forte[3,5,6]*, Luís Branquinho[1,7],
Ricardo Ferraz[8,9], Nuno Domingos Garrido[2,9], José Eduardo Teixeira[10,11,12]

ABSTRACT

Chronological age, relative age effects, and biological maturation are key factors influencing training load exposure and performance development in youth football. However, their combined and independent contributions to external and internal load, recovery status, and technical–tactical performance in sub-elite pre-pubertal players remain insufficiently understood. Forty sub-elite pre-pubertal male football players (U11 = 30; U13 = 10) were monitored across four training sessions and one official match. External load was assessed using GPS-derived metrics (total distance, high-speed running [HSR], high-intensity distance, average speed [AvS], maximal running speed [MRS], accelerations, and decelerations). Internal load was quantified via heart rate and session rating of perceived exertion (s-RPE). Recovery status was evaluated using the Total Quality Recovery (TQR) scale. Technical–tactical performance was assessed through decision-making index, motor effectiveness index, and overall performance index. Relative age was classified by birth quartiles, and biological maturation was estimated using maturity offset (Mirwald method; median = -1.42 years). Group comparisons, effect sizes (Cohen's d), and multiple regression analyses were conducted. Chronological age showed a clear influence on locomotor intensity, with U13 players demonstrating higher HSR ($p = .02$, $d = 1.15$), MRS ($p = .03$, $d = .84$), and AvS ($p = .05$, $d = .82$) compared to U11 players. Relative age quartiles revealed negligible differences, except for a higher number of sprints in early-born players ($p = .03$, $d = -.64$). When classified by maturity offset, early pre-peak height velocity (pre-PHV) players performed more accelerations and decelerations ($p < .05$), whereas later pre-PHV players tended to reach higher running intensities. Regression analyses indicated that competition level (U13) was the strongest predictor of HSR ($\beta = .65$, $p < .01$) and MRS ($\beta = .52$, $p = .02$), while relative age and maturity offset showed minor effects ($R^2 = .15–0.33$). Internal load, recovery, and technical–tactical outcomes displayed low explained variance ($R^2 < .10$). Chronological age emerged as the primary determinant of external load in sub-elite pre-pubertal football players, whereas relative age and biological maturation exerted limited independent effects. These findings highlight the dominant role of competition level over maturation-related factors in shaping external load profiles during early developmental stages.

KEYWORDS: youths; training load; maturation; recovery; technical-tactical; performance.

[1]Instituto Politécnico de Portalegre, Biosciences Higher School of Elvas – Portalegre, Portugal.
[2]Universidade de Trás-os-Montes e Alto Douro, Department of Sport, Exercise and Health Sciences – Vila Real, Portugal.
[3]Instituto Politécnico de Bragança, Research Centre for Active Living and Wellbeing (Livewell) – Bragança, Portugal.
[4]Instituto Superior de Ciências Educativas do Douro, Department of Sports – Penafiel, Portugal.
[5]Instituto Superior de Ciências Educativas do Douro, Instituto Superior de Lisboa e Vale do Tejo – Penafiel, Portugal.
[6]Instituto Politécnico de Bragança, Department of Sports Sciences – Bragança, Portugal.
[7]Centro de Investigação Em Qualidade de Vida – Santarém, Portugal.
[8]Universidade da Beira Interior, Department of Sport Sciences – Covilhã, Portugal.
[9]Centro de Investigação em Desporto, Saúde e Desenvolvimento Humano – Vila Real, Portugal.
[10]Instituto Politécnico da Guarda, Department of Sports Sciences – Guarda, Portugal.
[11]Instituto Politécnico do Cávado e Ave, Department of Sports Sciences – Guimarães, Portugal.
[12]Centro de Investigação e Inovação em Desporto Atividade Física e Saúde – Guarda, Portugal.
*Corresponding author: Rua Vitorino da Costa, n. 96 – 4560-708 – Penafiel, Portugal. E-mail: pmvafonso@gmail.com

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INTRODUCTION

Monitoring and understanding the multifactorial nature of performance in youth football is essential for optimising player development while preventing overtraining and early specialisation (Teixeira et al., 2021a). In sub-elite environments, structured training coexists with academic and social commitments (Teixeira et al., 2021b), requiring practitioners to regulate training and recovery through both biological and contextual indicators (Teixeira, Encarnação, Branquinho, Morgans et al., 2024). Training load, recovery status, and technical–tactical behaviour represent interdependent dimensions that reflect readiness, adaptation, and learning progression (Teixeira, Alves et al., 2022; Teixeira, Forte et al., 2022). However, the extent to which these domains are shaped by chronological age and biological maturation remains insufficiently characterised, particularly in pre-pubertal players (Hill et al., 2020).

Youth development follows non-linear physical and physiological trajectories driven by growth, maturation, and accumulated training exposure (Gundersen et al., 2025; Malina, Kozieł, et al., 2021). Although chronological age traditionally underpins competitive categorisation (e.g., U11, U13), it serves only as a proxy for biological maturity. Players of identical age may differ substantially in growth status (Lovell et al., 2015), muscular development (Radnor et al., 2018), and coordination (Fortunato et al., 2024; Rodrigues et al., 2025), with direct implications for physical output and tactical behaviour (Borges et al., 2017; Figueira et al., 2018). Consequently, understanding how age-related variables relate to multidimensional performance markers is fundamental for developmentally appropriate training prescription (Teixeira, Branquinho et al., 2022).

Relative age (athlete's birth date) is another factor contributing to performance disparities (Bozděch et al., 2023). Known as the Relative Age Effect (RAE), this phenomenon reflects the advantages typically conferred to players born earlier in the competitive year, who tend to be older, larger, and more physically mature than their later-born peers (Hill et al., 2020). Although RAE has been well documented in talent identification and selection (Sarmento et al., 2018), its impact on training load, recovery dynamics, and tactical performance remains less explored, especially where players share equivalent exposure and coaching (Teixeira, Alves et al., 2022).

Another important factor is biological maturation, which significantly influences youth athletic development (Albaladejo-Saura et al., 2021). The timing and tempo of maturation vary widely among individuals and correlate with differences in anthropometric characteristics, muscle strength, and movement efficiency (Wilczyński et al., 2022). The Predicted Peak Height Velocity (PHV) method, commonly based, for example, on the Mirwald equation, provides a practical and validated estimate of biological maturity in field settings (Malina, Coelho-e-Silva, et al., 2021). The maturity offset, or Predicted Velocity of Growth (PVC-Mirwald), indicates the temporal distance from an athlete's expected growth spurt (Mirwald et al., 2002). Pre-pubertal athletes with negative PVC values are typically farther from PHV, showing lower muscle mass and power output than those approaching or surpassing it (Wilczyński et al., 2022). However, most studies examining the interaction between chronological age, relative age, and biological maturation have focused on adolescent cohorts, particularly around or after PHV (Badenhorst et al., 2021; Chen et al., 2024; Faude et al., 2026). During adolescence, rapid hormonal changes, accelerated neuromuscular development, and substantial increases in muscle mass amplify inter-individual variability. As a result, associations between maturity status and training load observed in adolescents may not be directly transferable to pre-pubertal players, who present lower anabolic hormonal influence, smaller strength differentials, and more homogeneous growth trajectories (Badenhorst et al., 2021; Cselkó et al., 2021). In pre-PHV stages, adaptations are predominantly mediated by neural coordination and motor learning rather than endocrine-driven mechanisms. This distinction underscores the need for population-specific investigation.

Integrating chronological age, relative age, and maturation within a singular analytical framework is essential to disentangle their overlapping effects on training, recovery, and performance (Teixeira, Alves et al., 2022). Previous studies have often examined these determinants separately, neglecting their interdependence and the moderating role of environmental standardisation (Teixeira, Alves et al., 2022). For instance, while older or more mature players frequently demonstrate superior locomotor performance, these differences may diminish when training exposure and session structure are consistent across groups (Teixeira, Branquinho et al., 2022). Moreover, few investigations have jointly examined these biological indicators alongside perceptual measures such as Rating of Perceived Exertion (RPE) or Total Quality of Recovery (TQR) (Coppus et al., 2022; Selmi et al., 2022; Teixeira, Encarnação, Branquinho, Ferraz, et al., 2024; Teixeira et al., 2025), and tactical cognition metrics like the Football Tactical Assessment System (FUT-SAT) (Costa et al., 2011; Teixeira, Branquinho, Ferraz, Morgans et al., 2024).

From an applied perspective, clarifying how biological and developmental factors relate to external training load (GPS-based metrics), internal training load (HR and RPE), and recovery status can inform more equitable training practices and mitigate early selection biases (Perroni et al., 2024). Additionally, determining whether technical–tactical performance follows a similar developmental trajectory to physical load is critical for understanding how players learn and apply tactical principles relative to their biological stage (Matos et al., 2023). This is particularly relevant in sub-elite contexts, where structured competition occurs amidst high heterogeneity in growth and training experience (Aquino et al., 2017).

Despite recent advances in load monitoring and tactical analysis (Castellano et al., 2017; Coito et al., 2022; Gonçalves et al., 2017), the literature still lacks integrative, multidimensional evidence in pre-pubertal players. Most studies focus on adolescent cohorts or cross-level comparisons (Teixeira, Forte et al., 2022), leaving limited data on how early biological factors shape the interplay between physical, physiological, and tactical domains within a typical training week (Toselli et al., 2021; Toselli et al., 2022). Consequently, little is known about how chronological age, relative age, and maturation collectively influence training demands and recovery responses in this population (Diker et al., 2021). Altogether, to address these gaps, the present study examined the relationships between chronological age, relative age (birth quartile), and biological maturation (PVC-Mirwald) with indicators of external load (GPS-based metrics), internal load (heart rate and perceived exertion), recovery status (TQR), and technical–tactical performance (FUT-SAT) across a standardised microcycle in sub-elite pre-pubertal male football players. Specifically, the aims were to: quantify the associations between age-related variables and multidimensional markers of training and performance; and determine which factor (chronological age, relative age, or maturation) better explains the observed inter-individual variability. It was hypothesised that chronological age would be the strongest predictor of external load, while relative age and biological maturation would exhibit weaker relationships once age is controlled (Radnor et al., 2021).

METHODS

Study design

This study used an observational, cross-sectional, correlational design conducted during a standard competitive microcycle during the 2024/2025 season. The investigation aimed to examine the associations between chronological age, relative age, and biological maturation (PVC-Mirwald) with multidimensional indicators of training load, recovery, and technical–tactical performance in sub-elite pre-pubertal football players. Baseline anthropometric and maturational data (chronological age, sitting height, leg length, body mass, stature, BMI, and PVC-Mirwald) were collected prior to the monitoring period. All assessments were performed under standardised environmental, temporal, and procedural conditions to ensure internal consistency. Detailed methodological procedures for each measure are described in the following subsections.

Before each training session, recovery status was recorded using the Total Quality of Recovery (TQR) scale. During training sessions and the official match, external load (total distance, high-speed running, high-intensity distance, sprints, maximal speed, accelerations, and decelerations) and internal load (heart rate and session-RPE) were continuously monitored. In addition, technical–tactical performance was evaluated using the Football Tactical Assessment System (FUT-SAT), which provides indices of decision-making (DMI), motor effectiveness (MEI), and overall performance. Figure 1 provides a schematic representation of the study design and variables assessed across the microcycle.

Participants

Forty male sub-elite football players aged between 8 and 13 years participated in this study. All players belonged to the same

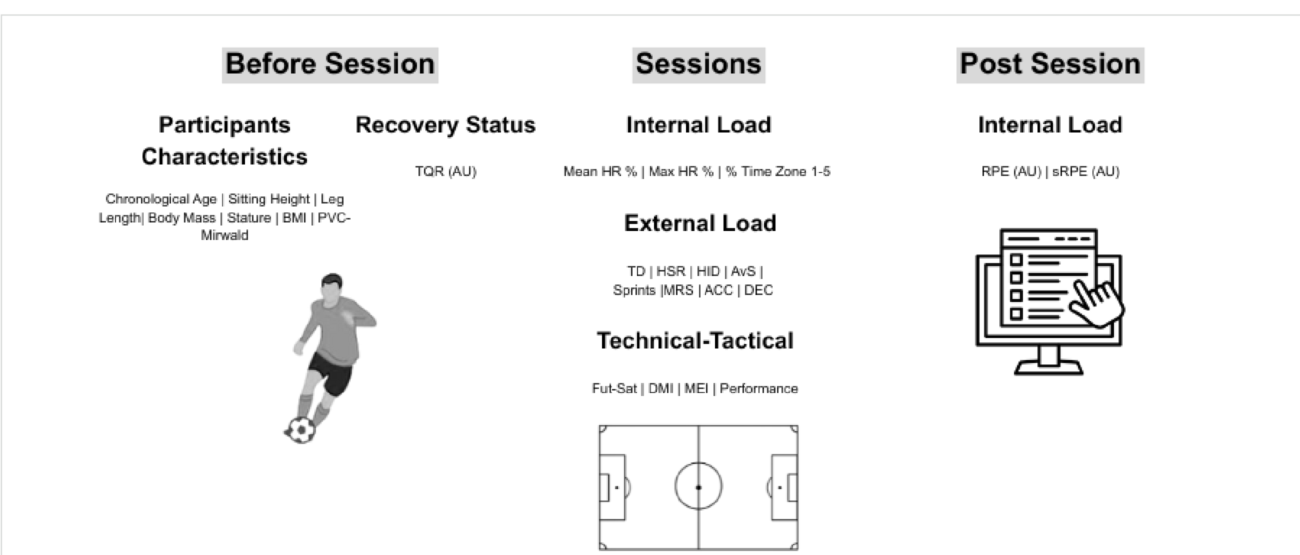

Figure 1. Schematic representation of the study design and variables assessed across the microcycle.

certified sub-elite football club and regularly participated in official training sessions (4 per week) and weekend competitions. Players were grouped according to official competition categories defined by the national football federation (U11-7vs7 and U13 9vs9), which reflect structured age-based competitive levels rather than arbitrary analytical divisions. This categorisation enabled the examination of competition-level effects while preserving ecological validity in real-world developmental settings. Eligibility criteria included: participation in a competitive week including one official match; completion of all four training sessions and the match; and absence of medical conditions or injuries that could interfere with data collection. Exclusion criteria comprised: missing any training session; unavailability for the match; incomplete GPS, HR, RPE, or TQR data; and injury during the observation period.

Players were classified as pre-pubertal according to their predicted peak height velocity (PHV) offset, calculated using the Mirwald equation (Mirwald et al., 2002), confirming negative PVC values (< 0) for all participants. Anthropometric measurements included standing height, sitting height, leg length, body mass, and body mass index (BMI), conducted using a digital scale (Tanita BC-545N®) and a digital stadiometer (SECA® 242) (Reis & Almeida, 2020).

Table 1 presents the descriptive characteristics of the sample (mean ± SD). All procedures complied with the Declaration of Helsinki for research involving human participants and were approved by the Ethical Committee of the Universidade de Trás-os-Montes e Alto Douro (Doc 104-CE-UTAD-2025). Written informed consent was obtained from the players' parents or legal guardians, and all players provided assent prior to participation.

Experimental approach

The monitored microcycle comprised four consecutive training sessions (MD-4, MD-3, MD-2, MD-1) and one official match (MD). All training sessions lasted approximately 90 minutes and were conducted on synthetic turf pitches (100 × 70 m) between 17:00 and 21:00 under similar environmental conditions. Matches lasted approximately 60 minutes and were played on official 7-a-side or 9-a-side pitches, in accordance with federation regulations.

Each training session began with a standardised warm-up including low-intensity running, dynamic stretching of major lower-limb muscle groups, technical drills, and possession-based exercises. This was followed by specific small-sided games and tactical exercises aligned with the weekly training plan defined by the coaching staff. The researchers did not intervene in the training content.

For analytical purposes, all variables were first calculated per session (MD-4 to MD). For each player, weekly mean values were then computed across the five sessions, representing an individual microcycle profile. These averages were used in all correlational and comparative analyses to reflect stable weekly patterns and minimise session-to-session variability. The overall structure of the microcycle is presented in Figure 2.

Table 1. Descriptive characteristics of the participants (mean ± SD).

Variable	U11 (n = 30)	U13 (n = 10)	Total (n = 40)
Chronological age (years)	9.67 ± 0.99	12.10 ± 0.74	10.28 ± 1.41
Height (cm)	140.23 ± 10.23	152.50 ± 5.52	143.30 ± 10.67
Sitting height (cm)	68.67 ± 5.16	71.50 ± 3.69	69.38 ± 4.95
Leg length (cm)	71.57 ± 7.02	81.00 ± 5.29	73.92 ± 7.76
Body mass (kg)	32.80 ± 8.84	39.80 ± 5.18	34.55 ± 8.58
BMI ($kg \cdot m^{-2}$)	16.50 ± 2.80	17.11 ± 2.06	16.65 ± 2.62
PVC-Mirwald (years)	-4.24 ± 0.74	-2.72 ± 0.90	-3.86 ± 1.02

Values are mean ± standard deviation (SD); BMI: Body Mass Index; PVC-Mirwald represents the predicted maturity offset (years from PHV); negative values indicate pre-pubertal status.

Procedures

External training load

External training load was monitored using STATSports Apex® GNSS/GPS tracking devices (18 Hz, Newry, Northern Ireland), which recorded raw position, velocity, and distance data. Each unit included a triaxial accelerometer (100 Hz), magnetometer (10 Hz), and gyroscope (100 Hz). Devices were worn in a custom-made vest pocket between the scapulae and were activated 30 minutes before data collection to ensure optimal satellite reception (≥ 8 satellites) (Jennings et al., 2010).

The external training load variables included: total distance (TD, km), high-speed running distance (HSR, m; > 18 $km \cdot h^{-1}$), high-intensity distance (HID, m; > 21 $km \cdot h^{-1}$), average speed (AvS, $m \cdot min^{-1}$), number of sprints, maximum speed ($m \cdot s^{-1}$), accelerations (ACC; > 2 $m \cdot s^{-2}$), and decelerations (DEC; < -2 $m \cdot s^{-2}$) (Beato et al., 2018; Nikolaidis et al., 2018; Whitehead et al., 2018). The reliability and validity of STATSports systems for youth football are well established, with typical error margins of 1–2% (Nobari, Alves et al., 2021; Teixeira, Branquinho et al., 2022). For each player, session data were averaged to compute weekly mean values across the microcycle. Each player wore the same GPS unit throughout the observation period to minimise inter-unit variability. After each session, raw data were visually inspected to confirm stable signal acquisition and absence of recording errors. Only complete and technically valid recordings were retained for analysis.

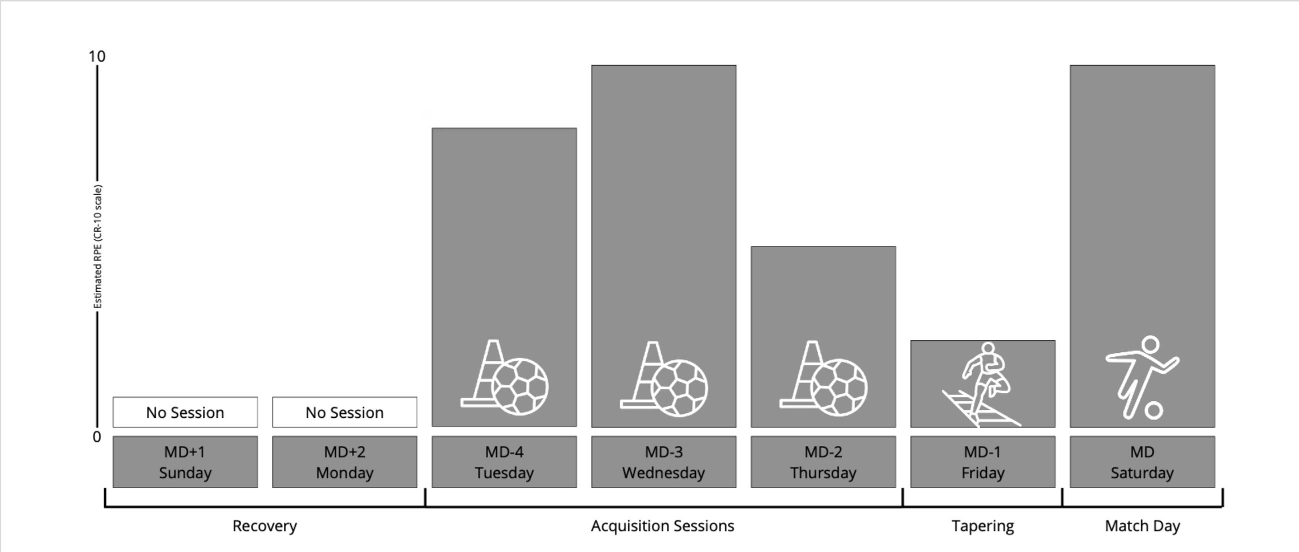

Figure 2. Structure of the competitive microcycle (MD-4 to MD), including training sessions and official match.

Internal training load

Objective internal training load was assessed via heart rate (HR) monitoring using the Polar Team Pro® system (Polar Electro, Kempele, Finland), which continuously recorded HR during training and matches. HR-derived variables included mean HR (%HRmax), maximum HR (%HRmax), and time spent in intensity zones (Z1–Z5, %HRmax). Individual %HRmax was determined from each player's highest HR observed during the week. No HR data were collected for U11; therefore, between-age comparisons were restricted to non-HR variables (Coppus et al., 2022; Costa et al., 2022). It was not implemented in the U11 group due to practical and compliance-related constraints. Specifically, the club's policy limited the use of chest-strap HR monitors in younger players to avoid discomfort and potential distraction during training and matches. Additionally, pilot testing revealed inconsistent adherence and frequent signal loss in this age group, compromising data reliability. Therefore, HR-derived analyses were restricted to the U13 category to ensure data quality and internal validity.

Subjective internal load was assessed using Borg's CR10 RPE scale (0–10 points) (Cabral et al., 2020; Gómez-Díaz et al., 2024; González-García & Romero-Moraleda, 2024). Approximately 30 minutes after each session or match, players were individually questioned using a digital form on an iPad. The scale contained both numerical anchors and emoji-based visual aids to facilitate comprehension in younger athletes. Session perceived exertion (sRPE) was calculated as RPE × session duration (min) and expressed in arbitrary units (AU) (Oliveira et al., 2023; Querido & Clemente, 2020; Teixeira et al., 2023). All players were familiarised with the RPE procedure before data collection. Data were exported and organised in Microsoft Excel® for consistency and quality control.

Recovery status

Recovery status was evaluated using the TQR scale (Kenttä & Hassmén, 1998), adapted to a 0–10-point version to facilitate comprehension in young athletes. 24. On this scale, 0 indicates "very poorly recovered", and 10 indicates "completely recovered" (Teixeira, Branquinho et al., 2022; Teixeira et al., 2021b, 2023). A familiarisation period preceded data collection to ensure response reliability. The TQR was administered individually ~30 minutes before each training session using a digital form (Google Forms) displayed on an iPad. Players verbally reported their recovery status while observing the adapted scale with emojis, and scores were immediately recorded. All data were subsequently exported to Excel® for standardised storage. Weekly mean TQR values were computed per player to assess recovery patterns across the microcycle.

Technical-tactical performance

Technical–tactical performance was assessed using the FUT-SAT system (Costa et al., 2011), which codes the execution of core game principles: offensive (penetration, offensive coverage, mobility, space) and defensive (delay, defensive coverage, balance, concentration) (Matos et al., 2023). Each player was evaluated during small-sided games (GK + 3 vs 3 + GK) played on a 36 × 27 m pitch, lasting 4 minutes per bout. All matches were recorded with a GoPro HERO® 4K camera, and tactical actions were analysed using

LongoMatch® software (Barcelona, Spain) by two experienced analysts trained in the FUT-SAT protocol. Inter-rater reliability was previously established (> 0.85) following standardised coding procedures described in validation studies (Júnior et al., 2020; Teh et al., 2019). To ensure consistency, both analysts followed the operational definitions and coding criteria of the original FUT-SAT framework. For each player, actions were classified by decision-making (appropriate vs inappropriate) and motor execution (effective vs ineffective). The Decision-Making Index (DMI) was defined as the ratio of correct to total decision-making actions, and the Motor Effectiveness Index (MEI) as the ratio of effective to total motor executions. Both range from 0 to 1, with higher values indicating superior performance. An overall performance score (PERF) integrated both dimensions across all principles (Matos et al., 2023).

Chronological age, relative age and maturation

Chronological age was calculated from each player's date of birth relative to the assessment period (March 2025). Relative age was categorised into quartiles (Q1–Q4) based on the annual selection cut-off (January 1): *Q1* = January–March, *Q2* = April–June, *Q3* = July–September, and *Q4* = October–December (Figueiredo et al., 2021).

The biological maturity was estimated using the Mirwald predictive equation (Mirwald et al., 2002), yielding the maturity offset (PVC-Mirwald) expressed in years from the player's predicted Peak Height Velocity (PHV) (Malina, Kozieł, et al., 2021). Negative PVC values indicate pre-PHV status. In this study, all players exhibited negative PVC values, confirming their pre-pubertal status (Monasterio et al., 2024).

To capture intra-stage maturational variability within this homogeneous pre-pubertal cohort, players were subdivided according to the sample-specific median PVC (≈ -1.42 years) into two groups: Early pre-PHV (< -1.42 years) and Late pre-PHV (≥ -1.42 years). This approach aligns with prior recommendations, which emphasised the significance of maturity offset as a key variable in assessing athletic potential and development during early growth phases (Malina, Kozieł, et al., 2021). The differentiation into Early and Late pre-PHV promotes the detection of subtle maturational timing differences, which may contribute to individual variations in locomotor and perceptual performance prior to the onset of puberty (Marinho et al., 2020). One study noted that growth and physical development during these stages significantly affect athletic performance and the risk of injury, reinforcing the need to categorise players based on growth velocity metrics. Furthermore, another study demonstrated differences in strength and agility training responses between maturity groups, indicating that early and late pre-PHV athletes exhibit distinct physiological adaptations (Fernández-Galván et al., 2022). Collectively, using the median PVC as a classification tool facilitates a nuanced understanding of how maturation affects performance outcomes in young athletes, supporting contemporary training paradigms that prioritise individualised approaches based on biological maturation (Fernández-Galván et al., 2022; Malina, Kozieł, et al., 2021).

Statistical analysis

All statistical analyses were performed in Python (version 3.11) using the following open-source libraries: pandas (v2.2.2) for data handling, NumPy (v1.26.4) for numerical computation, SciPy (v1.11.4) for inferential statistics, StatsModels (v0.14.2) for ordinary least squares (OLS) regression modelling, and Matplotlib (v3.8.4) for data visualisation. Descriptive data are presented as mean ± standard deviation (SD). Normality, missingness, and variance homogeneity were verified prior to analysis. Between-group comparisons (Chronological Age, Relative Age, and Maturational Status) were conducted using Welch's independent t-tests, which adjust for unequal variances and sample sizes. To examine the combined effects of Chronological Age, Relative Age (*Q1–Q2* = 0; *Q3–Q4* = 1), and Biological Maturity (PVC-Mirwald, continuous) on outcome variables, standardised multiple linear regressions (OLS) were computed for each dependent variable. All continuous predictors were z-scored, and regression outputs included standardised β coefficients, p-values, and coefficients of determination (R^2). Statistical significance was set at $p < .05$. Effect sizes for between-group comparisons were expressed as Cohen's d, interpreted as small ($d = .2$), moderate ($d = .5$), and large ($d \geq .8$) following conventional thresholds (Cohen, 2013).

RESULTS

Chronological age

Chronological age was positively associated with most external-load variables. U13 players covered greater HSR distances (36.06 ± 23.52 m vs. 13.57 ± 14.63 m, $p = .02$, $d = 1.15$) and achieved higher MRS (6.30 ± .36 vs. 5.98 ± .39 $m \cdot s^{-1}$, $p = .03$, $d = .84$) than U11 peers. They also presented higher AvS (54.08 ± 5.41 vs. 49.93 ± 4.62 $m \cdot min^{-1}$, $p = .05$, $d = .82$), whereas U11 players performed a greater number of ACC (26.48 ± 10.56 vs. 21.52 ± 4.11, $p = .04$, $d = -.62$) and DEC (30.01 ± 13.71 vs. 23.26 ± 5.36, $p = .03$, $d = -.65$). Differences in TD and HID were small and non-significant ($p > .05$).

In terms of internal load, U13 players reported slightly higher RPE (6.02 ± 1.01 AU vs 5.43 ± .98 AU, *p* = .04, *d* = .58), while sRPE values were comparable across groups (*p* = .07). HR–derived data were collected exclusively in U13, revealing mean HR values around 66 ± 2% HRmax, with ~10% of total time spent above 90% HRmax. The TQR was similar between age groups (*TQR* = 7.16 ± .87 vs 7.51 ± .76, *p* = .28, *d* = -.42).

Regarding technical–tactical performance, the DMI was marginally higher in the older players (U13) compared with U11 (Δ = .03, *p* = .48, d = -.24). Similarly, MEI (Δ = .01, *p* = .94, d = -.03) and overall performance (Δ = .00, *p* = .98, *d* = .01) showed trivial and non-significant differences between age categories. Overall, age explained a modest proportion of variance across locomotor outcomes ($R^2 \approx$ .10–.25), consistent with expected developmental gains in physical but not technical–tactical capacities. Table 2 summarises between-group comparisons for external, internal, recovery, and technical–tactical indicators according to chronological age category (U11 vs U13).

Relative age effect

Relative age quartiles showed negligible influence on performance across all domains. External-load indicators such as TD (4.51 ± .49 vs. 4.29 ± .53 km, *p* = .23), HSR (21.56 ± 20.14 vs. 13.68 ± 17.85 m, *p* = .23), and MRS (6.11 ± .40 vs. 5.93 ± .41 $m \cdot s^{-1}$, *p* = .19) did not differ meaningfully between early- and late-born players. Only the number of sprints presented a small but significant advantage for early-born athletes (.50 ± .82 vs. .12 ± .23; *p* = .03; *d* = -.64).

SRPE remained stable across groups (570.64 ± 63.57 vs. 592.00 ± 58.86 AU, *p* = .32), as TQR (*TQR* = 7.46 ± .77 vs. 7.33 ± .85, *p* = .67). Technical–tactical indicators (DMI, MEI, overall performance) also showed trivial, non-significant effects (all *p* > .30; *d* < .35). These results indicate an absence of meaningful RAE in this sample, with R^2 values below .05 for all domains. Table 3 presents the comparison between early-born (Q1–Q2) and late-born (Q3–Q4) players, representing relative age quartiles within the selection year. Analyses examined potential differences in load, recovery, and performance metrics associated with the RAE).

Maturation status

When players were divided by maturity offset (PVC median split), late-maturing individuals tended to demonstrate slightly higher locomotor intensity, although most comparisons did not reach statistical significance. TD was marginally higher in early-pre maturers (4.60 ± .42 vs. 4.29 ± .55 km, *p* = .05, *d* = -.63), whereas HSR and MRS showed small, non-significant advantages for late-pre maturers (23.32 ± 21.47 vs. 15.07 ± 17.07 m; 6.07 ± .45 vs. 6.05 ± .36 $m \cdot s^{-1}$; both *p* > .10). ACC (28.42 ± 9.20 vs. 22.06 ± 9.06, *p* = .03, *d* = -.70) and DEC (32.10 ± 12.92 vs. 24.54 ± 11.03, *p* = .05, *d* = -.63) were significantly higher in early maturers.

SRPE values were slightly higher among early maturers (583.8 ± 69.8 vs. 570.3 ± 54.7 AU, *p* = .50), whereas TQR values tended to be lower in later maturers (7.63 ± .75 vs. 7.21 ± .79, *p* = .09, *d* = -.55). No significant maturational effects were detected in DMI (10.25 ± 3.21 vs. 10.40 ± 2.91, *p* = .88) or MEI (8.45 ± 3.22 vs. 8.85 ± 2.41, *p* = .66), with trivial R^2 values (< .10).

These patterns suggest limited influence of biological maturity on physical or cognitive–technical performance within this age range. The Table 4 reports comparisons between early

Table 2. Between-group comparisons for external, internal, recovery, and technical–tactical indicators according to chronological age category (U11 vs U13).

Variable	U11 Mean ± SD	U13 Mean ± SD	Δ (U13–U11)	t	p-value	d	95%CI
Total Distance (km)	4.55 ± 0.44	4.13 ± 0.59	-0.42	2.06	.06	-0.80	[-1.54– -0.06]
High-Speed Running (m)	13.57 ± 14.63	36.06 ± 23.52	22.49	-2.85	.02*	1.15	[0.39–1.91]
High-Intensity Distance (m)	404.13 ± 128.72	423.70 ± 84.03	19.57	-0.55	.59	0.18	[-0.54–0.90]
Average Speed ($m \cdot min^{-1}$)	49.93 ± 4.62	54.08 ± 5.41	4.15	-2.17	.05*	0.82	[0.08–1.56]
Max Speed ($m \cdot s^{-1}$)	5.98 ± 0.39	6.30 ± 0.36	0.32	-2.36	.03*	0.84	[0.10–1.58]
Accelerations (n)	26.48 ± 10.56	21.52 ± 4.11	-4.96	2.13	.04*	-0.62	[1.35–0.11]
Decelerations (n)	30.01 ± 13.71	23.26 ± 5.36	-6.75	2.23	.03*	-0.65	[1.35–0.11]
Sprints (n)	0.28 ± 0.43	0.70 ± 1.22	0.42	-1.07	.31	0.46	[-0.26–1.18]
sRPE (a.u.)	585.20 ± 66.92	552.60 ± 38.31	-32.60	1.89	.07	-0.60	[-1.33–0.13]
TQR (a.u.)	7.51 ± 0.76	7.16 ± 0.87	-0.35	1.12	.28	-0.42	[-1.14–0.30]
DMI	10.50 ± 3.20	9.80 ± 2.49	-0.70	0.71	.48	-0.24	[-0.96–0.48]
MEI	8.67 ± 3.04 (30)	8.60 ± 2.12 (10)	-0.07	0.08	.94	-0.03	[-0.75–0.69]
Overall Performance	0.66 ± 0.17 (30)	0.66 ± 0.10 (10)	0.00	-0.02	.98	0.01	[-0.71–0.73]

Comparison between U11 and U13 players. Values are mean ± SD; * p < .05 indicates significant difference between age groups.

Table 3. Comparison between early-born (Q1–Q2) and late-born (Q3–Q4) players.

Variable	Q1–Q2 Mean ± SD n = 28	Q3–Q4 Mean ± SD n = 12	Δ (B–A)	t	p-value	d	95%CI
Total Distance (km)	4.51 ± 0.49	4.29 ± 0.53	-0.22	1.23	.23	-0.43	[-1.10–0.24]
High-Speed Running (m)	21.56 ± 20.14	13.68 ± 17.85	-7.87	1.23	.23	-0.41	[-1.08–0.26]
High-Intensity Distance (m)	426.66 ± 114.18	367.87 ± 122.82	-58.80	1.42	.17	-0.50	[-1.18–0.18]
Average Speed ($m \cdot min^{-1}$)	50.39 ± 5.27	52.32 ± 4.58	1.92	-1.16	.26	0.39	[-0.28–1.06]
Max Speed ($m \cdot s^{-1}$)	6.11 ± 0.40	5.93 ± 0.41	-0.19	1.36	.19	-0.47	[-1.15–0.21]
Accelerations (n)	27.03 ± 9.42	21.07 ± 8.92	-5.96	1.90	.07	-0.65	[-1.35–0.05]
Decelerations (n)	29.89 ± 11.93	24.67 ± 13.44	-5.22	1.16	.26	-0.41	[-1.08–0.26]
Sprints (n)	0.50 ± 0.82	0.12 ± 0.23	-0.38	2.27	.03*	-0.64	[-1.34–0.06]
Mean HR (%HRmax)	0.66 ± 0.03	0.67 ± 0.02	0.01	-0.34	.74	0.21	[-1.05–1.47]
Max HR (%HRmax)	0.89 ± 0.02	0.87 ± 0.02	-0.02	1.62	.15	-1.01	[-2.43–0.41]
Zone 1 (% time)	0.33 ± 0.05	0.33 ± 0.04	-0.01	0.20	.85	-0.12	[-1.35–1.11]
Zone 2 (% time)	0.19 ± 0.03	0.20 ± 0.02	0.01	-0.70	.51	0.43	[-0.83–1.69]
Zone 3 (% time)	0.21 ± 0.03	0.20 ± 0.01	-0.01	1.22	.27	-0.72	[-2.06–0.62]
Zone 4 (% time)	0.18 ± 0.04	0.15 ± 0.01	-0.03	1.58	.17	-0.92	[-2.31–0.47]
Zone 5 (% time)	0.08 ± 0.02	0.12 ± 0.05	0.04	-1.46	.22	1.01	[-0.41–2.43]
sRPE (a.u.)	570.64 ± 63.57	592.00 ± 58.86	21.36	-1.03	.32	0.35	[-0.32–1.02]
TQR (a.u.)	7.46 ± 0.77	7.33 ± 0.85	-0.12	0.43	.67	-0.15	[-0.81–0.51]
DMI	10.14 ± 2.80	10.75 ± 3.60	0.61	-0.52	.61	0.19	[-0.48–0.86]
MEI	8.36 ± 2.68	9.33 ± 3.11	0.98	-0.95	.36	0.34	[-0.33–1.01]
Overall Performance	0.65 ± 0.16	0.69 ± 0.13	0.04	-0.85	.40	0.28	[-0.39–0.95]

Values are mean ± SD; *$p < .05$ indicates significant difference between early- and late-born players. HR variables were calculated only for U13 players (Q1–Q2: $n = 6$; Q3–Q4: $n = 4$).

Table 4. Comparisons between early and late pre-PHV groups, based on the sample median PVC-Mirwald value (-1.42 years).

Variable	Early pre-PHV Mean ± SD	Late pre-PHV Mean ± SD	Δ (B–A)	t	p-value	d
Total Distance (km)	4.60 ± 0.42	4.29 ± 0.55	-0.31	2.00	.05	-0.63
High-Speed Running (m)	15.07 ± 17.07	23.32 ± 21.47	8.25	-1.35	.19	0.43
High-Intensity Distance (m)	428.16 ± 117.67	389.89 ± 119.04	-38.27	1.02	.31	-0.32
Average Speed ($m \cdot min^{-1}$)	50.48 ± 4.37	51.46 ± 5.80	0.98	-0.60	.55	0.19
Max Speed ($m \cdot s^{-1}$)	6.05 ± 0.36	6.07 ± 0.45	0.01	-0.11	.91	0.03
Accelerations (n)	28.42 ± 9.20	22.06 ± 9.06	-6.36	2.20	.03*	-0.70
Decelerations (n)	32.10 ± 12.92	24.54 ± 11.03	-7.56	1.99	.05	-0.63
Sprints (n)	0.30 ± 0.50	0.47 ± 0.88	0.17	-0.75	.46	0.24
sRPE (a.u.)	583.80 ± 69.76	570.30 ± 54.66	-13.50	0.68	.50	-0.22
TQR (a.u.)	7.63 ± 0.75	7.21 ± 0.79	-0.42	1.72	.09	-0.55
DMI	10.25 ± 3.21	10.40 ± 2.91	0.15	-0.15	.88	0.05
MEI	8.45 ± 3.22	8.85 ± 2.41	0.40	-0.44	.66	0.14
Overall Performance	0.66 ± 0.17	0.67 ± 0.14	0.01	-0.21	.84	0.07

Values are mean ± SD; * $p < .05$ indicates significant difference between early and late pre-PHV players; PVC: Predicted Velocity of Growth (Mirwald).

and late pre-PHV groups, based on the sample median PVC-Mirwald value (-1.42 years). This stratification captures intra-group maturational variability within a pre-pubertal cohort.

Integrated model

The integrated regression model combining competition level (U13 = 1), relative age (Later = 1), and biological maturity (PVC-Mirwald) explained small-to-moderate proportions of variance across external-load indicators (R^2 = .15–.33). According to conventional thresholds (Cohen, 2013), standardized regression coefficients were interpreted as small (β = .10–.29), moderate (β = .30–.49), and large (β ≥ .50). Model fit strength followed Ferguson (2009) (Ferguson, 2009), where small corresponds to R^2 < .10, moderate to .10–.25, and strong to R^2 > .25. Within this framework, competition level (U13) emerged as a large and significant predictor of both high-speed running (β = .65, *p* < .01) and maximal speed (β = .52, *p* = .02), representing a strong influence on external-load demands. Relative age demonstrated a moderate, negative contribution to high-speed running (β = -.30, *p* = .05), suggesting that later-born players tended to perform slightly less high-intensity running compared with earlier-born peers. Maturity offset (PVC-Mirwald) showed weak and non-significant associations across all external-load outcomes (*p* > .30).

For perceptual and recovery measures (sRPE, and TQR), the explained variance remained small (R^2 < .10), with no significant predictors, indicating that internal responses and perceived recovery were not substantially influenced by age, relative age, or maturity status. Similarly, technical–tactical variables—including DMI, MEI, and overall performance—displayed minimal explained variance (R^2 = .03–.07) and non-significant predictors (*p* > .20).

Collectively, these results indicate that physical performance metrics are primarily driven by competition level (U13 category) and, to a lesser extent, by relative age, whereas biological maturity (PVC-Mirwald) exerts minimal independent influence. This pattern highlights that in pre-pubertal sub-elite players, age-related exposure and competitive context outweigh maturational effects in shaping external-load responses. A graphical representation of significant predictors is provided in Figure 3.

DISCUSSION

The main objective of this study was to explore how chronological age, relative age, and biological maturation interact to shape external and internal training load, recovery, and technical–tactical performance in sub-elite pre-pubertal football players. The central hypothesis—that older and more mature players would demonstrate superior physical outputs without proportional differences in internal or tactical indicators—was partially confirmed.

Overall, the findings reveal a developmental imbalance between physical and cognitive domains: as expected, U13 players displayed greater high-speed running, maximal velocity, and overall mechanical output than U11 players, reflecting the natural progression of neuromuscular coordination, stride efficiency, and force–velocity capabilities during late childhood. However, internal-load, recovery, and technical–tactical measures remained largely unchanged, suggesting that while physical capacity evolves with age and maturation, perceptual and decision-making mechanisms are more resistant to short-term developmental variation.

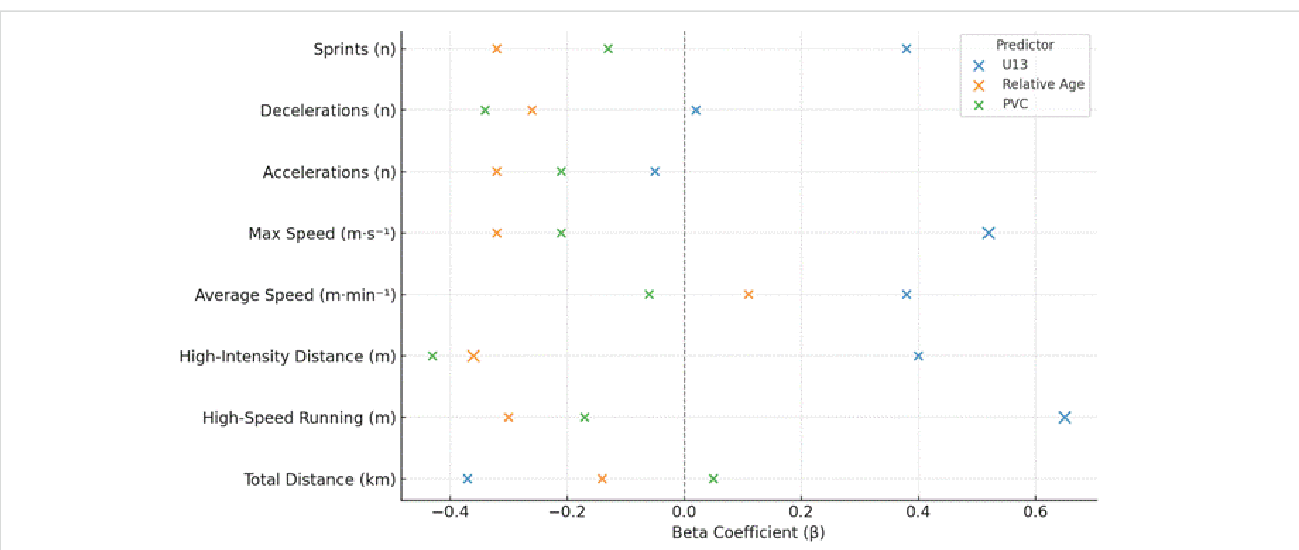

Figure 3. Coefficient plot illustrating the relationships between predictors (U13, Relative Age, and PVC) and match performance variables. Each point represents the standardized beta coefficient (β) from multiple regression models, with larger markers indicating statistically significant associations (*p* < .05). The dashed vertical line at β = 0 denotes the absence of an effect. Positive coefficients indicate a direct relationship between the predictor and the performance outcome, whereas negative coefficients reflect an inverse relationship.

These outcomes are consistent with current evidence indicating that biological growth enhances locomotor efficiency but does not automatically translate into tactical or perceptual advantage (Radnor et al., 2021; Teixeira, Alves et al., 2022). In this regard, the results support a multidimensional interpretation of youth performance, in which physical, physiological, and cognitive adaptations follow distinct yet interacting developmental trajectories.

Importantly, this study also provides practical insight into how age, relative age, and maturity contribute differently to player monitoring. Chronological age primarily affects physical load tolerance; relative age effects appear minimal under equitable training exposure; and maturational status influences external load only marginally before the peak height velocity phase. Collectively, these findings highlight the importance of monitoring growth-related variability within microcycles while maintaining an individualised approach to load and recovery management.

Chronological age

Such improvements are consistent with maturational gains in motor coordination and muscle architecture (Radnor et al., 2021; Toselli et al., 2021), as well as enhanced efficiency of stretch–shortening cycles (Kumar et al., 2024). Despite identical exposure to training and competition, U13 players displayed greater external intensities, suggesting that chronological development independently contributes to load tolerance and mechanical output.

The moderate differences in sRPE and TQR scores may suggest that although older players experience greater mechanical stress, they maintain effective physiological regulation and perceptual control. This is consistent with evidence indicating that older youths display superior interoceptive awareness and recovery pacing strategies (Gonzalo-Skok et al., 2025; Schlégl et al., 2016). The absence of significant differences in technical–tactical indicators reinforces the notion that cognitive and perceptual decision-making skills depend more on accumulated learning and contextual experience than on chronological age per se (Alhamady et al., 2024; Malina, Kozieł, et al., 2021). Together, these findings suggest that chronological age primarily influences physical and perceptual domains, whereas technical–tactical quality remains stable across adjacent age categories when training structures are uniform.

Relative age effect

No meaningful RAE was identified across external, internal, or technical–tactical domains. This result diverges from several large-scale reports demonstrating selection advantages for early-born players in academy settings (Kapoor et al., 2023; Ramachandran et al., 2024), but it aligns with recent studies showing that when training load and opportunity are standardised, RAE becomes negligible (Nasseri et al., 2021). The absence of systematic advantage in locomotor or perceptual metrics suggests that coaching methodology and equal playing exposure successfully mitigate maturational disparities often associated with birth-month distribution.

Additionally, the technical–tactical performance did not differ between quartiles, reinforcing the concept that decision-making and motor execution are not constrained by relative age but rather by the learning environment and task representativeness (Justino et al., 2020; Malina, Kozieł, et al., 2021). In youth sport development systems that prioritise individualised feedback, flexible grouping, and task representativeness, the influence of relative age on performance and participation tends to diminish markedly (Fernández-Galván et al., 2022). Overall, these findings indicate that when coaching design prioritises equitable engagement, RAE-related asymmetries in performance or load may be effectively neutralised.

Maturation status

Although late maturers tended to demonstrate slightly higher HSR and MRS, while early maturers performed more ACC and DEC, these differences were small and mostly non-significant. This pattern is consistent with prior evidence suggesting that maturational status exerts a transient influence on physical performance, modulated by training history and neuromuscular adaptation (Lloyd et al., 2016; Teixeira, Encarnação, Branquinho, Morgans et al., 2024). The lower TQR values observed in later maturers may reflect transient fatigue linked to rapid somatic growth and hormonal changes during the PHV phase (Read et al., 2018; Teixeira, Alves et al., 2022) and are corroborated by findings of reduced athletic performance due to rapid growth in adolescence (Kozieł & Malina, 2017).

The lack of maturational effects on decision-making and motor execution indicates that cognitive–technical development is more experience-driven than biologically determined. Comparable outcomes have been reported in the literature (Finnegan et al., 2024), indicating that tactical behaviour in youth players depends more on exposure to contextual learning than on maturity offset. These results seem to highlight the need to carefully monitor players' developmental timing, ensuring that training loads and recovery protocols are adapted to individual growth trajectories rather than relying solely on chronological groupings.

Integrated model

The integrated model combining chronological age, relative age, and maturity offset revealed that competition level (U13) and biological maturity were the most relevant predictors of external-load performance, while relative age contributed minimally. This reinforces the notion that physical and perceptual readiness are largely shaped by intrinsic developmental processes rather than selection bias. HSR and MRS were primarily explained by the interplay between chronological progression and biological maturity, echoing findings from longitudinal designs showing synergistic gains in both physical and perceptual dimensions (Lolli et al., 2023; Schlégl et al., 2016).

The negligible predictive power of relative age and the weak associations for recovery and technical–tactical metrics emphasise the multidimensional nature of youth performance. These domains are influenced by environmental, cognitive, and pedagogical factors that extend beyond biological maturation (Kumar et al., 2024; Nobari, Silva et al., 2021).

The relatively low explained variance observed for internal load and recovery indicators suggests that these dimensions may be influenced by factors beyond chronological age, relative age, and biological maturation. Internal load responses in pre-pubertal athletes are likely moderated by psychological traits, motivational states, sleep quality, and contextual variables not captured in the present design. Moreover, perceptual recovery measures such as TQR may reflect acute subjective states rather than stable developmental characteristics, which could explain the modest predictive capacity of biological variables.

Collectively, these outcomes underscore the importance of multivariate monitoring frameworks integrating physical, perceptual, and cognitive dimensions to capture the true complexity of player development.

Practical implications

From a practical perspective, although statistically detectable differences in external load were observed between groups, their small-to-moderate magnitude suggests that, in pre-pubertal contexts, chronological age and structured training exposure should remain primary reference points for organising training demands within early developmental stages. Coaches should therefore avoid over-segmenting players based solely on biological maturation or birth quartile at early ages, as such differentiation may not meaningfully alter accumulated training exposure.

Instead, emphasis should be placed on maintaining consistent exposure to training stimuli, progressive workload increases, and structured technical–tactical learning environments. Given the modest associations observed for internal load and recovery indicators, coaches are encouraged to adopt individualised monitoring strategies, integrating objective measures (e.g., GPS-derived metrics) with subjective tools (e.g., RPE and TQR) to capture day-to-day variability.

Importantly, psychophysiological responses in young athletes appear to be influenced by contextual and behavioural factors beyond biological maturity alone, reinforcing the need for flexible, developmentally appropriate planning rather than strict maturity-based load stratification.

Strengths, limitations and future directions

This study's main strength lies in its ecological validity, as data were collected in real competitive contexts, providing an integrated perspective of external load, internal load, recovery status, and technical–tactical performance in sub-elite pre-pubertal football players. The simultaneous consideration of chronological age, relative age, and biological maturation within a standardised microcycle enhances the interpretability of developmental influences on multidimensional performance indicators.

Nevertheless, several limitations should be acknowledged. The cross-sectional design precludes causal inference, and the relatively small sample size, particularly within competitive subgroups, may limit generalizability and statistical power. The use of weekly averaged values may also mask intra-week variability and acute fluctuations in load and recovery responses. Furthermore, biological maturation was estimated using the Mirwald equation, which, although practical and widely adopted in field-based research, may present reduced predictive accuracy in younger, pre-pubertal populations. Anthropometric prediction models can compress inter-individual variability and potentially overestimate or underestimate maturity timing in early and late maturers. Consequently, the associations observed between maturity offset and performance-related variables may be partially attenuated. Future research should prioritise longitudinal designs, multi-cohort samples, and alternative maturity assessments (e.g., skeletal age or longitudinal growth tracking), alongside integrative analytical approaches to better capture developmental dynamics and support individualised long-term athlete development.

CONCLUSIONS

This study highlighted that chronological age was the main determinant of physical load in pre-pubertal sub-elite youth football, while relative age and biological maturity had limited influence once chronological age was considered. Older players demonstrated higher locomotor performance, particularly in high-speed running and maximal velocity, which was consistent with expected neuromuscular progressions during late childhood. In contrast, internal load, recovery, and technical and tactical indicators were largely unaffected by biological or chronological factors, suggesting that perceptual and cognitive performance depended more on training structure and environmental context. The absence of a relative age effect reinforced the importance of equitable training environments that reduced developmental disparities.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT:

Pedro Afonso — Conceptualization; Methodology; Software; Data curation; Investigation; Visualization; Writing – original draft.

Pedro Forte — Conceptualization; Methodology; Resources; Funding acquisition; Project administration; Writing – review & editing.

Luís Branquinho — Methodology; Validation; Formal analysis; Writing – review & editing.

Ricardo Ferraz — Data curation; Formal analysis; Validation; Writing – review & editing.

Nuno Domingos Garrido — Supervision; Project administration; Resources; Writing – review & editing.

José Eduardo Teixeira — Conceptualization; Methodology; Formal analysis; Validation; Supervision; Writing – review & editing.

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