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OPTIMIZING TRAINING LOAD MONITORING IN YOUTH FOOTBALL: A FOCUS ON U17 AND U19 SUB-ELITE ATHLETES

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ABSTRACT

This study investigates TL variations in under-17 (U17) and under-19 (U19) sub-elite football players, focusing on the integration of external and internal load measures. Using global positioning systems (GPS) and Rate of Perceived Exertion (RPE), the study captured data across 24 training sessions during a six-week preseason. GPS metrics, including total distance, high-speed running, and sprint distance, quantified physical demands, while RPE assessed subjective effort. The study enrolled 26 players (13 - U17, 13 - U19), comparing TL patterns between age groups and across training days. Results revealed minimal differences in external load between U17 and U19 players, with U19 players showing slightly higher high-speed running and sprint metrics. RPE values were consistent across groups, supporting its reliability in capturing perceived effort. Regression analysis highlighted significant associations between RPE and external load variables, such as average speed and maximum running speed, emphasizing the interplay between objective and subjective measures. A heatmap analysis further demonstrated correlations among TL variables, underscoring the dynamic relationship between physical demands and effort perception. This study fills a gap in TL research for sub-elite youth football, offering insights into optimizing training programs tailored to developmental needs. The findings support the use of combined GPS and RPE metrics for comprehensive TL monitoring, providing a framework for balancing training demands with player well-being.

Key words: Training load monitoring. Sub-Elite. Youth football. Rate of perceived exertion.

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RESUMO

Otimizando o monitoramento da carga de treinamento no futebol juvenil: foco em atletas sub-elite sub-17 e sub-19

Este estudo investigou as variações de CT em jogadores sub-17 (U17) e sub-19 (U19) de futebol sub-elite, com foco na integração de medidas de carga externa e interna. Com recurso a sistemas de posicionamento global (GPS) e a Percepção Subjetiva de Esforço (PSE), o estudo recolheu dados de 24 sessões de treino ao longo de seis semanas de pré-temporada. As métricas de GPS, como distância total, corrida em alta velocidade e distância percorrida em sprints, quantificaram as demandas físicas, enquanto a PSE avaliou o esforço subjetivo. Participaram no estudo 26 jogadores (13 U17, 13 U19), tendo sido comparados os padrões de CT entre as categorias etárias e ao longo dos dias de treinamento. Os resultados revelaram diferenças mínimas na carga externa entre os jogadores U17 e U19, com os jogadores U19 a apresentarem métricas ligeiramente superiores de corrida em alta velocidade e sprints. Os valores da PSE foram consistentes entre os grupos, confirmando sua confiabilidade na avaliação do esforço percebido. A análise de regressão destacou associações significativas entre a PSE e as variáveis de carga externa, como velocidade média e máxima, enfatizando a interação entre medidas objetivas e subjetivas. A análise realizada com recurso a um heat map demonstrou ainda as correlações entre as variáveis de CT, enfatizando a relação dinâmica entre as solicitações físicas e a percepção de esforço. Os achados sustentam o uso combinado de métricas de GPS e PSE para um monitoramento abrangente de CT, fornecendo uma estrutura para equilibrar solicitações de treino e bem-estar dos jogadores.

Palavras-chave: Monitorização da carga de treino. Sub-elite. Futebol juvenil. Percepção subjetiva de esforço.

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INTRODUCTION

Training load (TL) management is a fundamental aspect of modern football, critical for optimizing performance, reducing injury risk, and enhancing recovery (Clemente et al., 2017; Teixeira et al., 2021).

In youth football, where players undergo pivotal physiological and psychological development stages, monitoring and managing TL is even more crucial to ensure long-term athletic success. TL encompasses two primary dimensions: external load, which measures the physical work performed during training or competition, and internal load, which reflects the physiological and psychological responses to that work (Vanrenterghem et al., 2017).

Achieving the right balance between these dimensions is essential for maximizing performance while avoiding overtraining or burnout in youth athletes (Dudley et al., 2023; Greenberg et al., 2022; Johnson et al., 2024).

Various methods have been developed to monitor TL, ranging from sophisticated technologies to simple subjective tools. External load is often quantified using global positioning systems (GPS), which provide detailed metrics such as total distance covered, high-speed running distance, sprint efforts, accelerations, and decelerations.

These data offer a granular view of the physical demands placed on players and are widely used in professional and elite football environments (Johnson et al., 2024; Kutson et al., 2024; Szigeti et al., 2022).

Conversely, internal load is commonly assessed using subjective measures like the Rate of Perceived Exertion (RPE), which captures an athlete's perceived effort during a training session or match. Despite its simplicity, RPE has been extensively validated as a reliable tool for TL assessment, correlating strongly with objective physiological markers such as heart rate and blood lactate concentrations (Scantlebury et al., 2018).

In recent years, there has been a growing interest in combining objective and subjective measures to gain a holistic understanding of TL in football.

The integration of GPS and RPE enables coaches and sports scientists to assess the physical demands of training and how players perceive and respond to those demands. This is particularly relevant in youth football, where individual variability in physical maturity, technical skills, and psychological resilience can significantly influence TL responses (Bjørndal et al., 2021; Greenberg et al., 2022; Johnson et al., 2024).

Monitoring TL using these combined methods provides valuable insights into how training programs can be tailored to individual needs, ensuring that young athletes are neither underloaded nor overloaded (Dudley et al., 2023; Johnson et al., 2024).

Youth football players, especially at sub-elite levels, represent a unique population for TL research. Players at these levels, such as under-17 (U17) and under-19 (U19) age groups, are in critical phases of development that require careful workload management. U17 players often undergo rapid physical and technical growth, while U19 players typically experience a transition toward more advanced competition and higher physical demands (Teixeira et al., 2024).

Understanding how TL varies between these age groups is essential for designing effective training programs that align with their developmental needs. Additionally, variations in TL across training sessions provide valuable information on how to periodize and balance workloads, ensuring adequate recovery and peak performance during the season's key moments (Bjørndal et al., 2021).

Despite the increasing use of TL monitoring in professional football, limited research focuses on sub-elite youth athletes, particularly concerning the integration of GPS and RPE metrics.

Most existing studies have centered on elite-level players, leaving a gap in understanding how these tools can be applied effectively in sub-elite contexts (Bjørndal et al., 2021; Kutson et al., 2024).

Furthermore, there is a lack of evidence on how TL varies across age groups and training days in youth football, which is critical for optimizing training programs and preventing injuries in this population (Bjørndal et al., 2021; Sampaio et al., 2023).

The importance of TL management in youth football is underscored by the potential consequences of improper load management. Excessive training loads can lead to overuse injuries, fatigue, and burnout, which are particularly concerning in young athletes whose bodies are still developing (Greenberg et al., 2022; Hartwig et al., 2019; Strosser, 2023).

Conversely, insufficient training loads may hinder athletic development and performance improvements. Therefore, a nuanced understanding of TL is essential for coaches and practitioners working with youth football players (Dudley et al., 2023; Greenberg et al., 2022; Johnson et al., 2024).

In addition to physical considerations, psychological factors play a significant role in TL management. Youth athletes often face pressure to perform, which can exacerbate the effects of training loads on their mental health.

Coaches and sports scientists must be aware of these psychological stressors and incorporate strategies to mitigate them, such as promoting a positive training environment and encouraging open communication about workload perceptions (Hartwig et al., 2019; Strosser, 2023).

This holistic approach to TL management not only optimizes physical performance but also supports the mental well-being of young athletes (Campos et al., 2022; Greenberg et al., 2022; Thompson et al., 2022).

Moreover, the integration of technology in TL monitoring has opened new avenues for data collection and analysis. Wearable devices and mobile applications can track various metrics, providing real-time feedback to coaches and athletes.

This data-driven approach allows for more precise adjustments to training loads based on individual responses, ultimately leading to improved performance outcomes (Branquinho et al., 2021; França et al., 2024).

However, the reliance on technology must be balanced with the subjective experiences of athletes, as their perceptions of training loads can significantly influence recovery and performance (Branquinho et al., 2021, França, et al., 2024; Teixeira et al., 2021).

As youth football continues to evolve, the emphasis on TL management will likely increase. Coaches and sports scientists must stay informed about the latest research and methodologies to ensure that training programs are evidence-based and tailored to the unique needs of young athletes.

Collaborative efforts among coaches, sports scientists, and medical professionals are essential to create a comprehensive framework for TL management that prioritizes both performance and athlete health (Branquinho et al., 2021; França, et al., 2024; Morgans et al., 2023).

By understanding the complexities of TL, including the interplay between external and internal loads, coaches and practitioners can optimize training programs that foster athletic development while minimizing the risk of injury (Campos et al., 2022; Greenberg et al., 2022; Thompson et al., 2022).

This study addresses these gaps by investigating TL in U17 and U19 sub-elite football players using GPS-derived metrics and RPE. Specifically, the study aims to explore patterns of TL variation across training days, evaluate the relationship between external and internal TL measures, and identify potential differences in TL between the two age groups.

It is hypothesized that U19 players will exhibit higher external TL metrics, reflecting greater physical maturity and training demands, while RPE will provide consistent insights across both age groups.

By providing a comprehensive analysis of TL in sub-elite youth football players, this study aims to inform evidence-based practices for TL monitoring and contribute to developing more effective training strategies tailored to the unique needs of young athletes.

MATERIALS AND METHODS

Participants

The study included 26 male sub-elite youth football players divided into two age groups: under-17 (U17) (n = 13) and under-19 (U19) (n = 13). All players were members of the same football academy, regularly engaged in structured training programs, and competed in regional and national tournaments. Participants were selected based on availability and consistent participation in the training sessions during the study period. Players with injuries or who missed more than two training sessions were excluded.

The research was approved by the Research Group in Sports and Physical Exercise (NIDEF) of the Higher Institute of Educational Sciences of the Douro (ISCE Douro), under opinion number 10.2021, in accordance with the ethical guidelines established by the Declaration of Helsinki for studies involving human subjects. The table 1

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presents descriptive statistics for age and body composition, showing similar anthropometric profiles between the two groups.

Table 1 - Descriptive statistics for the age and body composition per age group.

Variables	U18 (n=13)	U19 (n=13)
Age (y)	17.22 ± 0.42	18.46 ± 0.50
Height (cm)	170.07 ± 34.70	1.77 ± 0.52
Weight (cm)	67.20 ± 3.84	68.77 ± 6.24
BMI (Kg/m^2)	21.46 ± 1.11	21.92 ± 1.31

BMI - Body mass index.

Study Design

This observational study was conducted over a six-week preseason training period. Training sessions were monitored using both global positioning system (GPS) metrics and the Rate of Perceived Exertion (RPE) to capture external and internal training loads, respectively.

GPS devices recorded objective physical performance metrics during training, while RPE was collected immediately post-session to assess subjective effort.

Training sessions included a variety of technical, tactical, and physical exercises typical of football preparation, with a total of 24 sessions analyzed. The data collection aimed to capture variations in training load across different days and between age groups.

Data Collection and Variables

Data on external load were gathered using GPS units (STATSports Apex®, Newry, Northern Ireland). These devices recorded raw data on position, velocity, and distance at a sampling frequency of 10 Hz, along with accelerometer (100 Hz), magnetometer (10 Hz), and gyroscope (100 Hz) measurements.

Each athlete wore the GPS unit in a small pocket of a custom-designed vest provided by the manufacturer, positioned on the upper back between the shoulder blades. To ensure adequate satellite signal reception, all devices were activated 30 minutes prior to data collection.

For optimal accuracy in monitoring human movement, the dataset included only instances where at least eight satellite signals were available.

The following variables were extracted for analysis: Total distance (TD); High-speed running (HSR) ; Average speed (AvS); Maximum running speed (MRS); High-intensity distance (HSD); Number of sprints (SPR_N); Sprint distance (SPR_D); Accelerations (ACC); Decelerations (DEC); Calories (Cal); High-speed running per minute (HSR/min); High-intensity distance per minute (HID/min); Sprint distance per minute (SPR_D/min); Dynamic stress load (DSL); Rate of perceived exertion (RPE).

Internal Training Load (RPE)

Internal load was assessed using the Modified Borg CR-10 scale, where players rated their perceived effort for the session on a scale from 0 (no effort) to 10 (maximal effort). RPE values were collected individually within 10 minutes after each session to minimize recall bias.

The Modified Borg CR-10 scale is widely utilized for assessing perceived exertion, allowing athletes to rate their effort on a scale from 0 (no effort) to 10 (maximal effort) (Clemente et al., 2020; Haddad et al., 2017).

This method is particularly effective in minimizing recall bias, as ratings are collected shortly after training sessions, typically within 30 minutes (Teixeira et al., 2022, 2024).

The reliability and validity of the session-RPE (s-RPE) method have been established across various sports, demonstrating its utility in reflecting both physical and psychological stress experienced by athletes (Haddad et al., 2017; Halson, 2014; Impellizzeri et al., 2022).

Research indicates that the perception of effort can be influenced by various factors, including an athlete's psychological state, training history, and even the presence of competitors (Haddad et al., 2017; Impellizzeri et al., 2022).

For instance, athletes may report different RPE values for similar physiological stimuli based on their mental fatigue or stress levels, which can skew the interpretation of training loads (Halson, 2014).

Furthermore, studies have shown that the timing of RPE assessments is crucial; collecting data immediately after training sessions helps ensure that athletes' perceptions are fresh and less affected by subsequent activities or fatigue (Angel Campos-Vazquez et al., 2015; Garcia-Calvo et al., 2019).

The Modified Borg scale's application extends beyond mere effort assessment; it serves as a valuable tool for understanding the relationship between training loads and athletes' well-being (Ferreira et al., 2021; Hartwig et al., 2019).

This relationship underscores the necessity of integrating perceived exertion data with other physiological markers to create a comprehensive athlete monitoring system (Szigeti et al., 2022).

Statistical Analysis

Descriptive statistics (mean ± standard deviation) were calculated for all variables. Differences in GPS and RPE metrics between age groups (U17 and U19) and across training days were assessed using mixed-model analysis of variance (ANOVA).

The significance of interactions between age group and training days was evaluated to determine how these factors influenced training load. Post hoc pairwise comparisons were performed where significant interactions were detected. Additionally, linear regression analysis was conducted to evaluate the relationship between GPS metrics and RPE, focusing on the strength and significance of the associations.

A correlation matrix was generated to identify significant relationships between external and internal load variables, with heatmaps used to visualize the results. All statistical analyses were performed using IBM SPSS Statistics for Windows (Version 27.0., IBM Corp, Armonk, NY, USA), and significance was set at $p<0.05$ (Hopkins et al., 2009).

Assumptions of normality and homogeneity of variance were verified before analysis. Data visualizations, including line graphs and heatmaps, were created using Matplotlib and Seaborn libraries in Python (Haslwanter, 2016).

RESULTS

The tables provide a detailed summary of the physical characteristics, external training load, and internal training load of U18 and U19 sub-elite football players.

Table 2 highlights GPS-derived training load metrics and RPE values by age group, offering insights into differences in physical demands and perceived effort. Table 3 examines variations in training load metrics and RPE across six training days, illustrating the dynamic nature of workload distribution.

Together, these tables provide a comprehensive overview of the players' physical characteristics and training load patterns, aiding in understanding how age and session variability influence performance and effort perception.

Table 2 - Mean values for GPS measures and RPE by age group.

Variables	U18 (n=13)	U19 (n=13)
TD (m)	3.95 ± 3.21	3.51 ± 2.73
HSR	187.61 ± 244.83	134.24 ± 163.42
AvS (m·min^{-1})	45.25 ± 33.40	48.49 ± 29.84
MRS (m·s^{-1})	23.61 ± 16.59	22.03 ± 11.06
HSD (m)	604.24 ± 622.95	510.94 ± 442.36
SPR_N (n)	7.34 ± 9.69	6.13 ± 7.42
SPR_D (m)	143.11 ± 195.55	94.45 ± 130.99
ACC (n)	28.33 ± 22.59	30.12 ± 22.26
DEC (n)	29.53 ± 25.90	29.27 ± 25.20
Cal (kc)	513.05 ± 440.71	460.91 ± 362.68
HSR/min (n)	2.13 ± 2.60	2.21 ± 2.89
HID/min (n)	7.07 ± 6.53	7.58 ± 5.74
SPR_D/min (n)	1.61 ± 2.07	1.59 ± 2.27
DSL (au)	226.93 ± 251.28	178.76 ± 152.82
RPE (au)	5.20 ± 2.93	4.89 ± 2.93

Table 3 - Mean values for GPS measures and RPE by training day.

Variables	T1	T2	T3	T4	T5	T6
TD (m)	4.53 ± 4.17	3.23 ± 0.92	3.21 ± 2.57	4.16 ± 1.67	2.19 ± 1.81	5.07 ± 4.20
HSR	233.65 ± 8.67	197.74 ± 160.47	166.13 ± 132.18	58.73 ±72.85	299.08 ± 319.40	50.27 ± 40.04
AvS (m·min−1)	41.58 ± 36.96	43.23 ± 14.40	57.65 ± 30.74	62.92 ± 25.68	29.96 ± 23.30	21.34 ± 14.85
MRS (m·s−1)	19.46 ± 14.29	21.47 ± 2.34	23.76 ± 13.46	24.72 ± 9.90	26.27 ± 21.73	860.39 ± 807.73
HSD (m)	739.73 ± 692.60	321.08 ± 152.78	552.56 ± 438.63	620.96 ± 284.83	252.08 ± 262.32	860.39 ± 807.73
SPR_N (n)	9.5 ± 9.6	0.39 ± 0.70	8.77 ± 7.53	6.83 ± 5.9	2.85 ± 3.50	12.04 ± 12.68
SPR_D (m)	168.85 ± 184.77	2.50 ± 4.89	148.09 ± 126.85	119.42 ± 111.15	40.20 ± 56.30	230.85 ± 259.50
ACC (n)	30.81 ± 27.65	37.35 ± 15.56	24.35 ± 20.49	32.58 ± 19.02	17.76 ± 16.77	32.42 ± 27.64
DEC (n)	34.31 ± 32.16	31.50 ± 20.32	24.62 ± 22.00	32.54 ± 19.94	15.20 ± 14.13	37.92 ± 33.35
Cal (kc)	590.19 ± 541.59	425.35 ± 134.82	413.42 ± 349.82	521.83 ± 240.07	277.40 ± 245.40	685.31 ± 576.93
HSR/min (n)	2.08 ± 2.04	0.04 ± 0.20	4.69 ± 3.72	2.46 ± 1.91	0.76 ± 0.97	2.96 ± 3.07
HID/min (n)	6.92 ± 6.10	4.23 ± 2.32	11.19 ± 6.63	9.33 ± 4.28	3.28 ± 3.40	9.00 ± 8.04
SPR_D/min (n)	1.54 ± 1.61	-	3.58 ± 2.70	1.68 ± 1.61	0.58 ± 0.76	2.21 ± 2.47
DSL (au)	256.53 ± 288.33	176.58 ± 89.95	165.39 ± 144.74	215.58 ± 115.16	108.19 ± 107.81	293.92 ± 325.05
RPE (au)	4.62 ± 3.76	6.39 ± 1.36	4.46 ± 2.99	5.83 ± 2.43	3.85 ± 1.85	5.15 ± 3.75

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Table 4 showed the integration effect between age group, training day and both in GPS measures and RPE. Significant differences with minimum to strong effect were found in training day for TD ($F = 3.78$; $p = 0.003$; $\eta p2 = 0.11$), HSR ($F = 9.79$; $p <0.001$; $\eta p2 = 0.23$), AvS ($F = 5.14$; $p <0.001$; $\eta p2 = 0.14$), HSD ($F = 6.16$; $p <0.001$; $\eta p2 = 0.16$), SPR_N ($F = 8.79$; $p <0.001$; $\eta p2 = 0.22$), ACC ($F = 3.03$; $p =0.013$; $\eta p2 = 0.08$), DEC ($F = 3.05$; $p =0.012$; $\eta p2 = 0.01$), Cal ($F = 4.03$; $p = 0.002$; $\eta p2 = 0.11$), HID_min ($F = 9.01$; $p <0.001$; $\eta p2 = 0.22$), DSL ($F = 3.04$; $p = 0.012$; $\eta p2 = 0.01$), and RPE ($F = 2.84$; $p = 0.018$; $\eta p2 = 0.01$). Interaction between age group and training day were found for all ($F = 0.49$ to 4.60; $p = 0.001$ to $p = 0,003$; $\eta p2 = 0.07$ to 0.13), except MRS and RPE.

Table 4 - Interaction effect between age group, training day and both in GPS measures and RPE.

Variables	Age Group			Training Day			Age Group x Training day		
	F	p	ηp^2	F	p	ηp^2	F	p	ηp^2
TD (m)	1.09	0.297	0.006	3.78	0.003	0.106	3.14	0.010	0.088
HSR	3.78	0.054	0.018	9.79	<0.001	0.232	3.25	0.008	0.077
AvS (m·min−1)	0.33	0.565	0.002	5.14	<0.001	0.138	3.64	0.004	0.098
MRS (m·s−1)	0.58	0.448	0.004	0.85	0.519	0.028	0.49	0.781	0.017
HSD (m)	1.55	0.216	0.008	6.16	<0.001	0.163	2.94	0.015	0.078
SPR_N (n)	1.17	0.281	0.006	8.79	<0.001	0.219	2.74	0.022	0.068
SPR_D (m)	-	-	-	-	-	-	-	-	-
ACC (n)	0.42	0.519	0.002	3.03	0.013	0.084	4.60	<0.001	0.128
DEC (n)	0.61	0.974	0.060	3.05	0.012	0.088	3.22	0.009	0.093
Cal (kc)	0.62	0.413	0.003	4.03	0.002	0.112	3.71	0.003	0.103
HSR/min (n)	-	-	-	-	-	-	-	-	-
HID/min (n)	0.34	0.559	0.002	9.01	<0.001	0.219	3.930	0.002	0.095
SPR_D/min (n)	-	-	-	-	-	-	-	-	-
DSL (au)	2.40	0.124	0.014	3.04	0.012	0.088	2.62	0.027	0.076
RPE (au)	0.59	0.445	0.004	2.84	0.018	0.088	0.95	0.451	0.029

The heatmap (Figure 1) analysis was conducted to visualize the relationships among key variables significantly associated with the Rate of Perceived Exertion (RPE), including average speed (AvS), maximum running speed (MRS), high-intensity distance (HSD), and accelerations (ACC). The correlation coefficients highlight the strength and direction of these associations, providing insights into how these variables interact. Positive correlations were observed between RPE and metrics like AvS and MRS, while a negative relationship was evident with HSD.

These findings reinforce the regression analysis results, demonstrating the interplay between intensity-related measures and subjective perceptions of effort. The heatmap offers a comprehensive overview of the data, emphasizing statistically significant patterns relevant to athletic performance evaluation.

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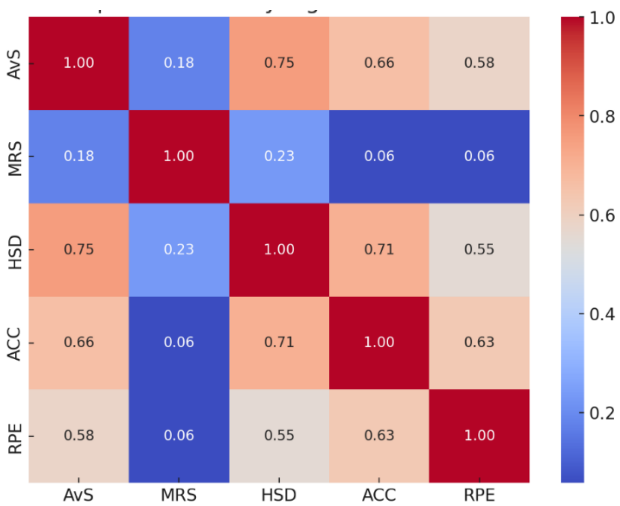

Figure 1 - Relationships among key variables significantly associated with the rate of perceived exertion.

The linear regression analysis demonstrated a significant model for predicting the rate of perceived exertion (RPE) based on GPS-derived measures, with an adjusted coefficient of determination (R^2 adjusted) of 0.719, indicating that the model explains 71.9% of the variance in RPE. The model showed a root mean square error (RMSE) of 1.552, and the F-test confirmed its statistical significance (F = 28.727; p<0.001).

The regression equation for the model is:

$$RPE=0.855+0.044 \cdot AvS+0.035 \cdot MRS-0.003 \cdot HSD+0.044 \cdot ACC+\varepsilon$$

The analysis revealed that average and maximum running speeds were positively associated with RPE, indicating that higher speeds contribute to greater perceived exertion. Similarly, the number of accelerations had a significant positive effect on RPE.

Conversely, high-intensity distance was negatively associated with RPE, suggesting that larger volumes of high-intensity activity were linked to lower subjective exertion ratings. Other variables, such as total distance, sprints, and decelerations, did not significantly predict RPE.

DISCUSSION

The primary aim of this study was to analyze training load (TL) in sub-elite youth football players (U17 and U19), using GPS-derived external metrics and RPE to assess internal load. It was hypothesized that U19 players would exhibit higher external TL metrics due to advanced physical maturity, while RPE would provide consistent internal load measures across age groups.

The principal results partially supported this hypothesis: U19 players demonstrated comparable external load metrics to U17 players for most variables, with minor differences in high-speed running and sprint-related metrics.

RPE values were also similar across groups, highlighting its reliability in capturing subjective effort. Furthermore, regression analysis revealed significant relationships between RPE and variables such as average speed, maximum running speed, and accelerations, emphasizing the interplay between internal and external TL metrics.

The methods employed in this study, including GPS and RPE, have demonstrated validity in previous research, providing a robust framework for assessing training load (TL).

GPS technology is widely regarded as an objective and reliable tool for measuring external load, while RPE has been validated as a cost-effective method for capturing internal load, correlating well with physiological markers such as heart rate and blood lactate (Rossi et al., 2019; Weston, 2018).

The integration of these tools in a sub-elite youth football context offers a balanced approach to understanding TL, as it allows for a comprehensive assessment of both external and internal demands placed on young athletes (Rossi et al., 2019).

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However, caution must be exercised when generalizing these results, as differences in competition level, training intensity, and age-related development may limit the applicability to other populations (Morgans et al., 2023).

When comparing the results to the existing literature, findings regarding external training load metrics align with studies that report similar TL distributions across youth football age groups.

Previous research has shown that U19 players often exhibit higher physical demands due to advanced tactical roles and physical development; however, these differences are not always statistically significant, particularly in sub-elite populations (Martín-López et al., 2021; Rumpf et al., 2014).

The observed RPE values also corroborate findings suggesting that RPE is a reliable and consistent measure of internal load, even when external metrics vary (Aloui et al., 2021; Sausaman et al., 2019).

However, the lack of pronounced differences between age groups in this study contrasts with some literature on elite-level players, which may reflect differences in training environments and athlete maturity levels (Hartwig et al., 2019; Morgans et al., 2024; Teixeira et al., 2022).

The regression analysis revealed significant associations between RPE and key external load metrics, such as average speed, maximum running speed, and accelerations, which are supported by the literature. Previous studies have established strong correlations between subjective effort (RPE) and objective metrics, particularly those reflecting intensity (Aloui et al., 2021; Askow et al., 2021).

The negative association between high-intensity distance and RPE observed in this study could reflect psychological mechanisms, such as adaptation to higher-intensity efforts or variations in perceived exertion thresholds, which align with theories in sports psychology (Ferraz et al., 2018; Teixeira et al., 2024).

Understanding these relationships is crucial for optimizing training loads and enhancing performance in athletes, as it highlights the importance of both physiological and psychological factors in exertion perception.

This study has several limitations and strengths. Limitations include the small sample size, which may limit the generalizability of findings, and the lack of physiological markers to complement RPE, which could provide a more comprehensive understanding of internal load.

Additionally, factors such as individual maturity levels and specific tactical roles were not fully accounted for, which might influence TL metrics. Despite these limitations, the study's strengths lie in its use of validated methods, the longitudinal nature of the data collection, and the focus on a relatively understudied population sub-elite youth football players.

These findings contribute to the growing body of knowledge on TL monitoring in youth athletes and offer practical insights for coaches aiming to optimize training programs tailored to developmental needs.

CONCLUSION

This study examined training load in sub-elite U17 and U19 football players using GPS metrics and RPE, revealing minimal differences in external load between age groups and consistent RPE values across sessions. Regression analysis identified significant associations between RPE and key external metrics, emphasizing its validity as an internal load measure.

These findings highlight the utility of combining objective and subjective methods to monitor training load in youth athletes, providing insights to optimize training programs.

Future research should explore larger samples and include physiological markers to enhance understanding of training load dynamics.

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