UNIVERSIDAD DE ALMERÍA

ANALYSIS OF PHYSICAL PERFORMANCE IN PROFESSIONAL SOCCER PLAYERS

AN APPROACH BASED ON LOAD MONITORING THROUGH ELECTRONIC PERFORMANCE AND TRACKING SYSTEMS

International Doctoral Thesis

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El Dr. José María Muyor Rodríguez, Profesor Titular de la Universidad de Almería informa que el trabajo de investigación titulado “Analysis of physical performance in professional soccer players: an approach based on load monitoring through electronic performance tracking systems” realizado por D. José María Oliva Lozano, ha sido supervisado bajo su dirección y autorizado para su defensa de Tesis Doctoral con Mención Internacional en esta Universidad ante el tribunal correspondiente.

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Fdo. Dr. José María Muyor Rodríguez

El Dr. José Juan Carrión Martínez, Coordinador del Doctorado de Educación de la Universidad de Almería autoriza que el trabajo de investigación titulado “Analysis of physical performance in professional soccer players: an approach based on load monitoring through electronic performance tracking systems” realizado por D. José María Oliva Lozano, sea defendido como Tesis Doctoral con Mención Internacional en esta Universidad ante el tribunal correspondiente.

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El autor

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LIST OF ABBREVIATIONS

ACC_{AVG}: average magnitude of accelerations (m/s^2)

ACC_{DIS}: total distance covered by accelerations

ACC_{HIGH}: total number of high-intensity accelerations (above 3 m/s^2)

ACC_{LOW}: total number of low-intensity accelerations (below 3 m/s^2)

ACC_{MAX}: maximum magnitude of accelerations (m/s^2)

ANOVA: analysis of variance

CD: central defenders

CI: confidence interval

DEC_{AVG}: average magnitude of accelerations (m/s^2)

DEC_{DIS}: total distance covered by decelerations

DEC_{HIGH}: total number of high-intensity decelerations (below -3 m/s^2)

DEC_{LOW}: total number of low-intensity decelerations (above -3 m/s^2)

DEC_{MAX}: maximum magnitude of decelerations (m/s^2)

$DIFF_{ACDC}$: ACC_{HIGH} - DEC_{HIGH}

DIS: distance

EDI: equivalent distance index

EPTS: electronic performance and tracking systems

ES: effect size

FB: full backs

FFT: Fourier transform

FIFA: Fédération Internationale de Football Association

FPC: full pitch coverage

FW: forwards

GNSS: global navigation satellite systems

GPS: global positioning systems

HMLD: high-metabolic load distance

HSRA: high-speed running actions

HSRD: high-speed running distance

LMM: linear mixed models

LPS: local positioning systems

LR: likelihood ratio

MD: match day

MDP: most demanding passages

MF: midfielders

OPT: optical

PCA: principal component analysis

PL_{AP}: anterior-posterior player load

PL_{ML}: medial-lateral

PL_{TOTAL}: total player load

PL_{V}: vertical player load

RPE: rating of perceived exertion

SD: standard deviation

SPA: total sprint actions (above 24 km/h)

SPD: total distance covered by sprinting (above 24 km/h)

SPD_{AVG}: average distance covered per sprint (above 24 km/h)

SPSS: statistical package for the social sciences

TAcc: total of accelerations

TD: total distance

V_{MAX}: maximum running velocity

V_{O}: start velocity of the action

WCS: worst-case scenarios

WMF: wide midfielders

ηp^2: the partial eta-squared

χ^2: chi-squared

+1MD: one day after the match

+2MD: two days after the match

-1MD: one day before the match

-2MD: two days before the match

-3MD: three days before the match

-4MD: four days before the match

-5MD: five days before the match

THESIS SUMMARY

In recent years, the use of electronic performance and tracking systems has allowed practitioners to have a better understanding of the physical demands in soccer. These are useful instruments for practitioners because the information obtained from player monitoring during competition can be used to guide decision making around the training schedule. The main purpose of this doctoral thesis was to answer questions that sport scientists and strength and conditioning coaches may have in relation to the analysis of physical performance of professional soccer players based on load monitoring through electronic performance and tracking systems. In this regard, we analyzed key load indicators, load variability, specific performance during high-intensity actions (e.g., sprints and most demanding passages of play), contextual variables associated with physical performance, and some methodological issues related to load monitoring using electronic performance and tracking systems.

RESUMEN DE TESIS

En los últimos años, el uso de sistemas electrónicos de monitorización del rendimiento ha permitido a los profesionales del rendimiento deportivo una mejor comprensión de las demandas físicas en el fútbol. Estos instrumentos son útiles para los profesionales porque la información obtenida de la monitorización de los jugadores durante la competición puede ayudar en la toma de decisiones a la hora de prescribir la carga de entrenamiento. El propósito principal de esta tesis doctoral fue responder a preguntas que los científicos del deporte y especialistas del acondicionamiento físico pueden tener en relación con el análisis del rendimiento físico de los jugadores de fútbol profesional a través de sistemas electrónicos de monitorización del rendimiento. Por tanto, se analizaron indicadores clave de carga, la variabilidad de la carga, el rendimiento específico durante acciones de alta intensidad (Ejemplo: *sprints* y escenarios de máxima exigencia), las variables contextuales asociadas con el rendimiento físico y algunas cuestiones metodológicas relacionadas con el control de la carga utilizando sistemas electrónicos de monitorización del rendimiento.

CHAPTER 1

Introduction

1. INTRODUCTION

Soccer is the world's most popular sport (Bandyopadhyay, 2017). Millions of people play it worldwide, but only a few players become professional (Bandyopadhyay, 2017). This team sport is characterized by an intermittent activity profile including high-intensity anaerobic actions interspersed with periods of lower intensity (Drust et al., 2000). The match contributes to the largest single session load of the training week (Anderson et al., 2016) and its effect is typically considered when planning the weekly microcycle (Oliva-Lozano, Muyor, Fortes, et al., 2021). This implies that sports performance and medical practitioners need to measure physical performance to ensure that the players are well prepared for the competitive demands (Oliva-Lozano, Muyor, Fortes, et al., 2021).

In recent years, the use of electronic performance and tracking systems (EPTS) has allowed practitioners to have a better understanding of the physical demands in soccer given that these data may be collected on each match and training session (Oliva-Lozano, Barbier, Fortes, et al., 2021; Pino-Ortega et al., 2021). These tracking systems include camera-based technologies and wearable devices, which are based on the combination of positioning systems (e.g., GPS: Global Positioning Systems; or LPS: Local Positioning Systems), inertial measurement units (e.g., accelerometers, gyroscopes, and magnetometers), and physiological monitors (e.g., heart rate monitors) (Oliva-Lozano & Muyor, 2021; Oliva-Lozano & Rago, 2020). Specifically, EPTS allow the collection of external load (i.e., the workload experienced by the player such as distance covered, accelerations, decelerations, or sprints) and internal load (i.e., psychophysiological response to exercise such has mean or peak heart rate) data (Oliva-Lozano & Rago, 2020). Consequently, these are useful instruments for practitioners because the information obtained from player monitoring in competition can guide decision making around the training schedule (e.g., programming of subsequent training or recovery activities (Oliva-Lozano, Martín-Fuentes, Granero-Gil, et al., 2021; Oliva-Lozano, Muyor, Fortes, et al., 2021).

In this regard, internal load variables are logistically difficult to capture in real-time, so a wider use of external load variables may be observed (West et al., 2021). Although external loads are not the stimulus for functional training adaptations, it is important to measure them to provide a useful and objective marker of physical performance output, which plays a key role in managing the training process (Impellizzeri et al., 2019). This is important in modern soccer because the teams have many matches during the season and they may play two matches within the same week or three matches within 7–10 days (Anderson et al., 2016; Palucci-Vieira et al., 2018).

However, one of the main challenges for sports performance and medical practitioners when using EPTS is the management of data and the interpretation of all the variables (Oliva-Lozano, Conte, Fortes, et al., 2021; Rojas-Valverde, Gómez-Carmona, et al., 2019). For example, practitioners may daily obtain physical performance reports with ~100 or ~200 variables (Rojas-Valverde, Gómez-Carmona, et al., 2019). This implies that large volumes of data need to be summarized and practitioners should use adequate methods to identify and select the key performance indicators after data is collected in each session (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Rojas-Valverde, Gómez-Carmona, et al., 2019).

Considering that the match is the most demanding session of the microcycle, each training session has a specific aim (Anderson et al., 2016; Kelly et al., 2020). For example, days right after the match are usually recovery days for the players who completed more than 60 minutes in the match, while the players, who did not get 60 minutes, complete a compensatory session to replicate competition loads. Then, the greatest training load is achieved 3-4 days before the match and load is reduced progressively on the days before the match (Martín-García, Gómez Díaz, et al., 2018). However, research on the load variability from each training and match day is necessary to understand how training loads are programmed across the season (Kelly et al., 2020; Martín-García, Gómez Díaz, et al., 2018). For example, strength and conditioning coaches may wonder if match-play demands are abnormally high or low, so the analysis of load variability might be a useful monitoring strategy to inform practitioner decision making around the training schedule and individual management in the days after competition (Oliva-Lozano, Muyor, Fortes, et al., 2021). Nevertheless, understanding the impact of contextual variables on physical performance is important as well. Previous studies observed that match-related contextual variables (e.g., match outcome, match location, opponent level, length of the microcycle) may have a confounding effect on training load interpretation (Brito et al., 2016; Curtis et al., 2019; L. Gonçalves et al., 2020; Owen et al., 2017; Rago, Rebelo, et al., 2019).

1.1. Analyzing physical performance with special focus on high-intensity actions and most demanding passages of play

Professional soccer players usually cover ~10 km per match (Palucci-Vieira et al., 2018; Rampinini et al., 2007), being only ~10% of the total distance performed at high-intensity (Rampinini et al., 2007). In this regard, the analysis of distances covered at high intensity (e.g., attaining speeds above 23-24 km/h) may provide valuable information for strength and conditioning coaches, but the analysis of the acceleration and deceleration characteristics of these running actions, which are highly common to the game of soccer, are important too (Carling et al., 2010). For example, high-intensity actions contribute to neuromuscular fatigue, which consequently increases the injury risk (Carling et al., 2010; Harper et al., 2019). Thus, a further analysis of the sprint and acceleration profiles is of interest for coaches to determine how the players sprint, accelerate, or decelerate during the game.

Moreover, a myriad of studies have analyzed the average physical demands of match day to allow strength and conditioning coaches design specific training drills that replicate the external load demands of competition (Bangsbo et al., 2006; Clemente, Rabbani, et al., 2019). However, recent investigations concluded that training tasks, which are aimed at replicating average demands, may underestimate competitive demands (Martín-García, Casamichana, et al., 2018; Martín-García, Gómez Díaz, et al., 2018). These studies suggested considering not only the average/general demands but also the peak locomotor demands that are experienced by the players in specific phases of match play (Delaney et al., 2018; Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Martínez-Puertas, Fortes, et al., 2021). These phases are known as the worst-case scenarios or most demanding passages of play (MDP) (Castellano et al., 2020; Fereday et al., 2020; Martín-García, Casamichana, et al., 2018; Martin-Garcia et al., 2019). Although there is a current debate on the term that should be used for this idea, little evidence related to the MDP in professional soccer has published to date.

1.2. Contextualizing high-intensity actions and most demanding passages of play

As mentioned above, the analysis of the sprint profile of professional soccer players in competitive match play is limited to date (Ingebrigtsen et al., 2015; Oliva-Lozano, Fortes, Krustrup, et al., 2020). Different components of the sprint profile such as the period in which the maximum running speed actions occur or how the players reach their maximum speed (e.g., with or without the ball, linearly or non-linearly, attacking or defending, sprinting in own team's field, or sprinting in opponent team's field) need to be studied considering that the sprinting ability is regulated by a complex interaction of multiple factors (Haugen et al., 2014). Specifically, a better understanding of maximum running sprints considering not only playing position and contextual variables (e.g., ball possession, sprint trajectory, role of the sprint) but also performance-related variables (e.g., distance covered, starting speed, acceleration, and deceleration) is necessary (Oliva-Lozano, Fortes, Krustrup, et al., 2020).

Furthermore, there is no information regarding the period in which these high-intensity actions (i.e., sprints and most demanding passages of play) occur during professional soccer matches. From a practical standpoint, this is important information given that experiencing maximum intensity actions in the first or last minutes of the match may significantly influence the training drills design and warm-up strategies in match days.

1.3. A 3-dimensional analysis of the locomotor load experienced by the players

Currently, the use of electronic performance and tracking systems for load monitoring is a common practice in professional soccer (Pino-Ortega et al., 2021). Most available tracking systems encompass inertial sensors (e.g., accelerometers, gyroscopes, and magnetometers), which allow a better understanding of the three-dimensional (3-D) nature of soccer (Barrett, Midgley, Reeves, et al., 2016; Oliva-Lozano et al., 2020). These sensors have been used to analyze external load through metrics such as the Player Load (PL_{TOTAL}), which is measured in arbitrary units (a.u.) and combines the accelerations in anterior-posterior (PL_{AP}), medial-lateral (PL_{ML}), and vertical (PL_{V}) planes (Boyd et al., 2011; Chambers et al., 2015; Gómez-Carmona et al., 2020; Hulin et al., 2018). However, little is known about the distribution of the load for each axis of movement (Barrett, Midgley, Reeves, et al., 2016).

In addition, soccer is played in a dynamic environment with considerable demands on the perceptual-motor skills of the players (Vaeyens et al., 2007; Vänttinen et al., 2010; Ward & Williams, 2003). As in other team sports in which the referees, teammates, opposition players, or ball are continually in motion, understanding the postural demands met by the players when performing sports-specific skills would provide practitioners with meaningful information about the performance in perception and action (Warman et al., 2019). However, there are limited data available concerning the postural demands of professional soccer players (Oliva-

Lozano, Maraver, Fortes, et al., 2020b). Thus, the integration of inertial sensors with positioning systems has been standardized for load monitoring purposes in team sports (Gómez-Carmona et al., 2020).

1.4. Some technical/methodological issues related to load monitoring in professional soccer using electronic performance and tracking systems

In this introduction, different issues related to the analysis of physical performance in professional soccer (e.g., variables that may be used or contextual variables that should be considered by the practitioners) have been mentioned and those issues have been directly discussed from a physical performance perspective. However, sports performance practitioners should understand that there are some technical or methodological issues, which are important, related to load monitoring when using EPTS. For instance, if a strength and conditioning coach is analyzing the MDP of play, he/she should understand that the MDP may be calculated using the fixed length method and the rolling average method.

Another methodological or technical issue related to the use of EPTS is the validity and reliability of these instruments. Sports organizations require EPTS to meet their needs, but it is crucial that the data generated are of acceptable quality (Linke et al., 2018; Malone et al., 2017). In recent years, FIFA has been working on the FIFA Quality Programme to set internationally-recognized industry standards for EPTS (FIFA, 2017). FIFA has invited EPTS providers to participate in its own testing and certification event. However, currently, sport scientists, coaches and other professionals openly debate the FIFA quality performance reports (e.g., through social networks) and unfortunately, many professionals do not interpret them according to how the data are collected.

Moreover, practitioners usually analyze the data collected by EPTS at the end of each session (Oliva-Lozano, Fortes, & Muyor, 2020; Rojas-Valverde, Gómez-Carmona, et al., 2019) but some EPTS provide these physical performance parameters in real time that may be very useful for practitioners since some decisions may be made during the session (Barrett, 2017; Rojas-Valverde, Gómez-Carmona, et al., 2019). Nevertheless, EPTS manufacturers use different protocols to obtain real-time data and post-session data (Weaving et al., 2017). Therefore, this implies that practitioners should understand this type of technical issues related to the use of EPTS given that wrong decisions may be made because of inaccurate data.

CHAPTER 2

Aims

2. AIMS

2.1. Analyze the key load indicators of professional soccer players in match and training sessions.

2.2. Analyze the load variability of professional soccer players in training and match.

2.3. Investigate contextual variables associated with the load variability in professional soccer players.

2.4. Analyze physical performance considering high-intensity actions and most demanding passages of play in professional soccer players.

2.5. Investigate contextual variables associated with high-intensity actions and most demanding passages of play in professional soccer players.

2.6. Highlight the importance of a 3-dimensional analysis of the locomotor load experienced by the players

2.7. Analyze some methodological issues related to load monitoring using electronic performance and tracking systems.

CHAPTER 3

Study I. Key load indicators and load variability in professional soccer players: a full season study

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3. KEY LOAD INDICATORS AND LOAD VARIABILITY IN PROFESSIONAL SOCCER PLAYERS: A FULL SEASON STUDY

3.1. Abstract

The aims of this study were to 1) determine the key load indicators in professional soccer through principal component analysis (PCA); and 2) analyze the load variability of each training and match day within the microcycle considering the principal components. A longitudinal study was conducted for a full season in LaLiga123. Data from 111 load variables were collected using electronic performance and tracking systems in both training and match days (MD). The results showed that 7 variables, which belonged to the first two components of the PCA, explained 80.3% of total variance. Specifically, these variables were: Metabolic power, total of steps, Fourier transform (FFT) duration, deceleration distance covered (2-3 m/s^2), total of running actions (12-18 km/h; 21-24 km/h), and distance covered (6-12 km/h) were the selected variables. When it comes to the analysis of the load variability of each training and match day within the microcycle considering the principal components, the lowest load variability was observed in -1MD (i.e., the day before the match). Also, a great load variability in +1MD (i.e., the day after the match) with significant differences compared to -5MD ($p < 0.001$; $d = 0.49$) and -4MD ($p = 0.01$; $d = 0.26$) was found. Therefore, strength and conditioning coaches may use the performance indicators obtained by the PCA for load monitoring purposes. In addition, this study suggests the use of the PCA in the context of team sports in order to reduce the large number of variables, which are daily managed by strength and conditioning coaches. Furthermore, the analysis of load variability of each training and match day within the microcycle is also recommended since this may help to optimize performance and reduce the injury risk.

3.2. Keywords

External Load, Training Load, Game Analysis, Team Sport, Competition, Performance

3.3. Introduction

One of the main challenges when using EPTS is the management of data and the interpretation of all the variables provided by the tracking systems (Rojas-Valverde, Gómez-Carmona, et al., 2019). For instance, strength and conditioning coaches may daily obtain reports with ~100 or ~200 variables (Rojas-Valverde, Gómez-Carmona, et al., 2019). In consequence, the identification and selection of the key performance indicators is necessary (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Rojas-Valverde, Gómez-Carmona, et al., 2019). This is one of the reasons why statistical methods such as Principal Components Analysis (PCA) are used in team sports to reduce the dimensionality of datasets (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Parmar et al., 2018; Rojas-Valverde, Gómez-Carmona, et al., 2019). This method selects the key performance indicators and disregards the least important components of the analysis (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Parmar et al., 2018).

In addition, the management of this information from load monitoring may guide the decision making around the training schedule (Oliva-Lozano, Muyor, Fortes, et al., 2021). Different studies have showed that professional soccer matches result in the most demanding session of the microcycle (Anderson et al., 2016; Kelly et al., 2020) and thus, each training day has a specific purpose within the microcycle. For example, the days right after the match are mainly recovery days while the greatest training load is achieved 3-4 days before the match (Martín-García, Gómez Díaz, et al., 2018). Then, training load is reduced progressively on the days before the match (Martín-García, Gómez Díaz, et al., 2018). However, the load variability from each training and match day, which has not been explored to date, may provide valuable information for strength and conditioning coaches to understand how training loads are programmed across the season (Kelly et al., 2020; Martín-García, Gómez Díaz, et al., 2018). For instance, a previous study showed that the Hooper's score, which serves as a representative measure of perceived wellness and psychometric player’s status in professional soccer, was sensitive enough to the variability of the training load (Moalla et al., 2016). In consequence, understanding load variability of each training and match day may help coaches determine why greater or lower variability is observed for a specific training day (e.g., -1MD) compared to another (e.g., -4MD). For example, if lower variability was observed in -1MD compared to -4MD, practitioners may need to investigate if this was normal or due to the effect of context-specific variables (e.g., length of the microcycle, season’s period, wellness or fatigue levels) (Oliva-Lozano, Gómez-Carmona, Rojas-Valverde, et al., 2021; Oliva-Lozano et al., 2022).

Therefore, the aims of this study were to: 1) determine the key load indicators in professional soccer through principal component analysis (PCA); and 2) analyze the load variability of each training and match day within the microcycle considering the principal components.

3.4. Methods

Study design

A longitudinal study was conducted for a full season in a professional soccer team competing in LaLiga123, which is the second division of the Spanish soccer league system, from August 2018 to June 2019. Specifically, a total of 22 teams participated in the league so each team played a total of 42 matches. The study was authorized by the Bioethics Committee.

Data were collected using electronic performance and tracking systems in both training and match days (MD) over the course of the competitive season. Each training session was categorized as -1MD (1 day prior to the match), -2MD (2 days prior to the match), -3MD (3 days prior to the match), -4MD (4 days prior to the match), -5MD (5 days prior to the match), +1MD (1 day after the match) and, +2MD (2 days after the match). In general, +1MD included regeneration exercises and low-impact activities for the players who competed more than 45 minutes in the match while the rest of players had to compensate demands through rondos, high-intensity circuits, possession drills, and small-sided games; +2MD were considered as day off; -5MD were characterized by rondos, possessions games, and 11 vs 11 matches in half pitch; -4MD consisted of strength training, small-sided games, and pressing tasks; -3MD consisted of transitions’ drills, moderate-intensity positional games, and 11 vs 11 matches; -2MD included preventive strength training, tactical drills, rondos, passing and control tasks; and, -1MD were characterized by activation drills, 6x6+6 small-sided games in addition to the review of tactical keys for the match.

Participants

A total of 30 male professional soccer players (age: 25.97 ± 3.73 years old; height: 1.80 ± 0.07 m; weight: 74.60 ± 6.61 kg; professional playing experience: 8.49 ± 2.92 years) took part in the study in the context of their team routine. Players who completed the training session or total duration of the match, were included in the analysis. Players who were under a rehabilitation program were excluded. In addition, goalkeepers were not included in the study given the differences in their activity-profile (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a). Informed consent was obtained by the club to use the data of the participants once the season was over. However, the players' names were coded to guarantee data anonymization.

Procedures

The players wore a performance tracking system WIMU Pro (RealTrack Systems, Almería, Spain) in the back pocket of a chest vest (Rasán, Valencia, Spain). These tracking systems consist of triaxial accelerometers, gyroscopes, and magnetometers as well as 10 Hz Global Positioning System (GPS), which are valid and reliable instruments for tracking physical performance in soccer (Bastida Castillo et al., 2018). Also, these systems have been certified by the FIFA Quality Programme for the collection of physical performance variables based on speed and position (FIFA, 2020). Every device was calibrated on a Smart Station (RealTrack Systems, Almería, Spain) following the manufacturer's instructions before the start of each match and training session. Once the match or training session finished, the data were transferred to SPro (RealTrack Systems, Almería, Spain) and the performance report was obtained (Table 1). All these variables were included in the analysis since this is a general performance report that practitioners may obtain for load monitoring purposes in their daily basis. In addition, these variables were selected considering that previous studies used them as representative variables of the external load profile from professional soccer players (Asian-Clemente et al., 2021; Gómez-Carmona et al., 2020; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Oliva-Lozano, Fortes, Krustrup, et al., 2020; Oliva-Lozano et al., 2022; Pons et al., 2019). Also, some of the variables were split into several zones, which represented different ranges of intensity, and were set based on absolute thresholds (e.g., above 24 km/h for sprinting actions or above 6 m/s^2 for very high-intensity accelerations). In this regard, although there is no consensus on how to determine these thresholds (e.g., for speed or acceleration) (Sweeting et al., 2017), the zones were defined according to procedures from previous research (Asian-Clemente et al., 2021; Gómez-Carmona et al., 2020; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Oliva-Lozano, Fortes, Krustrup, et al., 2020; Oliva-Lozano et al., 2022; Pons et al., 2019).

Table 1. Variables provided by the SPro performance report

Variable	Definition
Session duration	Total duration of the session in minutes
Total distance	Total distance covered in meters (m)
Distance covered by speed zone	Distance covered in zones (0-6 km/h, 6-12 km/h, 12-18 km/h, 18-21 km/h, 21-24 km/h)
Total of actions by speed zone	Total of actions in zones (0-6 km/h, 6-12 km/h, 12-18 km/h, 18-21 km/h, 21-24 km/h)
Time spent in different speed zones	Total of time (ms) spent (0-6 km/h, 6-12 km/h, 12-18 km/h, 18-21 km/h, 21-24 km/h)
Total of high-speed running actions	Total of actions above 21 km/h
High-speed running distance	Distance covered above 21 km/h
Total of sprints	Total of actions above 24 km/h
Sprinting distance	Distance covered above 24 km/h
Explosive distance	Distance covered with an acceleration greater than 1.12 m/s^2
Maximum speed	Maximum speed (km/h) registered in the session
Average speed	Average speed (km/h) registered in the session
Total of accelerations	Total of accelerations registered in the session
Total of accelerations by zones	Accelerations in zones (0-1 m/s^2, 1-2 m/s^2, 2-3 m/s^2, 3-4 m/s^2, 4-5 m/s^2, 5-6m/s^2, >6m/s^2)
Total of decelerations	Total of decelerations registered in the session
Total of decelerations by zones	Decelerations in zones (0-1 m/s^2, 1-2 m/s^2, 2-3 m/s^2, 3-4 m/s^2, 4-5 m/s^2, 5-6m/s^2, >6m/s^2)
Maximum acceleration	Maximum acceleration (m/s^2) registered in the session
Maximum deceleration	Maximum deceleration (m/s^2) registered in the session
Average acceleration force	Average acceleration G-force registered in the session
Average deceleration force	Average deceleration G-force registered in the session
Acceleration distance	Distance covered (m) in acceleration
Acceleration distance by zones	Distance covered (m) in different acceleration zones (0-1 m/s^2, 1-2 m/s^2, 2-3 m/s^2, 3-4 m/s^2, 4-5 m/s^2, 5-6 m/s^2, >6 m/s^2)
Deceleration distance (m)	Distance covered (m) in deceleration
Deceleration distance by zones	Distance covered (m) in different deceleration zones (0-1 m/s^2, 1-2 m/s^2, 2-3 m/s^2, 3-4 m/s^2, 4-5 m/s^2, 5-6 m/s^2, >6 m/s^2)
Time in acceleration zones	Time (ms) in zones (0-1 m/s^2, 1-2 m/s^2, 2-3 m/s^2, 3-4 m/s^2, 4-5 m/s^2, 5-6 m/s^2, >6 m/s^2)
Time in deceleration zones	Time (ms) in zones (0-1 m/s^2, 1-2 m/s^2, 2-3 m/s^2, 3-4 m/s^2, 4-5 m/s^2, 5-6 m/s^2, >6 m/s^2)
Impacts	Total of body impacts registered in the session
Impacts by zones	Total of body impacts registered in different zones (0-3 G, 3-5 G, 5-8 G, >8 G)
Steps	Total of steps registered in the session
Step balance	Asymmetry value (%) between the intensity of right and left steps. A negative value means that the right side is more loaded than the left side.
Jumps	Total of jumps registered in the session
Take-off force	Average take-off force (G) registered in the session
Landing force	Average landing force (G) registered in the session
FFT duration	Total of time (min) in which the intensity of the Fourier Transform (FFT) applied to the total acceleration data, which were registered by the 3D accelerometers is above 0.02.
Maximum frequency	Maximum vibration frequency (Hz) recorded by inertial sensors
Average frequency	Average vibration frequency (Hz) recorded by inertial sensors in horizontal acceleration
Maximum frequency in horizontal acceleration	Maximum vibration frequency (Hz) recorded by inertial sensors
Average frequency in horizontal acceleration	Average vibration frequency (Hz) recorded by inertial sensors in horizontal acceleration
Time spent by frequency zone	Time spent (ms) in different frequency zones (0-0.5 Hz, 0.5-1 Hz, 1-1.5 Hz, >1.5 Hz)
Player Load	Accelerometers-derived load (a.u) that represents the load in x-, y-, and z-axis
Metabolic Power	Metabolic power (W/kg) representing the metabolic expenditure per kilogram
Maximum equivalent distance index	Value of the maximum equivalent distance index (EDI), which represents the energy expenditure divided by the distance covered
High metabolic load distance (m)	Distance covered (m) when the player's metabolic power is above 25.5 W/kg
High-metabolic load actions	Total of actions when the player's metabolic power is above 25.5 W/kg
Locomotor efficiency	Ratio representing the player load divided by the distance covered
High-intensity acceleration profile	Difference between the high-intensity accelerations and decelerations (above 3 m/s^2)

Statistical analysis

The statistical analysis was run on RStudio (PBC, Boston, MA, USA). Firstly, Principal Component Analysis (PCA) was used as a linear dimension reduction method of the dataset. Specifically, PCA is a descriptive multivariate statistical analysis that explores a set of quantitative variables and computes a set of new synthetic variables, which are also known as components. This method selects the significant variables and disregards the least important components of the analysis (Parmar et al., 2018) so it may enhance data visualization and interpretation from large datasets (Rojas-Valverde et al., 2020). From a practical perspective, this is important given that fast evaluation of training and competition performance is required in professional soccer (Rojas-Valverde et al., 2020). In this regard, 111 variables of match and training activities were used for this analysis (Table 1). Specifically, the dataset was organized on a spreadsheet containing player's id, date, type of session (i.e., MD, +1MD, +2MD, -5MD, -4MD, -3MD, -2MD, and -1MD) and the data related to each performance variable from Table 1. Prior to performing the PCA, training and match data were centered and scaled. Considering that cos2 is often used to assess the meaningfulness of the variables in the PCA, a threshold of cos2 > 0.5 was used for the first selection of variables (Dubois et al., 2020). Then, the variables that showed a correlation with PCA components that exceeded ± 0.7 were used as an indicative of a well-defined relationship with the extracted dimension (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Weaving et al., 2018). Also, a correlation matrix was used to evaluate collinearity between these new selected variables and when these variables had significant collinearity, only one variable was selected (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). Then, a final PCA was computed using the selected variables.

Secondly, each observation was projected on the first principal components plane (PC1, PC2). Then, the analysis of the load variability of each training and match day within the microcycle was assessed using the Euclidean distance (*d*) from each training or match day to their respective cluster centroids. In this case, the Euclidean distance allowed to evaluate the similarity or dissimilarity from each training or match day (i.e., the greater the distance, the greater the load variability). Finally, one-way analysis of variance (ANOVA) with Tukey's method was used to compare variability between each training and match day within the microcycle. The level of significance was set at $p \leq 0.05$.

3.5. Results

Regarding the first aim of the study, 22 variables from a total of 111 variables were found to match cos2 > 0.5. These variables were: session duration, FFT Duration, Metabolic Power, total of steps, time spent in different speed zones (0-6 km/h, 6-12 km/h, 12-18 km/h, 18-21 km/h, and 21-24 km/h), time spent in acceleration zones (1-2 m/s^2), time in spent in deceleration zones (1-2 m/s^2), total of accelerations by zones (1-2 m/s^2 and 3-4 m/s^2), total of decelerations by zones (1-2 m/s^2 and 3-4 m/s^2), deceleration distance covered by zones (2-3 m/s^2), total of running actions by speed zones (6-12 km/h, 12-18 km/h, 18-21 km/h, 21-24 km/h), and distance covered by speed zones (0-6 km/h and 6-12 km/h) were the selected variables. Then, session duration, total of accelerations by zones (3-4 m/s^2), and total of decelerations by zones (3-4 m/s^2) were removed since the correlation with PCA components did not exceed ± 0.7. Finally, the collinearity assessment was done and a total of 7 variables, which belonged to the first two components of the PCA and explained 80.3% of total variance, were selected. Specifically, FFT Duration, Metabolic Power, total of steps, deceleration distance covered (2-3 m/s^2), total of running actions (12-18 km/h; 21-24 km/h), and distance covered (6-12 km/h) were the selected variables (Figure 1).

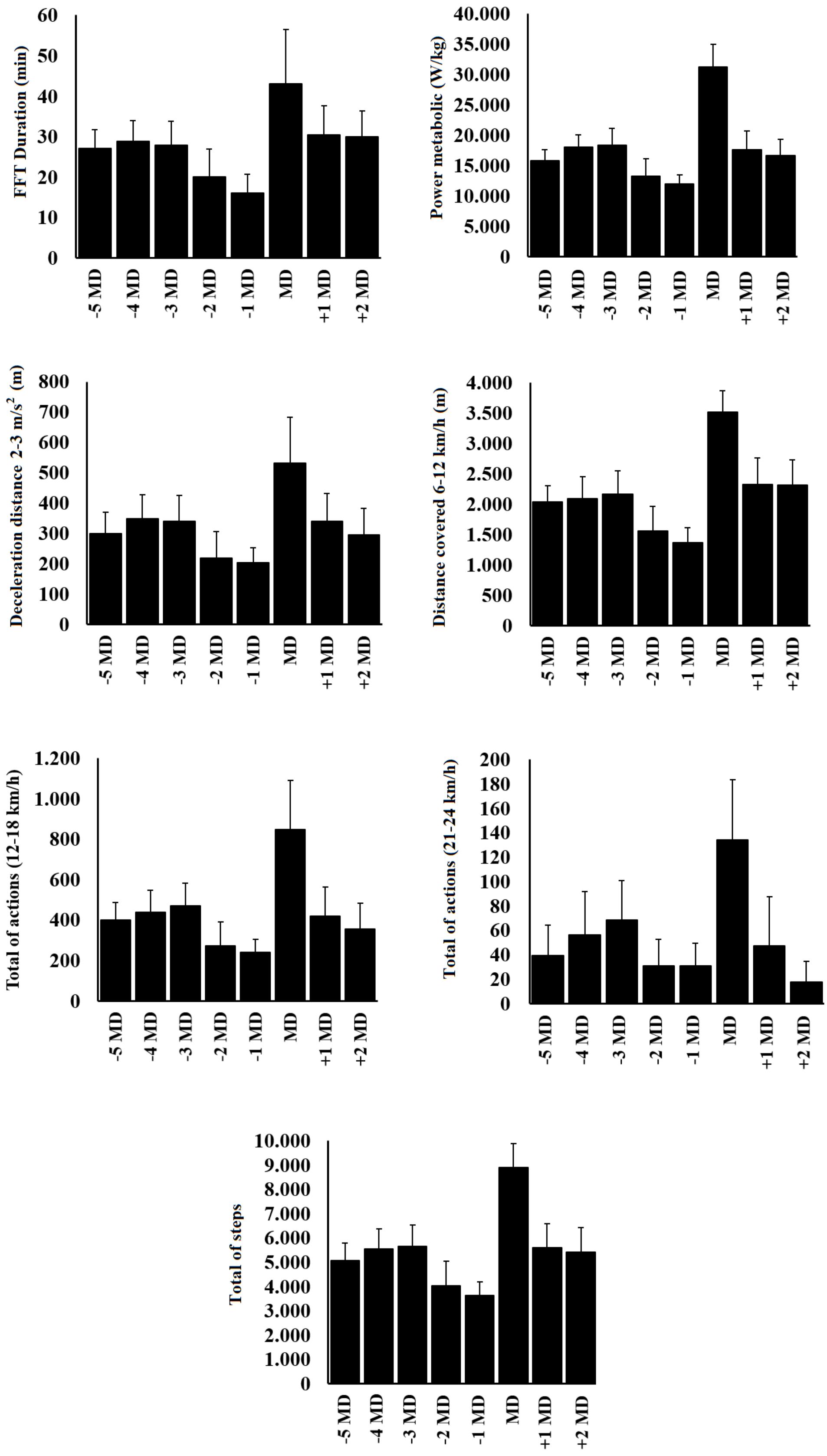

Figure 1. Descriptive statistics of performance indicators selected through PCA

When it comes to the analysis of the load variability of each training and match day within the microcycle considering the principal components (Figure 2), the results showed that the load variability in -1MD was significantly lower than MD (p < 0.001; d = 0.65) and the rest of training days: -5MD (p = 0.04; d = 0.30), -4MD (p < 0.001; d = 0.53), -3MD (p < 0.001; d = 0.60), -2MD (p < 0.001; d = 0.58), +1MD (p < 0.001; d = 0.79), and +2MD (p < 0.001; d = 0.47). Also, load variability in +1 MD was significantly greater than -5MD (p < 0.001; d = 0.49) and -4MD (p = 0.01; d = 0.26). In addition, significant differences in load variability between MD and -5MD were observed (p = 0.02; d = 0.35).

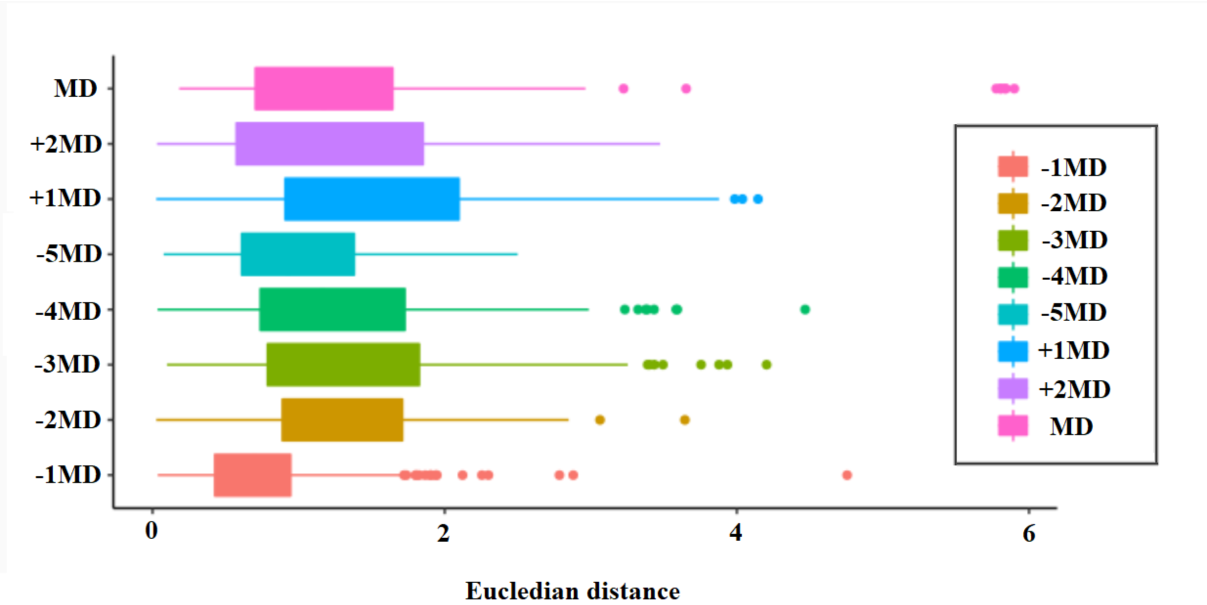

Figure 2. Euclidean distance (d) from each training or match day to their respective cluster centroids

3.6. Discussion

The aims of this study were to determine the key performance indicators in professional soccer through PCA; and analyze the load variability of each training and match day within the microcycle considering the principal components. One of the novel findings of this study was the PCA identified 7 performance variables from a dataset containing 111 variables. In addition, significant differences in load variability were observed within the microcycle depending on the training day. For instance, -1MD showed the lowest load variability.

Regarding the key load indicators that were selected through the PCA, coaches may consider them since they represent significant information from the physical performance of the players.

Also, this may be useful in terms of managing the dataset after each training or match session considering that only 7 out 111 performance variables were included. For example, variables regarding the activity time of the players such as the FFT duration, which represents the total of time in which the players were involved in actions of play (e.g., running, changing of direction, etc.) were found (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). In this regard, the results showed that although MD, for instance, last for ~90 minutes, only ~43 minutes were considered as the FFT duration. Since this is less than 50 % of the total duration of the match, this shows that soccer players may be involved in low-intensity actions (e.g., walking after game stops, corners, or fouls) for a great part of the match, which is in line with a previous study that reported only ~52 minutes of effective time in soccer match play (Castellano et al., 2011). Also, metabolic power and the total of steps may be of interest for strength and conditioning coaches considering that the former is an energy expenditure index strongly related to the player load (Osgnach et al., 2010; Reche-Soto et al., 2019) and the latter is representative of lower-limb load (Burland et al., 2021). In addition, the PCA showed that the distance covered (6-12 km/h) and the total of running actions (12-18 km/h; 21-24 km/h), which include low-to-high speed running actions (Rago, Brito, Figueiredo, Costa, et al., 2020), are suggested as key performance indicators. Specifically, these variables demonstrate the importance of understanding soccer as sport characterized by high-intensity actions interspersed with longer recovery periods of lower intensity (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a; Oliva-Lozano, Fortes, Krustrup, et al., 2020; M. Varley & Aughey, 2012). Finally, this study found that deceleration distance covered (2-3 m/s^2), which might increase the mechanical load and muscle damage post-session (De Hoyo et al., 2016; Harper et al., 2019; Harper & Kiely, 2018; Oliva-Lozano, Fortes, Krustrup, et al., 2020), should be considered as well.

In addition, one of the novel contributions of this study to the literature was the analysis of the load variability of each training and match day within the microcycle in professional soccer. Previous studies have mainly analyzed the differences between the workload profiles considering MD and training days (Malone et al., 2015; Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a; Stevens et al., 2017), but to the best of the authors' knowledge, this is the first study analyzing the load variability within the microcycle. For instance, different studies showed that the training load decreased in the days right before competition (e.g., greater workload in -4MD or -3MD compared to -2MD or -1MD) (Martín-García, Gómez Díaz, et al., 2018; Stevens et al., 2017). This study found that the lowest variability of all training days was observed in -1MD, which may be explained by the tapering strategies adopted by coaches the day before competition (Fessi et al., 2016). Also, the effect of the length of the microcycle (e.g., -4MD in 5-day microcycles may have a different purpose compared to 8-day microcycles) may be one of the reasons why the lowest variability was observed in -1MD (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). However, +1 MD showed a great load variability and significant differences with -5MD and -4MD. In this regard, the demands of each match may influence the creatine kinase concentrations, which are indicators of muscle damage, 24 hours post-match (M. Russell et al., 2016). Also, from a practical perspective, professional soccer players may experience this variability in +1MD depending on the competitive schedule. For instance, there may be MD in which the if the team plays too late or far away from home, stays at the hotel after the match, travels the day after and train in the evening. Nonetheless, the team may return sometimes right after the match and train the following morning, which has a direct impact on the recovery period and recovery quality (Nédélec et al., 2015). Finally, when it comes to the variability of MD, previous studies only analyzed load variability of different performance variables (e.g., distance covered, high-speed running distance, or total of accelerations) (Carling et al., 2016; Haddad et al., 2018; Oliva-Lozano, Muyor, Fortes, et al., 2021). In this regard, it has been observed that between-match variability may be dependent on the variable itself since variability tended to increase with running intensity (Gregson et al., 2010; Haddad et al., 2018; Oliva-Lozano, Muyor, Fortes, et al., 2021). For example, a recent study found a 4 % of between-match variability in distance covered while a 19 % of variability observed in high-speed running distance (Oliva-Lozano, Muyor, Fortes, et al., 2021).

However, this study has some limitations. Although the study was conducted during a full season, only data from one professional soccer team was collected. Also, the variables related to speed and accelerations zones were set based on absolute thresholds (e.g., speed: 0-6 km/h or 6-12 km/h; acceleration: 0-1 m/s^2 or 1-2 m/s^2). In this regard, future studies may consider the addition of individualized zones based on maximum speed (Rago, Brito, Figueiredo, Krustrup, et al., 2020) or maximum acceleration capacities (Harper et al., 2019) as well as a greater amount of teams to increase the statistical power of the PCA.

3.7. Conclusion

Strength and conditioning coaches may use the performance indicators obtained by the PCA for load monitoring purposes. Specifically, this study suggests the use of the PCA in the context of team sports in order to reduce the large number of variables, which are daily managed by strength and conditioning coaches. Thus, the PCA may help coaches visualize and interpret large training and match load data. Also, the PCA may help coaches select key load indicators in the context of each team (e.g., team level, team formation, style of play, etc.), regardless of the tracking system used for data collection. In addition, the analysis of load variability of each training and match day within the microcycle is also recommended since this may help to optimize performance and reduce the injury risk. For instance, coaches should be cautious in post-match training sessions (e.g., +1MD) given the high load variability.

CHAPTER 4

Study II. Decomposing the variability of match physical performance in professional soccer: implications for monitoring individuals

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4. DECOMPOSING THE VARIABILITY OF MATCH PHYSICAL PERFORMANCE IN PROFESSIONAL SOCCER: IMPLICATIONS FOR MONITORING INDIVIDUALS

4.1. Abstract

The aims of this study were to establish sources of variability in match physical performance of professional soccer players and provide a method for monitoring individual between-match changes. Eleven players meeting the final inclusion criteria were monitored through an entire in-season competition phase (n = 240 individual match observations, median [range] match observations per player = 21 [15–31]). Ten-Hertz global positioning systems were used to measure match total distance (TD), total high-speed running distance ($\geq$ 21 km·h^{-1}; HSRD), total accelerations (TAcc) and maximum running velocity (V_{MAX}). Between-player, between-position, between-match and within-player variability were determined through linear mixed effects models. These data were then used to establish the practical significance of individual changes using a Minimum Effects Testing framework. All sources of variability were greater for HSRD (13–36%) when compared with all other metrics (<6%). Using combined between-match and within-player variability along with the smallest worthwhile change (0.2 × between-player SD), between-match individual changes of ±~10–15% in TD, TAcc and V_{MAX} were established as practically significant. For HSRD, these thresholds were considerably higher (≥60%). In conclusion, the ability for soccer practitioners to identify meaningful changes in match physical performance can aid decision making around player management following competition. Our study provides a method to flag changes beyond the normal match-to-match variability and by a substantial magnitude. This may have implications for recovery but should be combined with other sources of data (internal load and response) and used only as an adjunct to practitioner domain knowledge and expertise.

4.2. Keywords

Team Sport, Match Performance, Competition, Game Analysis.

4.3. Introduction

Managing the training process of soccer players presents as a daily challenge for sports performance and medical practitioners. Information obtained from athlete monitoring during competition can be used to guide decision making around the training schedule, such as the programming of subsequent training or recovery activities. Soccer matches contribute to the largest single session load of the training week (Anderson et al., 2016) and their effects are typically considered when planning the weekly microcycle. Players are usually given 24–48 hours of complete rest or active recovery in anticipation of the physiological and neuromuscular responses to competition (Nédélec et al., 2012). However, the time-course of match-related recovery responses are extremely individual and may depend on the specific match load (Nédélec et al., 2012). Therefore, having the ability to determine whether match-play demands are 'unusual' or abnormally high/low might prove to be a useful monitoring strategy to inform practitioner decision making around the training schedule and individual management in the days after competition.

The need to interpret changes in match physical performance is not a new dilemma and over the past decade there have been several investigations attempting to shed light on this issue (Carling et al., 2016; Gregson et al., 2010; Haddad et al., 2018). Quantifying the match-to-match variability of physical performance can be a useful way to highlight changes that appear normal and those which seem higher or lower than usual. For instance, previous studies concluded that match-to-match variability was usually high (~14-53%) (Carling et al., 2016; Gregson et al., 2010; Haddad et al., 2018; Mohr et al., 2003; Rampinini et al., 2007) for high-speed activities (e.g., high-speed running distance) but low for variables such as total distance covered (~3-5%) (Haddad et al., 2018; Mohr et al., 2003; Rampinini et al., 2007). However, in isolation (i.e., without partitioning the usual sources of variability into their specific components), this approach does not identify the magnitude of a change. This can be achieved by scaling changes against so-called reference values for practical importance, such as the smallest worthwhile change. Probabilistic methods can then be used to determine the 'practical significance' of individual changes, taking into account both match-to-match variability and the smallest worthwhile change (McLaren et al., 2016; Weston et al., 2015). To our knowledge, this approach is yet to be applied in professional soccer.

The aims of our study were therefore twofold. We first aimed to provide a comprehensive breakdown of the variability in match physical performance of professional soccer players, including seasonal trends, variability between positions, players, and matches, and within players. Secondly, we aimed to apply a minimum effect testing framework for interpreting practically meaningful individual changes in soccer match physical performance.

4.4. Methods

Study design

A cohort study was conducted in a professional soccer team from LaLiga123 during 2018-2019 season. The team played a total of 42 official matches (21 home matches and 21 away matches). Every match was played on natural grass fields with a 4–4–2 playing formation. The length of between-match microcycles varied from 3 to 9 days. The club authorized the data collection, and this study was approved by the Bioethics Committee of the university.

Participants

An initial sample of fourteen professional soccer players were monitored over a single in-season phase (n = 515 individual match observations). Goalkeepers were not included in the analysis, given their vastly different match activity-demands (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a), and players were categorized as central defenders, full-backs, midfielders, wide-midfielders, and forwards. In an attempt to provide a representative seasonal profile of match external load, we elected to only include players who: a) completed the total duration of each match, b) played at least 5 matches during the season, and c) had at least one match observation in each trimester of the season (to avoid range effects). The final sample therefore included 240 individual match observations from 11 players (age: 28 ± 3 years; height: 180.9 ± 4.8 cm; body mass: 74.9 ± 4.1 kg; central defenders, n = 3 [67 individual match observations]; full-backs, n = 2 [42]; midfielders, n = 2 [48]; wide-midfielders, n = 2 [45]; forwards, n = 2 [38]. The median (range) number of match observations per player was 21 (15–31).

Procedures

Previous investigations employing dimension reduction techniques have suggested that 70% of the variance in soccer match external loads can be expressed by four principle components, each containing 2–4 variables (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). Variables within a given component are thought to be similar (i.e., highly correlated and interchangeable), while components themselves provide different information (i.e., uncorrelated and unique). We therefore used a combination of both the previously reported component loadings (where a greater loading indicates a higher importance to the component) and our professional judgment to select four match external load indicators. These were total distance (TD), total high-speed running distance ($\geq$ 21 km·h^{-1}; HSRD), total accelerations (TAcc) and maximum running velocity (V_{MAX}).

Instruments

Every player was given a WIMU Pro device (RealTrack Systems, Almería, Spain) in order to collect physical performance variables. The device was placed on a vertical position in the back pocket of a specific vest (Rasán, Valencia, Spain). This device is considered as an electronic performance tracking system which mainly consists of 3D accelerometers, gyroscopes, and magnetometers as well as positioning sensors through 10 Hz Global Positioning System (GPS). These GPS have demonstrated good criterion validity (bias in mean velocity: 1.18-1.32 km·h^{-1}; bias in distance: 2.32-4.32 m) and reliability (intraclass correlation coefficients: > 0.93) for the collection of physical performance variables in soccer (Bastida Castillo et al., 2018).

All the devices were calibrated following manufacturer’s instructions (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Oliva-Lozano, Fortes, Krustrup, et al., 2020). Prior to data collection, all the devices were first fully charged and placed on a Smart Station (RealTrack Systems, Almería, Spain). The station was placed on a flat surface without magnetic devices surrounding and then, the devices were turned on. Sixty seconds later, the start recording button was pressed and the calibration procedure was completed. Once this procedure finished, the devices were given to the players, who were familiar with the tracking systems, 15 minutes before the start of the match. Finally, the session was analyzed at the end of the match using SPro software (RealTrack Systems, Almería, Spain).

Statistical analysis

Our design located units of analysis (individual match observations) nested within clusters of units (Players), which were nested within larger clusters of clusters (Positions). To properly account for this hierarchical (correlated) nesting and to accurately quantify the variability in match physical performance, data were analyzed using separate three-level linear mixed effect models. We used the MIXED procedure in SAS® Software (University Edition, SAS Institute Inc., Cary, NC, USA) to analyze both the original and log-transformed data, to quantify effect estimates in raw and percentage units. Model appropriateness was verified by examining plots of the studentized residual and predicted values, which were well behaved for both the raw and log-transformed data.

To determine the linearized seasonal trend in each external load measure (the change in a given variable across the entire season), season week was re-scaled to range from -0.5 to 0.5 before being specified as a fixed effect (continuous covariate). Subsequently, separate random effects were added for Player ID, Position and Match Number. These effects were specified with a variance components covariance structure and estimated via Restricted Maximum Likelihood. Estimates—expressed as standard deviations (SD) and coefficients of variation (CV)—therefore included between-player, between-position, between-match and the remaining (residual) within-player variability, which is analogous to the typical error from a re-test reliability design. Uncertainty in all effects and ranges of values compatible with our data and statistical models were expressed as 90% confidence limits (CL). Boundary constraints were removed from covariance estimates to allow for negative variance. While negative variance (variability below zero) is illogical, it allows for appropriate approximation of the uncertainty in the estimate when the true variability is close to zero.

Building on previous approaches (McLaren et al., 2016; Weston et al., 2015), we used our variability estimates to provide a framework for practitioners to interpret individual changes in match physical performance indicators. This approach is founded on identifying changes that that appear unusual and potentially meaningful. Here, an unusual change can be viewed as one beyond the normal match-to-match variability seen in any given player, after accounting for any seasonal trend and positional differences. We determined the observed match-to-match variability as the pooled (added) between-match SD and within-player typical error. These values were then multiplied by the square root of 2 and the appropriate value from the *t* distribution with the model degrees of freedom to establish 80% and 90% confidence limits, giving likely ranges for a normal or 'usual' individual change. A meaningful change can be viewed as one which exceeds a pre-established threshold of practical importance. Through lack of a known conceptual or empirical anchor between our match physical performance indicators and key match outcomes (e.g., result), we used a distribution-based approach to establish these boundaries (Cook et al., 2018). Upon electing for a threshold equivalent to a small standardized change, reference values were given as 0.2 multiplied by the between-player SD or CV. Finally, we applied minimum effects tests (MET) (Murphy & Myors, 1999) to establish probabilistic reference values for interpreting individual changes in match external loads, which combine both match-to-match variability and thresholds of practical importance. The *t* statistic for a change relative to practical importance (change – threshold/ [match-to-match variability × √2]) was converted to a probability via the one-tailed *t*-distribution. These probabilities were represented as continuous estimates across a plausible range of changes, as well as the changes associated with more conventional alpha levels (0.10 and 0.05).

4.5. Results

The overall (mean) match external loads for TD, HSRD, TAcc and V_{MAX} were 10257 m, 699 m, 2976 (n) and 31.6 km·h^{-1}. Observed external loads and the associated seasonal trends (individual and mean) are presented in Figure 3. There was a seasonal reduction in TD (mean slope: -220 m [90% confidence interval: -638 to 197], -2.1% [-6.1% to 1.9%]), and a seasonal increase in both HSRD (126 m [3 m to 249 m], 25% [3% to 52%]) and TAcc (112 [-16 to 241], 3.8% [-0.8% to 8.5%]). The magnitude and direction of the seasonal trend in V_{MAX} was inconclusive (0.23 km·h^{-1} [-0.49 km·h^{-1} to 0.95 km·h^{-1}], 0.8% [-1.5% to 3.2%]).

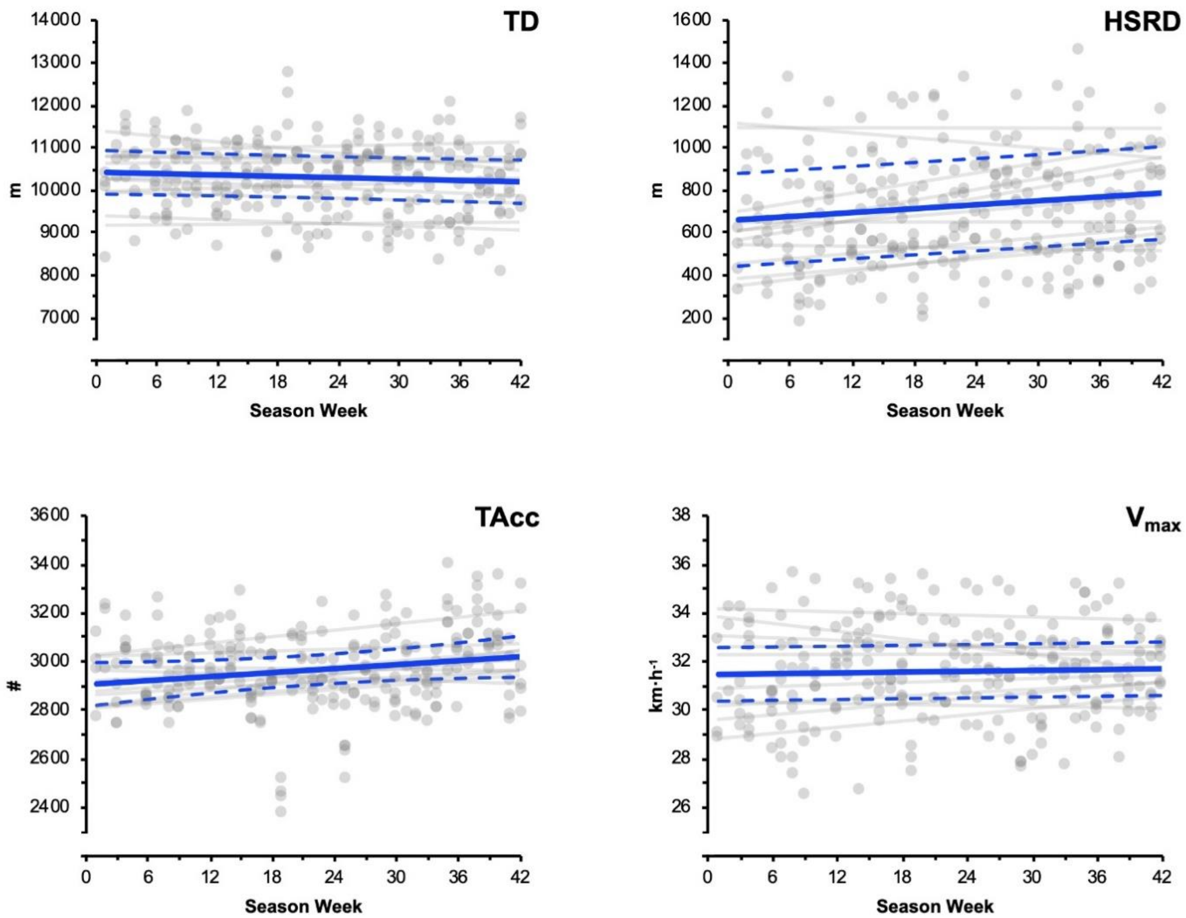

Figure 3. Seasonal trends in match external loads. Data are presented as individual match observations (grey points), individual linear trends (grey lines) and the overall mean trend (thick blue line) with 90% confidence intervals (blue dotted line).

Estimates of between-player, between-position, between-match and within-player variability in each external load metric, expressed in raw (SD) and percentage (CV) units, are presented in

Table 2, respectively. The observed match-to-match variability (combined between-match and within-player) for TD, HSRD, TAcc and V_{MAX} was 568 m (5.7%), 159 m (31%), 157 (5.6%) and 1.58 $km \cdot h^{-1}$ (5.2%). All sources of variability were greater for HSRD (13–36%) when compared with all other external load metrics (<6%). For each external metric, the greatest sources of variability were: between-player for TD (5.6%), between-position for HSRD (36%), between-match for TAcc (4.9%) and within-player for V_{MAX} 4.9%; Table 2 & 2).

Table 2. Variability of match physical performance expressed in raw units and coefficients of variations (%).

	Metric	Variability			
		Between-player	**Between-position**	**Between-match**	**Within-player**
(SD; 90% CI)	TD (m)	546 (147 to 759)	376 (-416 to 675)	428 (322 to 513)	373 (344 to 408)
	HSRD (m)	72 (-24 to 104)	222 (-107 to 331)	101 (72 to 123)	124 (114 to 136)
	TAcc (#)	74 (12 to 104)	27 (-60 to 72)	137 (106 to 162)	76 (70 to 83)
	V_{MAX} ($km \cdot h^{-1}$)	0.90 (-0.30 to 1.31)	0.93 (-0.86 to 1.57)	0.44 (-0.23 to 0.66)	1.52 (1.40 to 1.66)
(CV; 90% CI)	TD (%)	5.6 (1.5 to 7.8)	3.8 (-4.2 to 6.9)	4.3 (3.2 to 5.1)	3.7 (3.4 to 4.1)
	HSRD (%)	12.7 (-3.9 to 18.9)	36 (-17 to 59)	19 (13 to 23)	23 (21 to 25)
	TAcc (%)	2.5 (0.4 to 3.5)	0.9 (-2.0 to 2.4)	4.9 (3.8 to 5.8)	2.6 (2.4 to 2.8)
	V_{MAX} (%)	2.8 (-1.0 to 4.2)	3.0 (-2.7 to 5.1)	1.5 (-0.6 to 2.2)	4.9 (4.5 to 5.4)

Reference values and methods for interpreting individual changes in match external loads are presented in Table 3 and Figure 4. Based on our thresholds for practical importance (0.2 × between-player SD or CV), between-match individual changes of ±10–12% (for a 80% CI/ α = 0.10) and ±13–15% (for a 90% CI/ α = 0.05) in TD, TAcc and V_{MAX} would be required to suggest practical significance or substantially unusual. For HSRD, these thresholds were considerably higher (±58% and ±74%, respectively).

Table 3. Reference values for interpreting individual changes in match physical performance.

Metric	Unit	± Confidence limits for a true change*		Change (±) required to be practically significant*#	
		80%	**90%**	**α = 0.10**	**α = 0.05**
TD	m	1036	1333	1145	1442
	%	10.4	13.4	11.5	14.5
HSRD	m	291	374	305	389
	%	56	72	58	74
TAcc	#	286	368	301	383
	%	10.2	13.1	10.7	13.6
V_{MAX}	$km \cdot h^{-1}$	2.88	3.71	3.06	3.89
	%	9.4	12.1	10.0	12.7

#Based on the combined between-match and within-player variability (Table 2): TD = 568 m (5.7%), HSRD = 159 m (31%), TAcc = 157 (5.6%), V_{MAX} = 1.58 $km \cdot h^{-1}$ (5.2%). See methods section for more details.

*The threshold for a practically important change is given as a small effect size: 0.2 multiplied by the pure between-player SD (Table 2). Changes are then estimate based on a minimum effects test against these thresholds at the given alpha level.

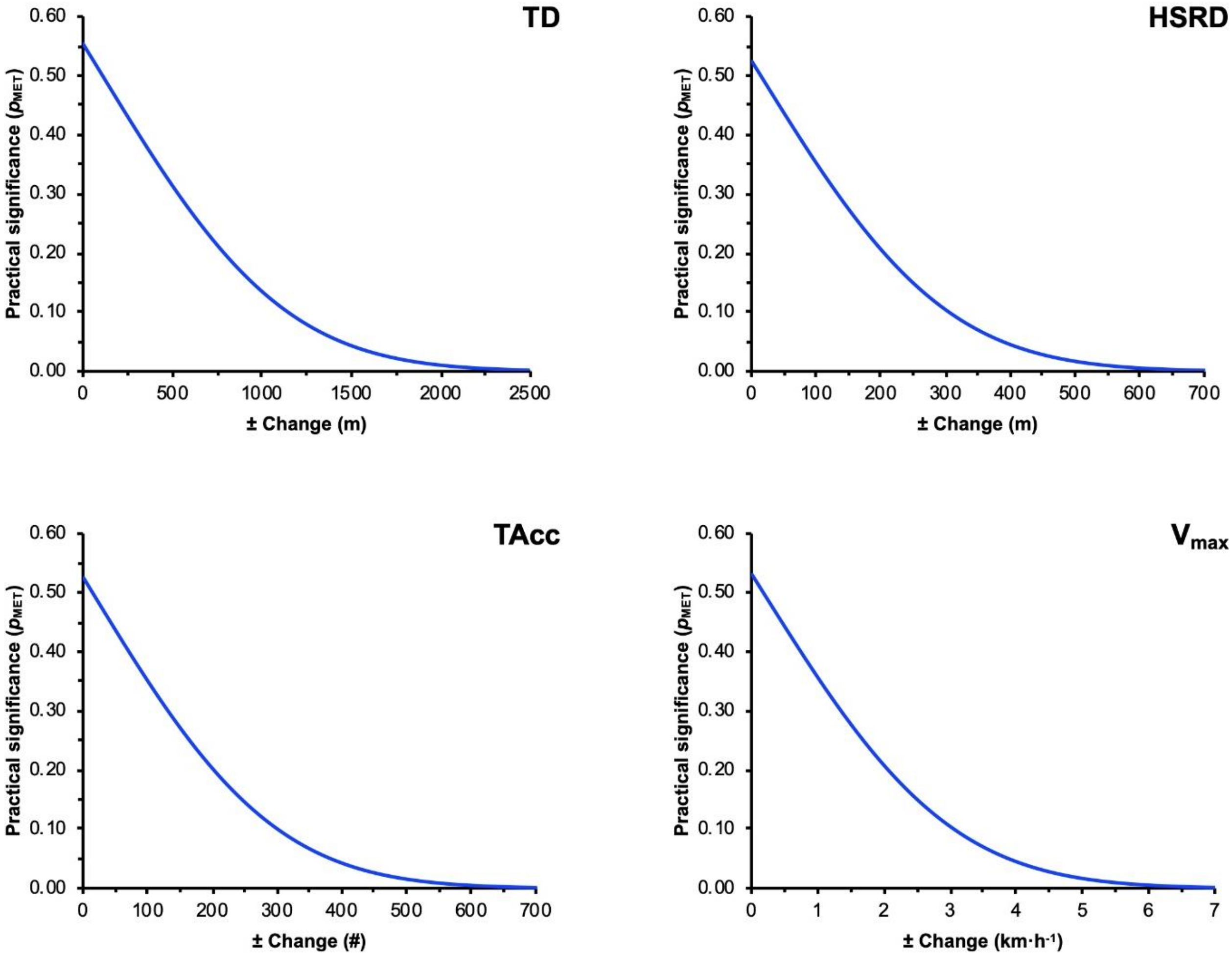

Figure 4. Probabilistic reference values for interpreting individual changes in match physical performance. Practical significance is given as the probability value from a minimum effects test (p_{MET}; Y-axis). The combined between-match and within-player variability estimates (Table 2) multiplied by the square root of 2 are used as the error term. The threshold for a meaningful change is given as a small effect size (0.2 multiplied by the pure between-player SD; Table 2). A smaller p_{MET} indicates a greater likelihood that the change is meaningful, that is; 'unusual' or substantially beyond the normal match-to-match variability.

4.6. Discussion

The ability for soccer practitioners to identify meaningful changes in match physical performance has the potential to aid decision making around player management following competition. Through a detailed examination into the variability of match physical performance and using a minimum effect testing framework, our study is the first to apply a probabilistic method for monitoring individuals in professional soccer. Our main finding was that after accounting for seasonal trends and inter-position heterogeneity, between-match individual changes of ±~10–15% in representative GPS-derived measures of match physical performance (TD, TAcc and V_{MAX}) can be considered practically significant within the current sample. This was with the exception HSRD, where thresholds were considerably higher ($\gtrapprox$ 60%).

Our match physical performance values appear similar to those reported in other investigations and may therefore be considered representative of professional soccer competition (Haddad et al., 2018; Palucci-Vieira et al., 2019). Previous investigations have also observed that professional soccer players usually cover ~10 km per match (Haddad et al., 2018; Palucci-Vieira et al., 2019), but only 4–6% of the TD is covered at high intensity (Haddad et al., 2018). In addition, soccer players are exposed to bouts of activity requiring running speeds in excess of 30 $km \cdot h^{-1}$ (Aquino, Munhoz-Martins, et al., 2017; Haddad et al., 2018), as well as multiple changes of direction and duels, which significantly contribute to TAcc (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). This supports the professional level population that participated in this study. We found HSRD and TAcc to increase throughout the season, whereas TD reduced and the trend in V_{MAX} was not clear. Previous studies have also found HSRD to increase from the start to the end of the season (Mohr et al., 2003; Rampinini et al., 2007), but our observed decline in TD is not consistent with these studies (Mohr et al., 2003; Rampinini et al., 2007), which reported a lower TD at the start of the season when compared to the middle and end. In this regard, there are several factors (e.g., ball possession, tactics, improved fitness, or adaptations to competitive league) that may explain these different trends (Rampinini et al., 2007). For example, the team analyzed in our study adopted a direct style of play with fast transitions and high defensive lines during the season, which may be another factor to explain the increase in HSRD and TAcc (Fernandez-Navarro et al., 2018). Also, although HSRD and TAcc are key performance indicators (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d), a previous investigation observed that the teams with low-percentage ball possession covered more TD than teams with high-percentage ball possession (da Mota et al., 2016). Therefore, the seasonal trends need to be analyzed from a context-specific perspective in order to understand the potential practical applications of this type of analysis.

Regarding the estimates of between-player, between-position, between-match and within-player variability in each physical performance metric, a key finding was that sources of variability were greater for HSRD (13–36%) in comparison with all other external load metrics (<6%). These results are consistent with previous investigations which reported that the variability tended to increase with running intensity (Carling et al., 2016; Gregson et al., 2010; Haddad et al., 2018; Mohr et al., 2003; Rampinini et al., 2007). For instance, the match-to-match variability in TD from professional soccer players has been shown to be around 3.1% (Mohr et al., 2003), 2.4% (Rampinini et al., 2007) and 5.3% (Haddad et al., 2018) while the variability for HSRD was around 9.2% (Mohr et al., 2003), 14.4% (Rampinini et al., 2007), 17.7% (Gregson et al., 2010), 19.8% (Carling et al., 2016) and 53% (Haddad et al., 2018). Compared to previous investigations, however, a novel approach of our study was the ability to further partition the usual sources of variability into their specific components. We show, for example, that HSRD is far more variable between positions (36%) than it is between players within a given position (13%). Furthermore, we separate the observed match-to-match variability into true between-match variability (i.e., factors occurring at the level of a match) and within-player variability (i.e., factors occurring at the level of an individual). To our knowledge, this is the first attempt to do so in soccer. Our results indicate that the between-match and within-player variability of HSRD are similar, whereas the within-player variability of V_{MAX} was over 3 times that of the between-match variability. However, V_{MAX} did appear relatively stable, for all sources of variability (<5%), which is supported by previous research (Haddad et al., 2018). Our lower estimates (between match: 1.5%, within-player: 4.9%) compared to Haddad and colleagues (observed match-to-match: 6–8%) are likely due to variance partitioning, but may also be influenced by different positional roles or playing styles (Haddad et al., 2018).

The primary aim of our study was to break down the sources of variability in soccer match physical performance and use these data to shed light on monitoring individual between-match changes. We approached this twofold. First, between-match and within-player variability were combined to construct confidence intervals for an individual change in physical performance. This is similar to principles of the minimum detectable change (smallest detectable difference) and can be used to determine those which are beyond the observed match-to-match variability. For example, a change in whole match TD of +10.4% could be interpreted as higher than usual, using an alpha of 0.1 (80% CI). This can be a useful way to incorporate performance variability into decision making, but it does not consider the practical importance of a change. Building on the TD example, a whole match change of + 10.5% is greater than the smallest detectable difference for an 80%, but only by 0.1% which is unlikely to have any real-world relevance. Therefore, we additionally used effect size principles to estimate values of the smallest worthwhile change, given as 0.2 of the pure between-player variability (Table 2). Using a minimum effects testing framework, we then calculated the probability (p_{MET}) that a match change could be considered truly meaningful; that is, ‘unusual’ (beyond the normal match-to-match variability) by a substantial magnitude. A smaller p_{MET} indicates a greater practical significance and intuitively, p_{MET} of 0.10 and 0.05 correspond to individual changes where the respective 80% and 90% CI fall completely beyond the threshold of practical importance. For TD, this value was 11.5% for an 80% CI.

We have presented p_{MET} as both the value associated with fixed and conventional alpha levels (Table 3) and also as continuous estimates (Figure 4). The former is typical to making inference from sample-based research studies but in the practice of monitoring individuals, this approach may be to conservative. The reality is that soccer practitioners are likely to interpret match physical performance data in a heuristic sense, so knowing if individual changes are trending towards practical significance might be of better use. The charts presented in Figure 4 could therefore be used to determine the actual practical significance, by drawing a vertical line up from the observed change (X-axis) and drawing a perpendicular horizontal line at the intercept of the Y-axis to determine the corresponding p_{MET}. These values can then be interpreted in the context of the decisions being made and the contextual constraints (e.g., associated time, resources and impact on players). For example, a lower p_{MET} for a positive change in HSRD and/or TAcc might be indicative of substantially more high-intensity match activity than normal. This might warrant the considerations for additional recovery, medical or nutritional intervention in the days following the match to ensure appropriate regeneration prior to the next competitive fixture.

We understand that it would be naïve to directly make an inference on fatigue or recovery from match physical performance alone, and this should be taken into consideration when making decisions using the aforementioned methods. External load is the means by which an internal load is induced; which is then the stimulus for consequential responses to the body’s systems and functional performance (e.g., fatigue and recovery). Therefore, we do not advocate that changes in match physical performance are used to make direct and definitive inference on fatigue or recovery. Rather, these changes could imply a differential fatigue or recovery time-course response when compared to usual. For example, if practitioners detect changes in match physical performance that are substantially higher than usual (e.g., +10–15% for TD, TAcc or V_{MAX}) then an assessment of the subsequent 'response' might be warranted to inform athlete management decisions. This could include post-day subjective measures of fatigue or objective measures such as heart rate variability or stiffness (e.g., leg/ whole body). Or, it may simply be used as an avenue to start a conversation with the player, where clinical and practical judgment can precede generic advice (e.g., sleep, nutrition) or further intervention. However, there are some general limitations, which need to be acknowledged and may also guide future investigations. First, only one professional soccer team was included in the analysis, so the sample size was limited to the most regular players of the league (*n* = 13) and these findings are representative of this sample. A multi-club study would therefore help extend our current findings. Additionally, recently implemented local positioning systems may provide more accurate data than GPS (Bastida Castillo et al., 2018; Linke et al., 2018), particularly for match physical performance measures such as HSRD and V_{MAX} (Martin Buchheit & Simpson, 2017), and should therefore be considered both for interpreting our findings to data collected with these systems and future research into the variability of soccer match physical performance. Nonetheless, the changes in external load-based measures do not necessarily lead to a "worthwhile" change in the performance outcome. Finally, we have stressed the importance of including concepts such as the smallest worthwhile change to interpret differences in match physical performance, but this distribution-based approach is in itself limited. The extent to which group-based effect sizes principles can be used at the individual level can be questioned and this is likely a less-robust approach than using anchor-based methods, which are yet to be established for match physical performance in soccer.

4.7. Conclusion

Competitive fixtures present as the most demanding sessions within a professional soccer microcycle. However, the variability of match physical performance is often overlooked. Practitioners are responsible for quantifying weekly match demands to inform subsequent player management and devise an appropriate training schedule. Understanding the variability of match physical performance can aid this decision-making process by determining the practical significance of between-match changes. In our study applying this approach alongside a minimum effect testing framework, we found that individual changes in representative GPS-derived measures of match physical performance (TD, TAcc and V_{MAX}) of ±~10–15% can be considered practically significant. That is, beyond the normal match-to-match variability and by a magnitude greater than the smallest worthwhile change. This was with the exception of HSRD, where thresholds were considerably higher ($\gtrapprox$ 60%). Soccer practitioners might therefore consider this approach to facilitate decision making. However, we maintain that other sources of data (internal load and the associated response) are needed to properly evaluate match demands and any athlete management decisions should be primarily based on domain knowledge (training principles and physiological or biomechanical theory) and experience.

CHAPTER 5

Study III. Impact of match-related contextual variables on weekly training load in a professional soccer team: a full season study

Oliva-Lozano, J. M., Rago, V., Fortes, V., & Muyor, J. M. (2021). Impact of match-related contextual variables on weekly training load in a professional soccer team: a full season study. *Biology of Sport*, *39*(1), 125–134. https://doi.org/10.5114/biolsport.2021.102927

5. IMPACT OF MATCH-RELATED CONTEXTUAL VARIABLES ON WEEKLY TRAINING LOAD IN A PROFESSIONAL SOCCER TEAM: A FULL SEASON STUDY

5.1. Abstract

The purpose of this study was to analyze the impact of match-related contextual variables (match location, match outcome and level of the opponent) on the weekly training load in a professional soccer team throughout a full competitive season. Total distance, high-speed running distance (HSRD, > 18 $km \cdot h^{-1}$), high-metabolic load distance (HMLD, > 25.5 $W \cdot kg^{-1}$), player load and total of impacts (above 3 G), were collected from training and match sessions in professional soccer players ($n = 25$) competing in LaLiga123. Comparisons in external load parameters by each match-related contextual variables were examined using a mixed-effect model. Differences between playing positions were found for total distance ($p < 0.05$; $r = 0.11$-0.15), HSRD ($p < 0.05$; $r = 0.13$-0.19), HMLD ($p < 0.05$; $r = 0.12$-0.19), player load ($p < 0.05$; $r = 0.11$-0.19) and impacts ($p < 0.05$; $r = 0.15$-0.26). However, no significant interaction was observed between match-related contextual variables and playing position in any variable ($p > 0.05$). In addition, a significant impact of match outcome ($p < 0.05$; $r = 0.11$-0.15), opponent level ($p < 0.05$; $r = 0.11$-0.17) and match location ($p < 0.05$; $r = 0.14$-0.20) on the weekly training load (before and after the match) was observed. In conclusion, match-related contextual variables seem to slightly affect weekly external training load. Thus, coaching and medical departments could consider the influence of these contextual variables when prescribing the training load relative to the match demands.

5.2. Keywords

Analysis, Competition, Performance, Team Sport, Training

5.3. Introduction

Training load monitoring has become one of the most common practices in high-performance soccer (Hader et al., 2019; Jaspers et al., 2017). The main purpose of this monitoring process is to analyze how each player is coping with daily load and how the player is adapting to the training stimulus (Gabbett, 2016). The availability of this information, which may be collected by electronic performance tracking systems among other methods (Cardinale & Varley, 2017; Linke et al., 2018; Rojas-Valverde, Gómez-Carmona, et al., 2019), may assist coaching and medical staff to minimize the injury risk or overtraining, and maximize fitness, readiness and performance (Cummins et al., 2013; Rago, Brito, Figueiredo, Costa, et al., 2020).

In consequence, coaches consciously prescribe training load seeking a balance between loading the players for adaptation purposes and avoiding fatigue accumulation as match day approaches (Gabbett, 2016; Martín-García, Gómez Díaz, et al., 2018; Oliva-Lozano, Fortes, & Muyor, 2020). Thus, it is important to understand external training loads (i.e., workload performed by the player in training sessions) relative to match demands, specifically when attempting to optimize position-specific loads (Martín-García, Gómez Díaz, et al., 2018; Vanrenterghem et al., 2017). In this regard, several studies, which provide a comprehensive insight into the load monitoring process, have reported seasonal training loads from a variety of professional soccer leagues (Clemente, Owen, et al., 2019; Clemente, Rabbani, et al., 2019; Martín-García, Gómez Díaz, et al., 2018; Stevens et al., 2017). However, the implementation of training programs at such high-performance level is difficult given the practical constraints which are related to the competitive calendar in professional soccer (Morgans et al., 2014).

Previous investigations have also suggested that match-related contextual variables (e.g., match location, opponent level, match outcome, length of the microcycle) may have a confounding effect on training load interpretation (Brito et al., 2016; Curtis et al., 2019; L. Gonçalves et al., 2020; Owen et al., 2017; Rago, Rebelo, et al., 2019). For instance, it is of interest for strength and conditioning coaches to know if the players experience different training demands during the week after losing the match compared to the week after winning (L. Gonçalves et al., 2020). In this regard, a recent study reported that weekly training load increased after losing a match, and before and after playing against a top-level team (Rago, Rebelo, et al., 2019). Therefore, these investigations recommend coaches to consider these contextual variables when prescribing weekly training load (Brito et al., 2016; Curtis et al., 2019; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Rago, Rebelo, et al., 2019).

Currently, only a few studies have analyzed the impact of match-related contextual variables on weekly training load in professional soccer teams during short competitive periods (L. Gonçalves et al., 2020; Owen et al., 2017; Rago, Rebelo, et al., 2019), so a full-season study is necessary. Similar investigations have been carried out to date, which included internal (e.g., heart rate recordings and rating of perceived exertion, RPE) (Brito et al., 2016; L. Gonçalves et al., 2020; Owen et al., 2017; Rago, Rebelo, et al., 2019) and external load (Curtis et al., 2019; L. Gonçalves et al., 2020; Owen et al., 2017; Rago, Rebelo, et al., 2019) variables. However, there is no data available concerning the relationship between contextual variables and weekly training load relative to peak match demands (i.e., relative training demands to match day). These considerations for quantifying training loads based on match demands may be a coaching strategy in the periodization training models (Martín-García, Gómez Díaz, et al., 2018). Hence, this study aimed to analyze the impact of match-related contextual variables (match location, match outcome and level of the opponent) on the weekly training load in a professional soccer team throughout a full competitive season.

5.4. Methods

Study design

A longitudinal study was designed to collect data from training and match sessions throughout the 2018/2019 competitive season of a Spanish professional soccer team in LaLiga123. The league consisted of a total of 42 matches (home, n = 21; away, n = 21) and the team started the matches with a standard 1-4-4-2 formation. However, this playing formation could vary based on situational variables. For all external load variables, the maximum values registered by each player in match days were considered for the calculation of relative training load through the following formula: (training session external load / competitive-match external load) × 100 (Martín-García, Gómez Díaz, et al., 2018). Thus, whereas match data were used to relativize training data, inferences were computed on training data only.

Since the length of the microcycle continually varied over the season from 5 to 9 days based on league calendar, the seven-day length of the microcycle was selected given the greatest number of cases (n = 879). This also implies that microcycles, which contained national cup (*Copa del*

Rey) matches, were not included in the analysis to avoid calendar congestion effects (Azcárate et al., 2018). It has been suggested that at least 80 individual recordings are needed to remove the inter-individual variability in observational studies (Gregson et al., 2010). Our study included 879 individual files. Then, the players' training load was weekly quantified. Every training session was classified based on match-related contextual variables, which included: last match outcome, opponent level and match location, and next match outcome, opponent level and match location (Figure 5). Match location was defined as home or away. The opponent level was categorized as: a) top, from first to sixth position; b) medium, from seventh to fourteenth position; and c) bottom, from fifteenth to twenty-second position considering weekly ranking. Match outcome was defined as win, draw and loss.

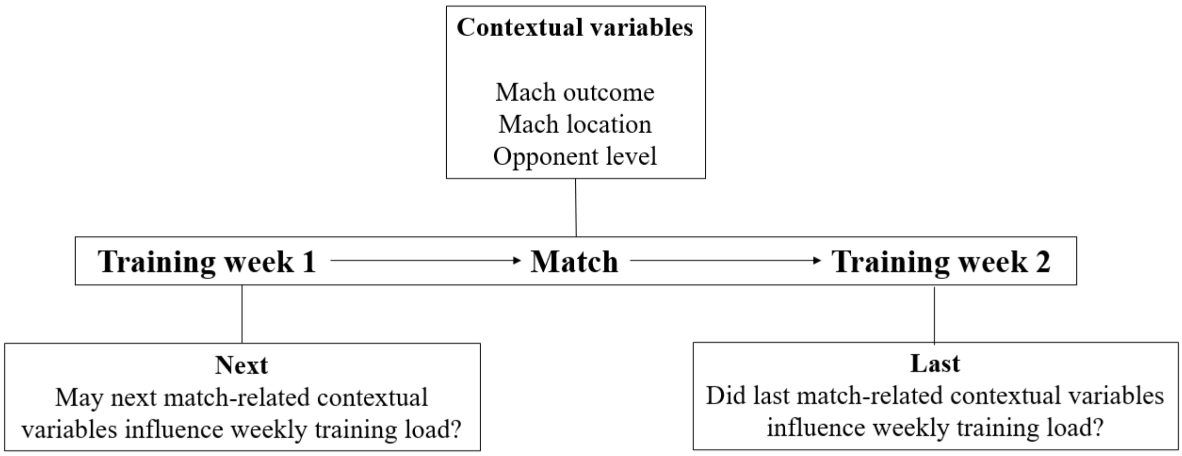

Figure 5. Sample weekly structure for interpretation of the impact of match-related contextual variables on weekly training load.

Participants

Twenty-five professional soccer players (age: 26.1 ± 3.8 years old; height: 1.8 ± 0.1 m; body mass: 75.5 ± 6.7 kg) participated in the study. The club provided consent to conduct the research and therefore, use anonymously the data by ensuring anonymity and confidentiality of the participants once the season had finished. Only players who met the following inclusion criteria were considered for the study: i) each player had to complete a minimum of one microcycle (i.e., training days from a seven-day microcycle) from the competitive season; and, ii) each player had to complete at least one full-match in order to calculate the relative training load and the effect of contextual variables. Players undergoing any rehabilitation process and goalkeepers were excluded from this study given the different nature of training and match demands profile (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a; Palucci-Vieira et al., 2018). This study was designed and conducted in line with the Ethical Standards in Sports and Exercise Science Research (Harriss & Atkinson, 2015). In addition, it was approved by the Bioethics Committee at the University of Almeria (UALBIO2020/032).

Procedures

WIMU Pro (RealTrack Systems, Almeria, Spain) was the electronic performance tracking system used to collect the external load variables. These systems registered positioning-derived variables through Global Positioning System (GPS) and inertial variables through four 3D accelerometers, three 3D gyroscopes, a 3D magnetometer, and a barometer. The validity and reliability of WIMU Pro for measuring soccer-specific external load variables have been successfully tested by previous investigations (Bastida Castillo et al., 2018; Gómez-Carmona, Bastida-Castillo, García-Rubio, et al., 2019; Muñoz-López et al., 2017). Based on previous studies (Bastida Castillo et al., 2018; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e, 2020d), the sampling frequency of the units was set at 10 Hz for the GPS and 100 Hz for the inertial sensors. According to the manufacturer's instructions (RealTrack Systems, Almeria, Spain), the units had to be calibrated at the beginning of each data collection session. Therefore, the units had to be turned on and placed on a flat surface within the Smart Station (RealTrack Systems, Almeria, Spain) for 30 seconds. Then, the units started to record data and were vertically placed in the back pocket of a chest vest (Rasán, Valencia, Spain). The players wore always the same device in order to avoid inter-unit error (Rago, Rebelo, et al., 2019). Once the training or match session had finished, the data was transferred to SPro software for analysis (RealTrack Systems, Almeria, Spain) by activating "PC mode" on the Smart Station. This software provided a specific report which was stored on WIMU Cloud (RealTrack Systems, Almeria, Spain). Finally, full-season data was downloaded from the WIMU Cloud in order to run the statistical analysis.

Variables

Five external load variables were collected from training and competitive matches: total distance covered, high-speed running distance (HSRD, above 18 $km{\cdot}h^{-1}$), high-metabolic load distance (HMLD, above 25.5 $W{\cdot}kg^{-1}$), player load (calculated through the vector sum of accelerometry-derived measures from vertical, anterior-posterior and medial-lateral movements) and the total of body impacts (collisions registered by the accelerometers with a magnitude above 3G) (Gastin et al., 2019; Gómez-Carmona, Pino-Ortega, et al., 2019; Martín-García, Gómez Díaz, et al., 2018; Oliva-Lozano, Muyor, Fortes, et al., 2021; Torreño et al., 2016). External training load was reported as the mean volume of work during the training days from the microcycle (i.e., training periods which count from the first training day of the period to the following match) (Clemente, Rabbani, et al., 2019; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). Weekly external training load was reported as the relative percentage to match training load, considering the highest match value recorded for each player.

Statistical analysis

Shapiro-Wilks test revealed that external training load data were normally distributed in all weeks for all variables (p > 0.05). Considering the longitudinal nature of this study (i.e., each player was measured repeatedly at several points in time), comparisons in external load parameters by each match-related contextual variable were examined using a mixed-effect model with restricted likelihood, taking into account missing data (e.g., injured players or reconditioning sessions) and that players took part in a different number of practice sessions (Cnaan et al., 1997). Match-related contextual variables were set as fixed effect, the individual player was set as random effect, and external load parameters were set as dependent variables. When a significant effect was found, pairwise comparisons were examined using a Bonferroni post- hoc test. To describe the magnitude of differences, the *t* statistics derived from the mixed model were converted to effect sizes' correlations (*r*) and associated 95% confidence intervals (95% CIs) (Rosnow et al., 2000). Effect sizes were qualitatively interpreted using the following criteria: trivial ($r \leq 0.1$), small ($r = 0.1 – 0.3$), moderate ($r = 0.3 – 0.5$), large ($r = 0.5 – 0.7$), very large ($r = 0.7 – 0.9$) and almost perfect ($r \geq 0.9$) (Cohen, 1988; Hopkins et al., 2009). Descriptive statistics are presented as mean and 95% CIs unless otherwise stated. Statistical significance was set at $p < 0.05$. Data analyses were performed using Statistical Package for Social Science software (IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY).

5.5. Results

Figure 6 shows descriptive statistics of the mean weekly training load of total distance, HSRD, HMLD, player load and impacts by playing position. Statistically significant differences between playing positions with a small effect size were found in total distance ($p < 0.05$; r = 0.11-0.15), HSRD ($p < 0.05$; r = 0.13-0.19), HMLD ($p < 0.05$; r = 0.12-0.19), player load (p <

0.05; r = 0.11-0.19) and impacts ($p < 0.05$; r = 0.15-0.26). In this regard, FB, WMF, and MF showed greater total distance, HSRD, HMLD, player load and impacts than CD and FW during the training sessions.

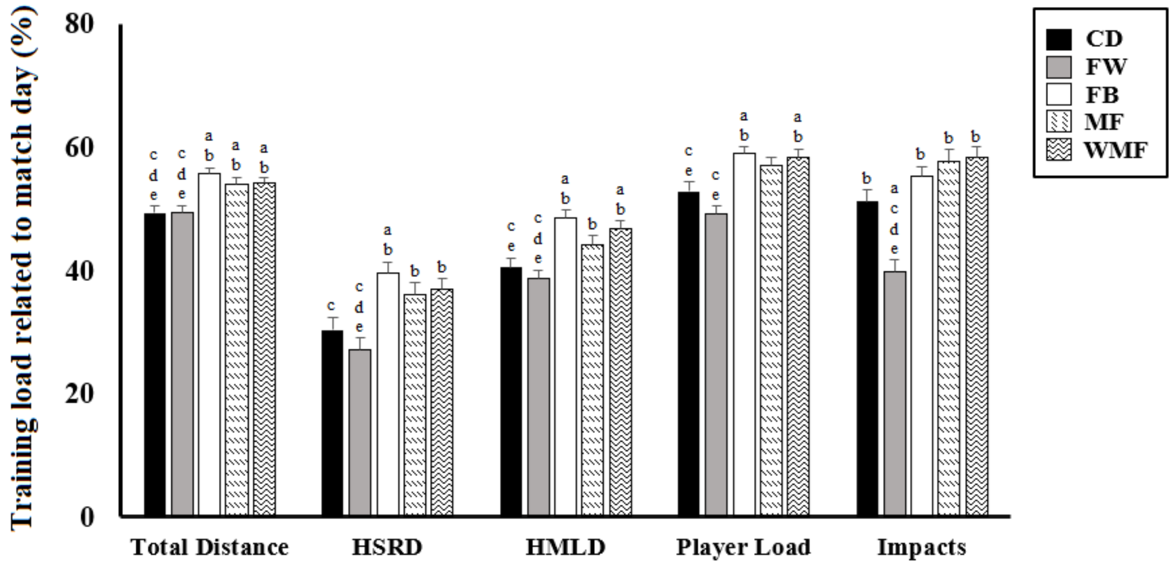

Figure 6. Differences between playing position in the mean weekly training load of total distance, high-speed running distance (HSRD), high-metabolic load distance (HMLD), player load and impacts. [a]Significant differences compared to central defenders (CD); [b]Significant differences compared to forwards (FW); [c]Significant differences compared to full-backs (FB); [d]Significant differences compared to midfielders (MF); [e]Significant differences compared to wide-midfielders (WMF).

Weekly training load by match outcome

Regarding match outcome, player load was significantly greater the training weeks after winning (~4.5%; $p < 0.05$; r = 0.11-0.13). Also, the results showed greater training load with a small effect as well during the training weeks after winning compared to the training weeks after losing for total distance (~4.4%; $p < 0.01$; $r = 0.13$) and HMLD covered (~4.1%; $p < 0.01$; $r = 0.10$). However, weekly training load was slightly greater for the training weeks before winning than before losing in total distance (~3.1%; $p = 0.02$; $r = 0.10$) and HSRD (~7.5%; $p < 0.01$; $r = 0.14$). In addition, no significant interaction was observed between match outcome and playing position in any variable ($p > 0.05$).

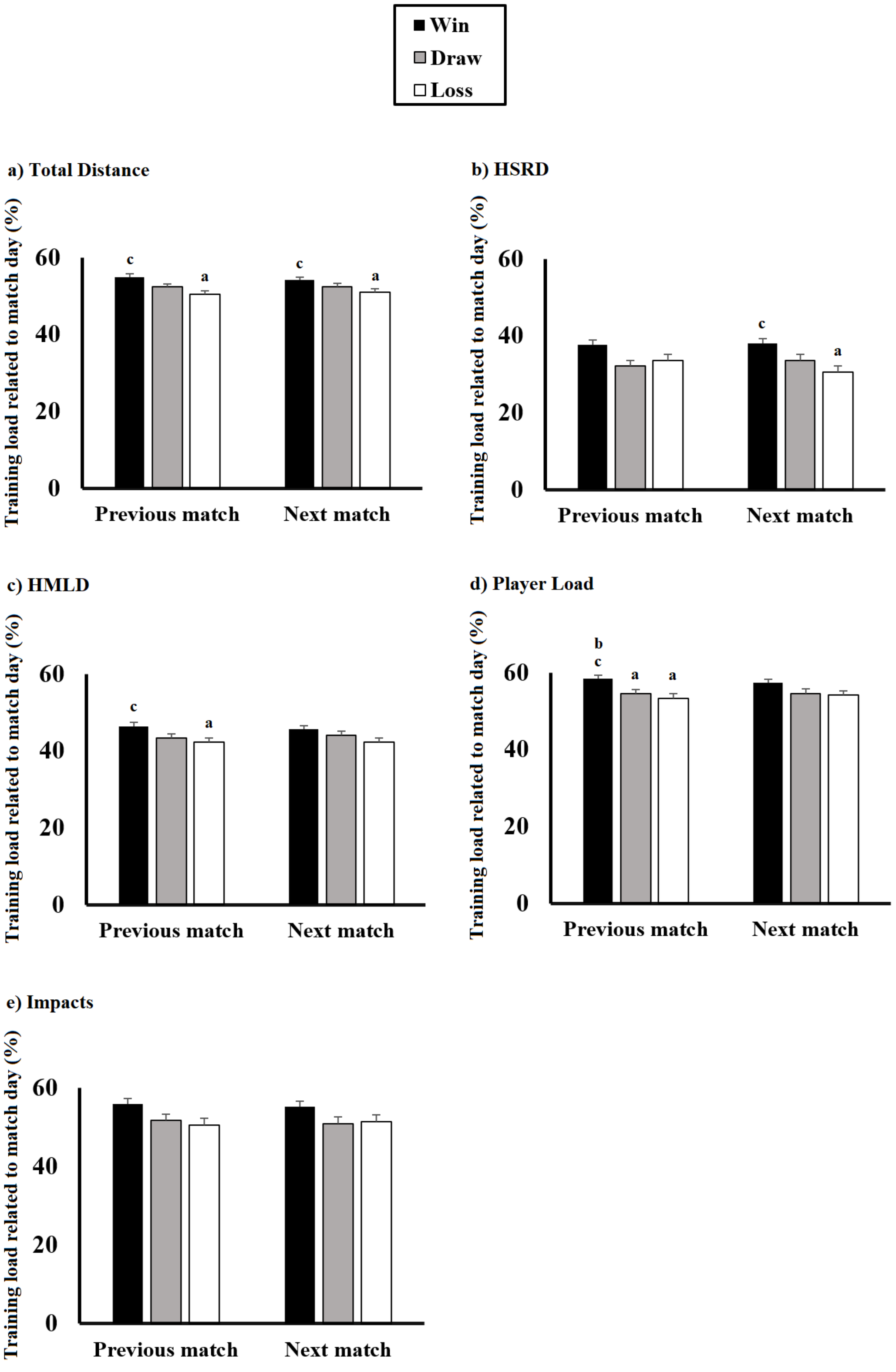

Figure 7. Weekly training load according to match outcome (% of the match).

Weekly training load by opponent level

Weekly training load of HSRD and impacts after playing against bottom-level teams was slightly greater than weeks after playing top-level (mean difference: ~12.5%; $p < 0.01$; $r = 0.17$) or medium-level teams (mean difference: ~6.4%; $p < 0.01$; $r = 0.14$). However, the training weeks before playing against bottom-level teams showed the greatest total distance (~55.4%; $p < 0.01$; $r = 0.11$-0.14), impacts (~58.5%; $p < 0.01$; $r = 0.15$-0.16) and player load (~59.2%; $p < 0.01$; $r = 0.13$-0.15). In addition, slightly greater HSRD (mean difference: ~7.4%; $p < 0.01$; $r = 0.15$) and HMLD (mean difference: ~5.7%; $p < 0.01$; $r = 0.15$) were observed before playing bottom-level teams compared to medium-level teams. No significant interaction was observed between opponent level and playing position in any variable ($p > 0.05$).

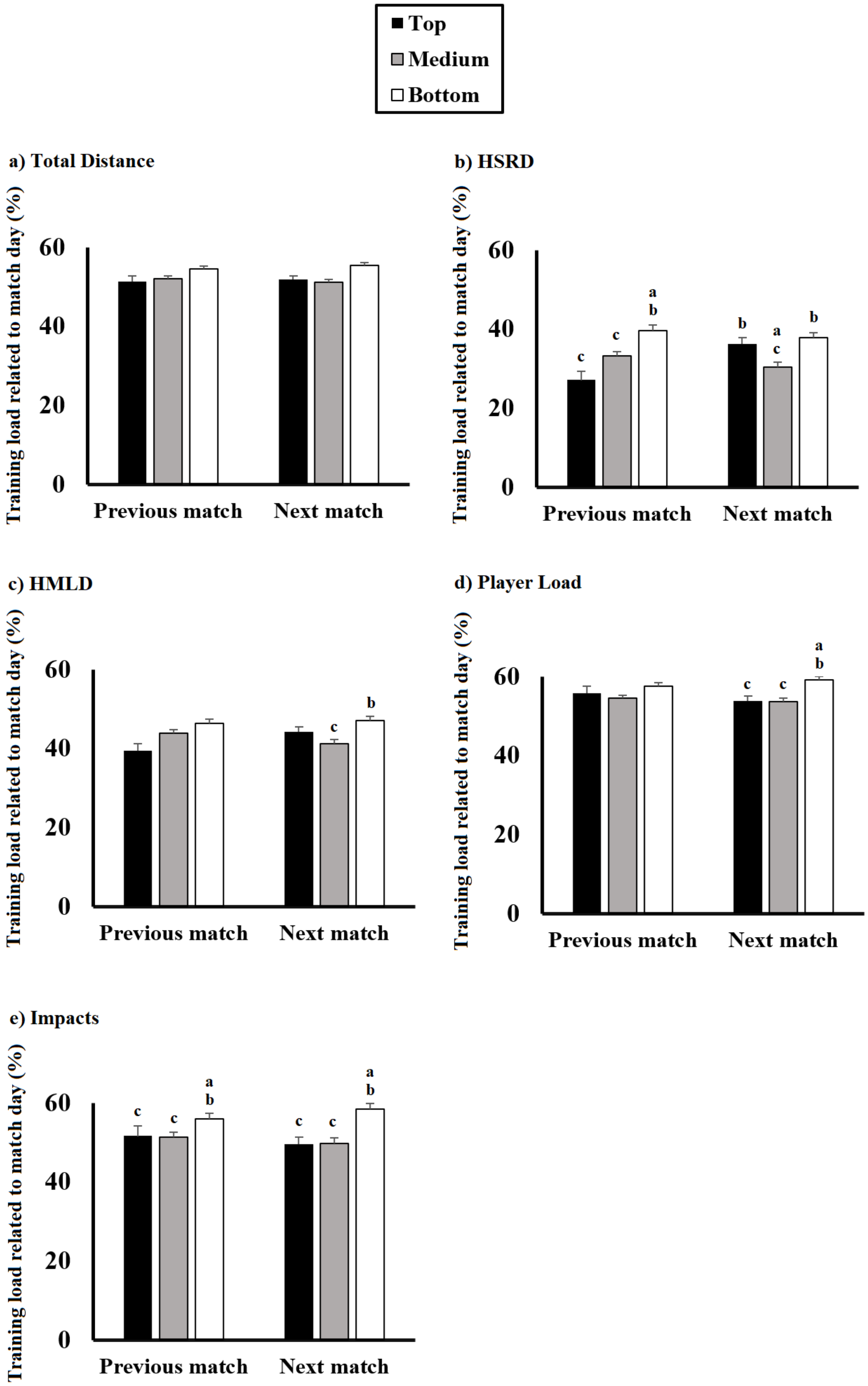

Figure 8. Weekly training load according to opponent level (% of the match).

Weekly training load by match location

When it comes to the effect of match location, there were no differences ($p > 0.05$) in weekly training load after playing at home or away. However, a significant increase in total distance (mean difference: ~4.6%; $p < 0.01$; $r = 0.17$), impacts (mean difference: ~7.6%; $p < 0.01$; $r = 0.16$), player load (mean difference: ~7.1%; $p < 0.01$; $r = 0.20$) and HMLD (mean difference: ~4.5%; $p < 0.01$; $r = 0.14$) was observed the training weeks before playing away with a small effect size. In addition, no significant interaction was observed between match location and playing position in any variable ($p > 0.05$).

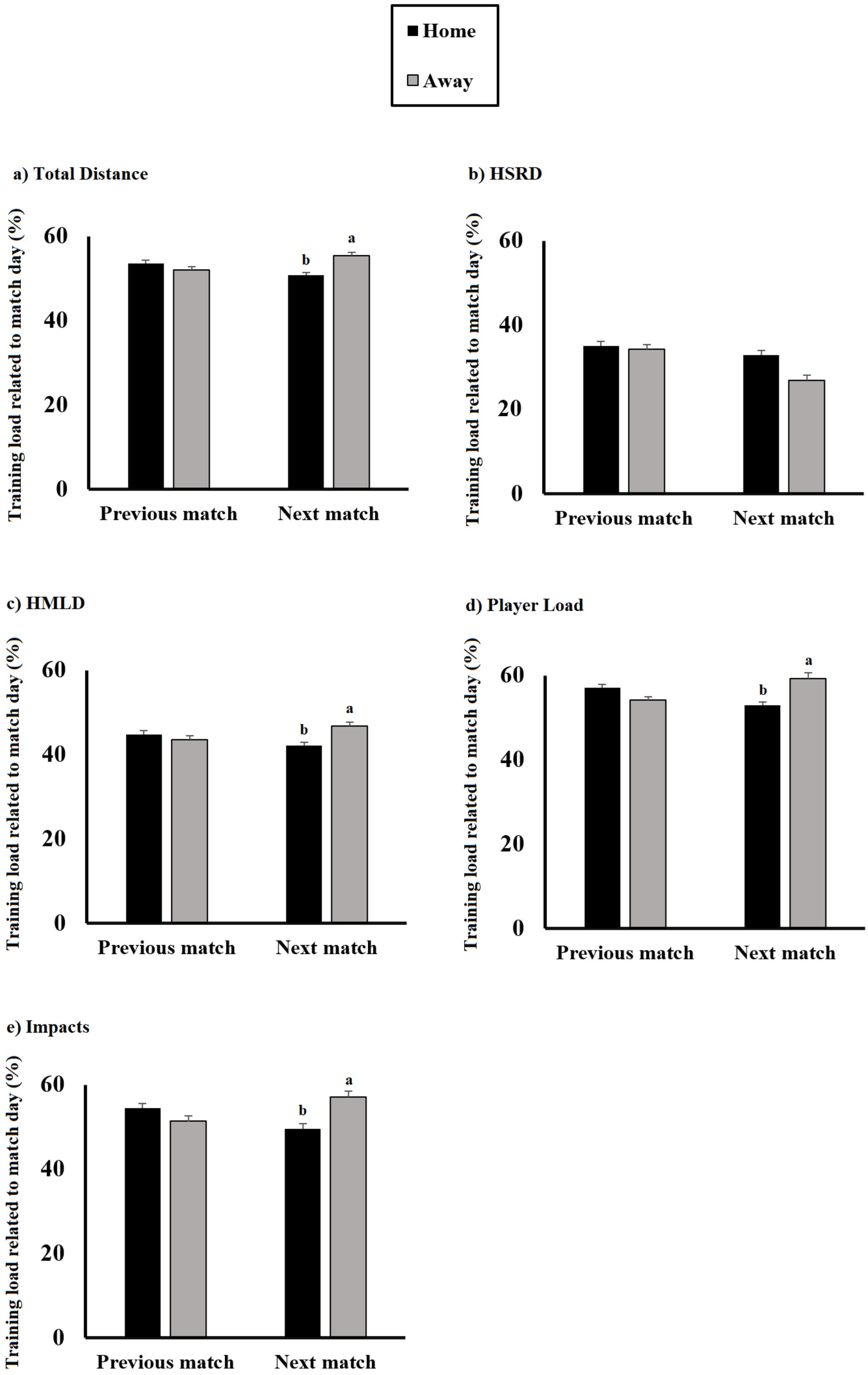

Figure 9. Weekly training load according to match location (% of the match).

5.6. Discussion

The purpose of this study was to analyze the impact of match-related contextual variables (match location, match outcome and level of the opponent) on the weekly training load during a full season study. The main finding of this study was that despite the positional differences observed in training load, match-related contextual variables (match outcome, opponent level and match location) had a significant effect on weekly training load before and after the match regardless of the playing position.

This study found that professional soccer players experienced positional differences in training load, which have also been reported in previous investigations (Akenhead et al., 2016; Malone et al., 2015; Martín-García, Gómez Díaz, et al., 2018; Owen et al., 2017). However, a further novel finding of this study was the interaction between match-related contextual variables and playing position was not significant in any external training load variable. Although only four studies have investigated the impact of match-related contextual variables on weekly training load (Brito et al., 2016; Curtis et al., 2019; Owen et al., 2017; Rago, Rebelo, et al., 2019), our study adds evidence to the literature by concluding that match-related contextual variables had a significant impact on weekly training load independently of the playing position. In this regard, weekly tactical strategies, which depend on matches characteristics, may explain these results. For example, coaches may decide to decrease the volume of tasks with high-intensity actions in order to have more time to prepare corner kicks because the upcoming team is good in these strategic actions. In consequence, the whole team is affected by a match-related contextual variable while playing position does not determine the training load.

Specifically, one of the match-related contextual variables which had an impact on training load was match outcome. Contrary to previous findings (Brito et al., 2016; Curtis et al., 2019; Owen et al., 2017; Rago, Rebelo, et al., 2019), which showed lower external and internal training load (e.g., distance covered, average speed, HSRD, RPE) the training weeks after winning in comparison with losing or drawing, our study observed greater training load in training weeks after winning (e.g., total distance, high-metabolic load distance and player load). This finding suggests that despite the effect of match-related contextual variables on the training load, the coaching strategies applied by each team are different (Rago, Rebelo, et al., 2019). However, our study found that training load (e.g., total distance and HSRD) was significantly greater when preparing for wins. This is in line with a recent investigation which reported that internal training load (i.e., session-RPE) increased too (Brito et al., 2016). Furthermore, a recent study also showed that the training load parameters were specifically greater the day before winning the match (i.e., -1MD) (L. Gonçalves et al., 2020). Nevertheless, future research should be done in order to investigate the effect of match outcome on both external and internal training load in professional soccer.

A further novel finding was that weekly training load varied based on opponent level. The greatest amount of impacts and HSRD covered was observed after playing against bottom-level teams. Several studies concluded that playing against weaker teams resulted in lower high-intensity match demands (e.g., HSRD, high-intensity accelerations or decelerations) (Aquino, Munhoz-Martins, et al., 2017; Castellano et al., 2011; Folgado, Duarte, et al., 2014; Rago et al., 2018), which suggests that degree of neuromuscular fatigue may be lower too during the following week. Nevertheless, this may be also dependent on the training day (L. Gonçalves et al., 2020). Besides, the results showed that volume-related training load variables such as total distance, impacts and player load were the greatest when preparing for bottom-level teams (Fernandez-Navarro et al., 2018). The team tactical behavior in match-play may explain these results since weaker teams require lower high pressure or direct style of play than top-level teams, which suggests that weaker teams keep players closer by increasing the density of players per area (Fernandez-Navarro et al., 2018). However, it is to highlight that our results are inconsistent with previous research on professional soccer players (Rago, Rebelo, et al., 2019). Although the same study also found an impact of this match-related contextual variable on weekly training load on training load (Rago, Rebelo, et al., 2019), the coaching strategies from each team may have been different regarding opponent level.

Finally, the results concerning the impact of match location on training load partly support the findings from a recent study (Owen et al., 2017; Rago, Rebelo, et al., 2019). This study found that there were no significant changes in weekly training load (e.g., total distance, HSRD, mean heart rate, RPE) after playing home matches or away matches (Rago, Rebelo, et al., 2019), which is in line with our results. Since there are studies which found that the overall match demands did not significantly vary based on match location (Castellano et al., 2011; Zhou et al., 2019), these results may explain why the training load from the following week is not significantly affected (Rago, Rebelo, et al., 2019). However, the training load may be significantly influenced when preparing for the upcoming match (Brito et al., 2016; Rago, Rebelo, et al., 2019). In this regard, our study observed that training load (e.g., increased the week before playing away matches. This may be a coaching strategy to prepare the players for the competitive demands since home teams tend to look for a dominant style of play (e.g., by increasing ball possession) (Fernandez-Navarro et al., 2018; Lago-Peñas & Lago-Ballesteros, 2011), which implies that the away team may need to maximize the physical output. This may not be the case for all the training days since a recent study showed that the players experienced lower external and internal training load before playing away compared to playing at home during -5MD training sessions (i.e., five days before the match) (L. Gonçalves et al., 2020). Although these results did not replicate the previously reported in the literature, the conclusion is similar given the significant impact of match location on weekly training load (Brito et al., 2016; L. Gonçalves et al., 2020; Rago, Rebelo, et al., 2019).

However, several limitations need to be considered. For example, data was collected from one professional soccer team so adding more teams to the analysis would be of interest to increase the power of the analysis. In this regard, although there were significant differences, the magnitude of the effect sizes was usually small, which implies that there may be additional contextual variables that should be considered (Rago, Rebelo, et al., 2019). Although a total of five external training load variables were included in the study, internal load variables were not included (Brito et al., 2016; Rago, Rebelo, et al., 2019). Also, the mean weekly training load was scaled to the match demands, which implies that there is a lack of consideration for the specificity of each training day within the microcycle (e.g., higher loads are usually concentrated in the middle of the microcycle to prevent excessive loading right before the match) (Brito et al., 2016; Rago, Rebelo, et al., 2019). In addition, some of the variables included in the study were collected by GPS and the limitations associated with this technology (e.g., satellite connection variability) need to be acknowledged (Malone et al., 2017). Although most measurements from training and match days were taken in the same stadium, away matches implied different stadiums and geographical locations (Pons et al., 2019). Nonetheless, the growth of local positioning systems for load monitoring purposes implies that future studies may include local positioning systems (e.g., ultrawideband technology) to improve the accuracy of the data during professional soccer matches (Bastida Castillo et al., 2018).

5.7. Conclusion

Match-related contextual variables, which included match outcome, opponent level and match location, had an impact on the subsequent weekly training load. This study also found that professional soccer players experienced positional differences in training load, which have also been reported in previous investigations. However, the interaction between match-related contextual variables and playing position was not significant in any variable of the weekly training load. In consequence, strength and conditioning coaches need to consider match-related contextual variables when planning and prescribing the weekly training load. Gaining knowledge of external training loads relative to the match is important for applied practitioners, particularly when attempting to optimize individualized loads. In this regard, this study allows coaches to understand the weekly training load experienced by professional soccer players. Specifically, load quantification relative to the match may be an advantageous strategy to be used by coaches within the training periodization models. In addition, this full season study may serve as a source of data and comparison for future investigations on the effect of match-related contextual variables on the weekly training load.

CHAPTER 6

Study IV. Acceleration and sprint profiles of professional male soccer players in relation to playing position

Oliva-Lozano, J. M., Fortes, V., Krustrup, P., & Muyor, J. M. (2020). Acceleration and sprint profiles of professional male football players in relation to playing position. *PLOS ONE, 15*(8), 1–12. https://doi.org/10.1371/journal.pone.0236959

6. ACCELERATION AND SPRINT PROFILES OF PROFESSIONAL MALE SOCCER PLAYERS IN RELATION TO PLAYING POSITION

6.1. Abstract

The study aims were to describe positional differences in the acceleration and sprint profiles of professional soccer players in match-play, and analyze start speeds required based on the intensity of accelerations and decelerations. This longitudinal study was conducted over thirteen competitive microcycles in a professional soccer team from LaLiga 123. Data were collected through electronic performance tracking systems. Every player was categorized based on the playing position: central defender (CD), full-back (FB), forward (FW), midfielder (MF), and wide midfielder (WMF). In respect of acceleration profile, positional differences were found for all variables ($p < 0.05$), except average magnitude of accelerations (ACC_{AVG}, p=0.56) and decelerations (DEC_{AVG}, p=0.76). The sprint profile also showed positional differences for all variables ($p < 0.05$), apart from sprint duration (p=0.07). In addition, although low-intensity accelerations required significantly greater start speeds (Vo) than high-intensity accelerations in WMF (0.4 ± 0.2 km/h; $p < 0.05$) and FW (0.4 ± 0.2 km/h; $p < 0.05$), no significant differences ($p > 0.05$) were found in CD, FB, and MF. However, high-intensity decelerations were performed at significantly higher Vo than low-intensity decelerations in MF (2.65 ± 0.1 km/h; $p < 0.05$), FW (3.3 ± 0.1 km/h; $p < 0.05$), FB (3.9 ± 0.4 km/h; $p < 0.05$), WMF (4.3 ± 0.3 km/h; $p < 0.05$), and CD (4.1 ± 0.7 km/h; $p < 0.05$). Therefore, positional differences exist for most variables of the acceleration and sprint profiles. In addition, different Vo were observed between high-intensity and low-intensity accelerations as well as high-intensity and low-intensity decelerations.

6.2. Keywords

Acceleration, Soccer, Game Analysis, Performance, Team Sport.

6.3. Introduction

High-speed running actions, or sprints, are considered a prerequisite for successful performance in soccer (Martin Buchheit et al., 2014; Haugen et al., 2013). In fact, sprinting skills are of prime importance in modern soccer (Martin Buchheit et al., 2014; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). For instance, straight sprints are the actions most frequently performed when scoring a goal (Faude et al., 2012), evading an opponent, and creating a shot on goal (Sweeting et al., 2017). Thus, selection, testing, and physical conditioning of players should put emphasis on developing sprinting skills (Haugen et al., 2013). In addition, careful monitoring of these actions is necessary (Harper et al., 2019; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d), taking into consideration different playing positions (Ingebrigtsen et al., 2015; Miñano-Espin et al., 2017). For example, a wide midfielder (WMF) may cover 294 ± 76 m of sprinting distance per match, whereas a central defender (CD) may cover 123 ± 48 m (Ingebrigtsen et al., 2015). However, research on the sprint profile of professional soccer match-play has so far been limited (Ingebrigtsen et al., 2015), while different components of the sprint profile, such as sprint duration, start speed of each sprint or distance covered per sprint, have not yet been studied.

In addition, another determinant factor of soccer performance is the acceleration profile (Martin Buchheit et al., 2014; Haugen et al., 2013; Ingebrigtsen et al., 2015). The acceleration profile is understood as a group of acceleration-based variables that are physically demanding (M. Varley & Aughey, 2012) given the rate of change in velocity performed by the player (Little & Williams, 2005). High-intensity accelerations and decelerations have a significant impact on soccer players' mechanical load (Harper et al., 2019; Vanrenterghem et al., 2017) and indicators of muscle damage post-match (De Hoyo et al., 2016). Accelerations have a high metabolic cost (Hader et al., 2016), while decelerations increase the mechanical load (Dalen et al., 2016). Moreover, these actions are significantly associated with the neuromuscular fatigue (Harper et al., 2019) and rating of perceived exertion (RPE) (Gaudino et al., 2015). For example, a previous investigation reported that the total of accelerations performed by professional soccer players in training sessions was significantly correlated with their session RPE (Gaudino et al., 2015). Consequently, previous research suggests that understanding the acceleration profile would help to understand the potential impact that this profile might have on match performance and risk of injury (Harper et al., 2019).

Some studies have tried to individualise (based on playing position) and contextualise both acceleration (Dalen et al., 2016; De Hoyo et al., 2018; Ingebrigtsen et al., 2015; M. Varley & Aughey, 2012) and sprint profiles (Martin Buchheit et al., 2014; Ingebrigtsen et al., 2015; Miñano-Espin et al., 2017), but most studies have analyzed these profiles separately. Also, little is known, for example, about the start speed required to perform a high-intensity acceleration or deceleration (De Hoyo et al., 2018). The aims of this study were therefore to: 1) describe the acceleration profile of players and compare it by playing position; 2) describe the sprint profile of players and compare it by playing position; and 3) analyze the start speed (Vo) required based on the intensity of the acceleration and deceleration by playing position. Regarding the first and second aims, we hypothesized that greater positional differences may be found, particularly, between defensive and offensive positions. When it comes to the third aim, we hypothesized that high intensity accelerations and decelerations would elicit greater start speeds than low intensity accelerations or decelerations.

6.4. Methods

Study design

The study was conducted over thirteen competitive microcycles in a professional soccer team from LaLiga 123. The team played one match per microcycle. The match location (home or away) alternated with each microcycle; seven matches were played away and six at home. The playing formation was 4-4-2 for all matches. Data were collected using wearable sensors (RealTrack Systems, Almería, Spain). In addition, every player was categorized based on their playing position: central defender (CD), full-back (FB), forward (FW), midfielder (MF), and wide midfielder (WMF).

Participants

Twenty-three professional male soccer players (age: 26.79 ± 3.78 years; height: 180.81 ± 6.20 cm; weight: 75.71 ± 6.88 kg; professional career: 8.40 ± 2.80 years) voluntarily took part in the study. Each player had a specific playing position: CD (n = 4), FW (n = 5), FB (n = 5), MF (n = 5) and WMF (n = 4). Given the very different nature of goalkeeping, this position was not included in the study (White et al., 2018). Additionally, only players who completed the total duration of the match were analyzed. Consequently, although a total of 13 matches were analyzed, not all the players from the sample participated in all the matches. The club allowed the research team to access players' data and informed consent was provided. The study was conducted ethically according to Declaration of Helsinki, and it was approved by the Bioethics Committee at the University of Almeria.

Procedures

Data were collected using WIMU Pro 10 Hz global positioning system (GPS) devices (RealTrack Systems, Almería, Spain). This device also contains inertial sensors (four 3D accelerometers, three 3D gyroscopes, one 3D magnetometer and one barometer), which collected data at 100Hz. The validity and reliability of this device has been analyzed for the collection of time-motion variables and is considered a suitable instrument for this purpose in soccer (Bastida Castillo et al., 2018). Regarding the validity of the device, the total bias in mean velocity measurement was between 1.18 and 1.32 km/h while the bias in distance was between 2.32 and 4.32 m (Bastida Castillo et al., 2018). In addition, good inter-unit and intra-unit reliability was reported (intraclass correlation coefficients > 0.93) (Bastida Castillo et al., 2018). The devices were calibrated according to the manufacturer's instructions before the start of each match. All the devices were placed in the Smart Station (RealTrack Systems, Almería, Spain). First, the battery of the devices had to be fully charged. Then, a flat surface was found without any nearby magnetic devices in order to turn on the devices. After 60 seconds, the recording button was pressed. Once the calibration procedure was complete, the devices were placed in a vertical position in the back pocket of a chest vest (Rasán, Valencia, Spain).

The devices were placed in the Smart Station (RealTrack Systems, Almería, Spain) at the end of the match in order to transfer the data to the SPro software (RealTrack Systems, Almería, Spain). This software reported a database with the performance variables which were categorized into the acceleration and sprint profile as indicated in Table 4. In addition, the start speed of the action (Vo) for each high or low-intensity acceleration and deceleration was calculated in order to investigate the third aim of this study. This variable (i.e., Vo) was obtained from the "Sprint Extended" section of the "Intervals Pro" report, which was created by SPro (RealTrack Systems, Almería, Spain).

Table 4. Description of acceleration and sprint profile variables.

Profile	Variable	Definition
Acceleration	ACC_{DIS}	Total distance covered by accelerations (m)
	DEC_{DIS}	Total distance covered by decelerations (m)
	ACC_{LOW}	Total number of low-intensity accelerations (below 3 m/s^2)
	ACC_{HIGH}	Total number of high-intensity accelerations (above 3 m/s^2)
	DEC_{LOW}	Total number of low-intensity decelerations (above -3 m/s^2)
	DEC_{HIGH}	Total number of high-intensity decelerations (below -3 m/s^2)
	$DIFF_{ACDC}$	ACC_{HIGH} - DEC_{HIGH}
	ACC_{AVG}	Average magnitude of accelerations (m/s^2)
	DEC_{AVG}	Average magnitude of decelerations (m/s^2)
	ACC_{MAX}	Maximum magnitude of accelerations (m/s^2)
	DEC_{MAX}	Maximum magnitude of decelerations (m/s^2)
Sprint	SPA	Total sprint actions (above 24 km/h)
	SPD	Total distance covered by sprinting (above 24 km/h)
	SPD_{AVG}	Average distance covered per sprint (above 24 km/h)
	V_{MAX}	Maximum speed reached in the match (km/h)
	Sprint time	Duration of sprint(s)

Statistical analysis

First, descriptive statistics were produced for all variables of the acceleration and sprint profiles. Playing position was set as an independent variable. Then, the Shapiro-Wilk test was used to analyze the normality of the variables and Levene's test for homogeneity. Parametric and non-parametric tests were used, since only ACC_{DIS}, ACC_{LOW}, DEC_{LOW}, $DIFF_{ACDC}$, V_{MAX} and sprint time were variables with normal distribution. On the one hand, when comparing the acceleration and sprint profiles relative to playing position, one-way analysis of variance (ANOVA) with Bonferroni post-hoc and Kruskal Wallis tests was used. On the other hand, when comparing the intensity of the accelerations (low-intensity accelerations, high-intensity accelerations, low-intensity decelerations, and high-intensity decelerations) based on start speed (Vo), the Mann-Whitney U test was used. The statistical power, which was calculated by G * Power software (Heinrich-Heine-Universität Düsseldorf, Düsseldorf, Germany), was greater than 0.85 in all the variables that were analyzed with the sample size of this study. The level of significance was set at $p \leq 0.05$ and the statistical analysis was carried out using IBM SPSS Statistics version 25 (SPSS Inc., Chicago, IL, USA). Effect sizes (ES) were also calculated and categorized as trivial (0–0.19), small (0.20–0.49), moderate (0.50–0.79) and large (0.80 or higher) effect (Cohen, 1988).

6.5. Results

Table 5 shows the descriptive statistics of the data collected for all variables of the acceleration profile and the positional differences. Significant positional differences (p < 0.05) were found for all variables, except $DIFF_{ACDC}$ (F_4 = 1.15; p = 0.33), ACC_{AVG} (p = 0.56) and DEC_{AVG} (p = 0.76). WMF was the position with the greatest ACC_{DIS} covered (436.5 ± 86.3 m; F_4 = 13.63; p < 0.05; ES = 0.9 – 2.3) and resulted in a greater DEC_{DIS} covered compared to CD (104.4 ± 17.2 m; p < 0.05; ES = 1.7), FW (75.2 ± 17.2 m; p < 0.05; ES = 1.1), and MF (105.7 ± 16.9 m; p < 0.05; ES = 1.6). In addition, WMF performed greater ACC_{HIGH} than CD (8.5 ± 2.1; p < 0.05; ES = 1.3) and MF (7.8 ± 2.0; p < 0.05; ES = 1.3), greater DEC_{HIGH} than CD (13.6 ± 3.6; p < 0.05; ES = 1.1), and greater ACC_{MAX} (0.3 ± 0.1 m/s^2; p < 0.05; ES = 0.6) and DEC_{MAX} (0.4 ± 0.2 m/s^2; p < 0.05; ES = 0.5) than MF. MF showed significantly greater ACC_{LOW} than WMF (62.1 ± 14.7; F_4 = 5.93; p < 0.05; ES = 1.1), FW (54.1 ± 14.7; F_4 = 5.93; p < 0.05; ES = 0.9), and CD (51.2 ± 14.7; F_4 = 5.93; p < 0.05; ES = 0.9). MF also resulted in greater DEC_{LOW} than FW (46.8 ± 13.9; F_4 = 3.96; p < 0.05; ES = 0.9) and WMF (43.9 ± 13.9; F_4 = 3.96; p < 0.05; ES = 0.8). However, MF showed lower ACC_{DIS} than WMF (175.8 ± 25.5 m; F_4 = 13.63; p < 0.05; ES = 2.3) and FB (90.5 ± 26.1 m; p < 0.05; ES = 1.1). In addition, FW showed higher values of DEC_{MAX} compared to CD (0.6 ± 0.2 m/s^2; p < 0.05; ES = 0.8).

Table 5. Acceleration profile of professional soccer players and differences between playing positions.

	Position						
Variables	**CD (M ± SD)**	**FB (M ± SD)**	**MF (M ± SD)**	**WMF (M ± SD)**	**FW (M ± SD)**	**p**	**ES**
ACC_{DIS} (m)	290.8 ± 76.0^{d}	351.3 ± 99.3^{cd}	260.7 ± 64.1^{bd}	436.5 ± 86.3^{abce}	333.6 ±118.1^{d}	0.01	0.17-2.32
DEC_{DIS} (m)	229.9 ± 43.0^{d}	271.2 ± 66.3	228.7 ± 54.5^{d}	334.4 ± 74.5^{ace}	259.2 ± 55.9^{d}	0.01	0.03-1.72
ACC_{LOW} (total)	354.7 ± 54.5^{c}	378.1 ± 45.8	405.9 ± 61.9^{ade}	343.8 ± 48.0^{c}	351.7 ± 46.2^{c}	0.01	0.06-1.11
ACC_{HIGH} (total)	26.5 ± 6.1^{d}	30.4 ± 7.6	27.1 ± 5.5^{d}	34.9 ± 6.7^{ac}	29.9 ± 9.6	0.02	0.06-1.32
DEC_{LOW} (total)	355.9 ± 46.9	371.6 ± 45.9	387.4 ± 59.0^{de}	343.5 ± 15.8^{c}	340.6 ± 40.1^{c}	0.01	0.06-0.92
DEC_{HIGH} (total)	50.9 ± 8.6^{d}	54.1 ± 13.3	54.8 ± 12.4	64.5 ± 15.8^{a}	55.2 ± 12.1	0.02	0.04-1.07
$DIFF_{ACDC}$ (total)	-24.4 ± 7.8	-23.7 ± 11.0	-27.7 ± 11.6	-29.5 ± 13.5	-25.3 ± 10.0	0.33	0.07-0.47
ACC_{AVG} (m/s^2)	0.6 ± 0.1	0.6 ± 0.1	0.6 ± 0.1	0.6 ± 0.1	0.5 ± 0.1	0.56	0.03-0.22
DEC_{AVG} (m/s^2)	-0.6 ± 0.1	-0.6 ± 0.1	-0.6 ± 0.1	-0.6 ± 0.1	-0.6 ± 0.1	0.76	0.01-0.26
ACC_{MAX} (m/s^2)	4.5 ± 0.4	4.5 ± 0.3	4.4 ± 0.6^{d}	4.70 ± 0.31^{c}	4.5 ± 0.6	0.01	0.06-0.67
DEC_{MAX} (m/s^2)	-5.7 ± 0.5^{e}	-6.1 ± 0.6	-5.8 ± 0.8^{d}	-6.20 ± 0.9^{c}	-6.3 ± 0.9^{a}	0.04	0.11-0.77

Note. M: mean; SD: standard deviation; ES: effect size. [a]Statistical difference to CD (p < 0.05); [b]Statistical difference to FB (p < 0.05); [c]Statistical difference to MF (p < 0.05); [d]Statistical difference to WMF (p < 0.05); [e]Statistical difference to FW (p < 0.05).

Table 6 gives the descriptive statistics for the sprint profile as well as the significant positional differences observed for all variables, apart from sprint time (F_4 = 2.18; p = 0.07). WMF reached greater V_{MAX} compared to CD (1.4 ± 0.5 km/h; F_4 = 14.47; p < 0.05; *ES* = 0.9), MF (3.5 ± 0.5 km/h; F_4 = 14.47; p < 0.05; *ES* = 2.2), and FW (2.1 ± 0.5 km/h; F_4 = 14.47; p < 0.05; *ES* = 1.2). WMF also resulted in greater SPA compared to CD (7.3 ± 1.1; p < 0.05; *ES* = 1.7), MF (11.3 ± 1.1; p < 0.05; *ES* = 2.9) and FW (7.2 ± 1.1; p < 0.05; *ES* = 1.8). These differences were also observed for SPD covered, which was greater in WMF than CD (189.3 ± 22.5 m; p < 0.05; *ES* = 2.1), MF (250.1 ± 22.1 m; p < 0.05; *ES* = 3.06) and FW (172.9 ± 22.5 m; p < 0.05; *ES* = 2.05). WMF also showed higher SPD_{AVG} than CD (4.7 ± 1.2; p < 0.05; *ES* = 1.46). However, MF was the position with the lowest SPA (4.6 ± 2.9; p < 0.05; *ES* = 1.2 – 2.03) and V_{MAX} (28.5 ± 1.7 km/h; F_4 = 14.47; p < 0.05; *ES* = 0.7 – 2.1).

Table 6. Sprint profile of professional soccer players and differences between playing positions.

	Position						
Variables	**CD (M ± SD)**	**FB (M ± SD)**	**MF (M ± SD)**	**WMF (M ± SD)**	**FW (M ± SD)**	**p**	**ES**
SPA (total)	8.6 ± 3.7^{cd}	11.7 ± 3.9^{c}	4.6 ± 2.9^{abde}	15.9 ± 4.7^{ace}	8.7 ± 3.1^{cd}	0.01	0.04-2.87
SPD (m)	148.9 ± 73.1^{d}	228.3 ± 92.5^{c}	88.2 ± 53.9^{bde}	338.2 ± 103.9^{ace}	165.3 ± 58.1^{cd}	0.01	0.24-3.05
SPD_{AVG} (m)	16.9 ± 2.6^{d}	19.2 ± 3.2	20.1 ± 7.7	21.6 ± 3.8^{a}	19.6 ± 4.8	0.01	0.07-1.45
V_{MAX} (km/h)	30.6 ± 1.4^{acd}	30.7 ± 1.6^{c}	28.5 ± 1.7^{abde}	32.0 ± 1.6^{ace}	29.9 ± 2.0^{cd}	0.01	0.07-2.16
Sprint time (s)	2.5 ± 0.3	2.8 ± 0.4	2.8 ± 1.2	3.1 ± 0.5	2.9 ± 0.7	0.07	0.03-1.45

Note. M: mean; SD: standard deviation; ES: effect size.

[a]Statistical difference to CD (p < 0.05); [b]Statistical difference to FB (p < 0.05); [c]Statistical difference to MF (p < 0.05); [d]Statistical difference to WMF (p < 0.05); [e]Statistical difference to FW (p < 0.05).

Figure 10 describes the Vo required to perform low-intensity accelerations, high-intensity accelerations, low-intensity decelerations, and high-intensity decelerations. On the one hand, low-intensity accelerations required significantly greater Vo than high-intensity accelerations in WMF (0.4 ± 0.2 km/h; p < 0.05; *ES* = 0.12) and FW (0.4 ± 0.2 km/h; p < 0.05; *ES* = 0.13) (Fig. 1a), but no significant differences were found in CD, FB, and MF. On the other hand, high-intensity decelerations were performed at significantly higher Vo than low-intensity decelerations in MF (2.7 ± 0.1 km/h; p < 0.05; *ES* = 0.57), FW (3.3 ± 0.1 km/h; p < 0.05; *ES* = 0.64), FB (3.9 ± 0.4 km/h; p < 0.05; *ES* = 0.71), WMF (4.3 ± 0.3 km/h; p < 0.05; *ES* = 0.75), and CD (4.1 ± 0.7 km/h; p < 0.05; *ES* = 0.79) (Fig. 1b).

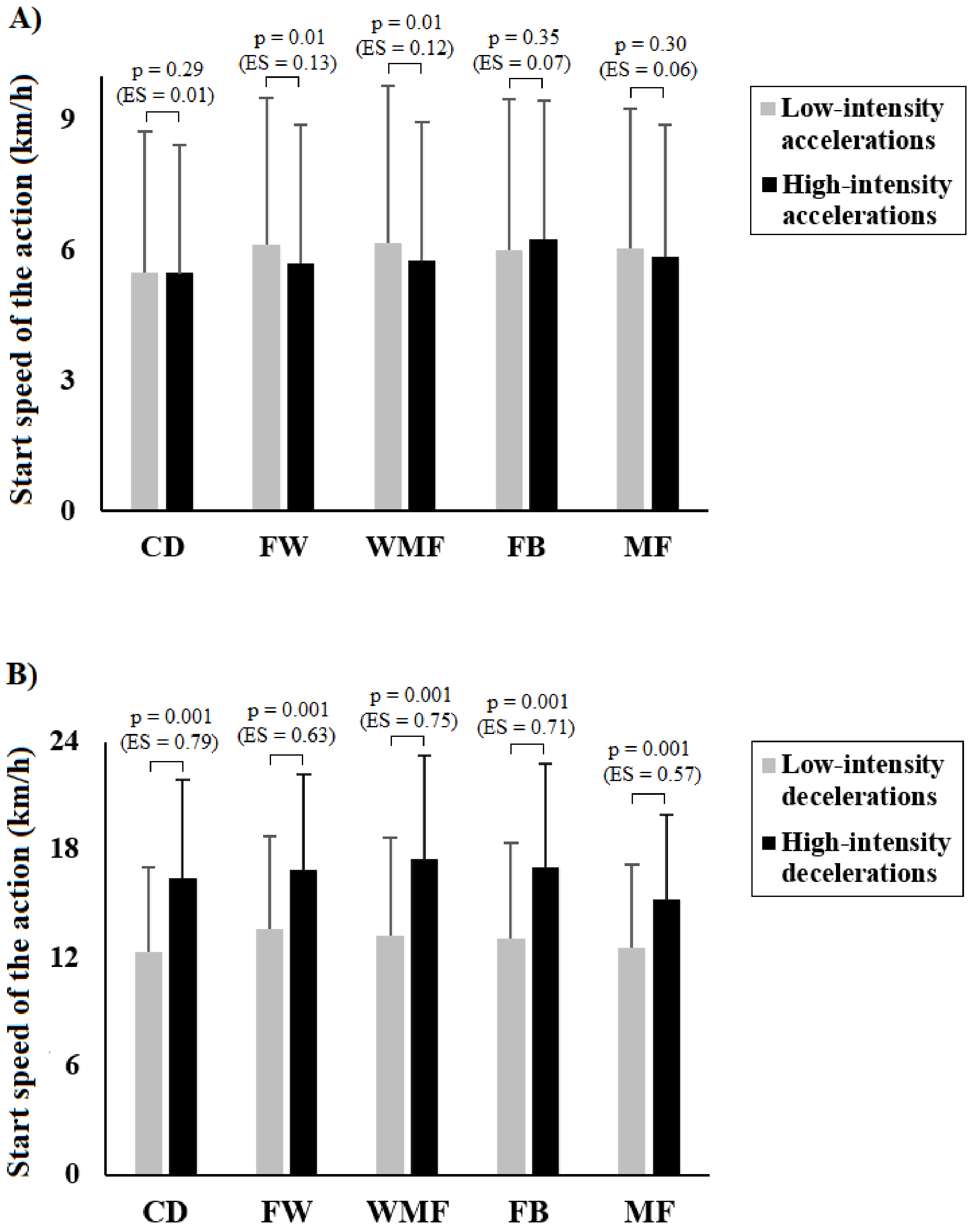

Figure 10. Differences on start speed of the action (Vo) based on the intensity of the accelerations/decelerations; a) Differences between low-intensity accelerations and high-intensity accelerations; b) Differences between low-intensity decelerations and high-intensity decelerations.

6.6. Discussion

The main purpose of this study was to describe the positional differences in the acceleration and sprint profiles of professional soccer players in match-play and to analyze the start speed (Vo) required based on the intensity of the acceleration and deceleration. This study showed positional differences for most variables of the acceleration and sprint profiles. Also, significant differences were observed in Vo when comparing high-intensity accelerations and high-intensity decelerations to low-intensity accelerations and low-intensity decelerations.

This study is the first to provide detailed information on the acceleration and sprint profiles of professional soccer players. Previous investigations (Dalen et al., 2016; Ingebrigtsen et al., 2015; Tierney et al., 2016) have described positional differences for some of the high-intensity profile variables examined in the present study but conclusions from most studies were limited because only a few variables, which are the most common in the literature, were analyzed. These studies have examined, for instance, professional Norwegian (Dalen et al., 2016; Ingebrigtsen et al., 2015) and British (Tierney et al., 2016) soccer teams, and found differences between playing positions for variables of the acceleration profile (Dalen et al., 2016; Ingebrigtsen et al., 2015; Tierney et al., 2016). For example, WMF covered significantly greater ACC_{DIS} (559 ± 232 m) and DEC_{DIS} (456 ± 107 m) than MF (ACC_{DIS}: 559 ± 232 m; DEC_{DIS} 360 ± 120 m) (Dalen et al., 2016). Similarly, our study showed that WMF covered significantly greater ACC_{DIS} (436.5 ± 86.3 m) and DEC_{DIS} (334.4 ± 74.5 m) than MF (ACC_{DIS}: 260.7 ± 64.1 m; DEC_{DIS} 228.7 ± 54.5 m). The same study also found that FB was another position with greater ACC_{DIS} covered (714 ± 298 m) than MF (559 ± 232 m) (Dalen et al., 2016). This suggests that playing in the lateral side of the pitch in addition to the offensive and defensive roles of FB let this position cover longer ACC_{DIS} compared to central playing positions such as MF (Konefał et al., 2015).

With regard to the frequency of the accelerations, another study clearly showed that the totals for ACC_{HIGH} and DEC_{HIGH} were lower than for ACC_{LOW} and DEC_{LOW} (Mark Russell et al., 2016), which represent the nature of soccer as a sport that involves intermittent repeated periods of high-intensity activity (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a) and thus, high neuromuscular fatigue may be developed (Harper et al., 2019). In addition, our results support previous research reporting that WMF always performed a higher amount of ACC_{HIGH} (35 ± 5 accelerations) and DEC_{HIGH} (62 ± 9 decelerations) than CD (ACC_{HIGH}: 27 ± 7 accelerations; DEC_{HIGH}: 45 ± 8 decelerations) (Tierney et al., 2016). Consequently, the variable $DIFF_{ACDC}$ also supports the same study, since the differences between playing positions were repeated once again and a higher number of DEC_{HIGH} than ACC_{HIGH} was observed in all positions (Tierney et al., 2016). However, MF performed significantly greater ACC_{LOW} and DEC_{LOW} than WMF (mean difference, ACC_{LOW}: 62.1 ± 14.7 accelerations; DEC_{LOW}: 43.9 ± 13.9 decelerations) and FW (mean difference, ACC_{LOW}: 54.1 ± 14.7 accelerations; DEC_{LOW}: 46.8 ± 13.9 decelerations) in our study, which may be explained by the fact that density increases (reduced area per player) as the ball is closer to the central zones of the pitch in match play (Fradua et al., 2013). Although WMF also had the highest $DIFF_{ACDC}$ (-27 ± 4), this study reported that FW had the lowest $DIFF_{ACDC}$ (-17 ± 4) (Tierney et al., 2016). Players, therefore decelerate at high-intensity more than they accelerate at high-intensity, so special focus on mechanical load indicators is recommended for strength and conditioning coaches (Dalen et al., 2016). When it comes to the magnitude of the accelerations and decelerations, the results cannot be compared to previous studies (Gaudino et al., 2014; Rago, Silva, et al., 2019), since this is the first study to carry out this analysis in match-play. However, when analysing this variable in training contexts, differences between playing positions remained low for ACC_{MAX} (0.17 ± 0.03 m/s^2) and DEC_{MAX} (0.26 ± 0.03 m/s^2) (Rago, Silva, et al., 2019). Consequently, this study supports the assertion that the acceleration profile is position-dependent and that different training strategies may be adopted to improve match performance and decrease risk of injury (Harper et al., 2019).

Positional differences were found in the sprint profile, and similar conclusions were reached by previous studies that analyzed some of the variables of this profile (Dalen et al., 2016; Palucci-Vieira et al., 2018; M. Varley & Aughey, 2012; Vigh-Larsen et al., 2018). For example, the total of SPA performed by FW (14 ± 6 actions), FB (12 ± 5 actions) and WMF (8 ± 4 actions) was also greater than CD (5 ± 3 actions) in previous research (M. Varley & Aughey, 2012). When it comes to MF, this position showed the lowest amount of SPA not only in our study (5 ± 3 actions) but also in previous research (4 ± 4 actions) (M. Varley & Aughey, 2012). These results may be explained by the fact that this position is limited to reach high-speed actions given its tactical role (e.g., keeping ball possession, passing) and playing area (Bradley et al., 2013; Carling, 2010; Fradua et al., 2013). Also, other studies (Ingebrigtsen et al., 2015; Vigh-Larsen et al., 2018) found that WMF covered the highest SPD (294 ± 76 m and 185 ± 23 m, respectively) whereas CD covered the lowest (123 ± 48 m and 77 ± 17 m, respectively). Thus, SPD_{AVG} was also position-dependent in this study. However, no significant differences (p >

0.05) were observed in a previous study in European professional players (Andrzejewski et al., 2015). In this sense, it is interesting to note that data were collected from players who belonged to ten different teams, which might explain differences in the conclusions reached (Andrzejewski et al., 2015). However, the same study found significant differences between playing positions when comparing V_{MAX}, which is in line with our study (Andrzejewski et al., 2015). Specifically, the V_{MAX} reached by WMF (32.0 ± 1.6 km/h) and FW (29.9 ± 2.0 km/h) was significantly higher compared to CD (30.6 ± 1.4 km/h) in our study as well as in the above-mentioned study (WMF: 32.9 ± 2.0 km/h; FW: 33.1 ± 1.9 km/h; CD: 31.7 ± 1.8 km/h) (Andrzejewski et al., 2015). Similarly, MF showed the lowest V_{MAX} (31.0 ± 1.7 km/h) (Andrzejewski et al., 2015). In this regard, the V_{MAX} from WMF and FW may be explained by their greater SPD_{AVG} (WMF: 21.6 ± 3.8 m; FW: 19.6 ± 4.8 m), which allow them to maximize their acceleration capacity (Andrzejewski et al., 2015). On the contrary, MF are limited to the increase in density of players in central zones of the pitch as explained above (Fradua et al., 2013). The only variable from the sprint profile that did not show significant differences in our study was sprint time, which was in line with previous research, where the largest differences observed between positions ranged from 0.1 to 0.2 seconds (Suárez et al., 2014). Overall, these findings imply that offensive positions such as WMF and FW are subjected to the highest sprint demands, whereas CD, a defensive position characterized by short runs (Ingebrigtsen et al., 2015; M. Varley & Aughey, 2012; Vigh-Larsen et al., 2018), is the least demanding position in respect of the sprint profile in professional soccer.

Finally, another novel finding of this study was that soccer players required significantly higher Vo when performing high-intensity decelerations than low-intensity decelerations across all playing positions (mean difference, CD: 4.1 ± 0.7 km/h; WMF: 4.3 ± 0.3 km/h; FB: 3.9 ± 0.4 km/h; FW: 3.3 ± 0.1 km/h; MF: 2.7 ± 0.1 km/h). However, Vo was significantly greater for low-intensity accelerations than high-intensity accelerations, and only in specific positions (WMF and FW: 0.4 ± 0.2 km/h). These results indicate that the ability to accelerate or decelerate is highly dependent on the Vo of the player, particularly, when decelerating at high-intensity ($p < 0.01$; $ES \sim 0.69$). In this regard, a recent study, which tested maximal accelerations during sprint actions at different Vo, observed a linear decrease in the maximal acceleration when Vo increased (Sonderegger et al., 2016). This may be explained by a typical speed-time curve from any sprint test in which the largest increase in speed is at the start of the action and then, the curve is flattened with increasing running speed (Morin & Sève, 2011; Sonderegger et al., 2016). In consequence, the acceleration capacity decreases at higher speeds (Sonderegger et al., 2016). Training drills could take this into consideration, since it is not only the frequency and intensity of the acceleration that is important, but also the Vo required to perform the acceleration (De Hoyo et al., 2018). However, it is important to understand that players occupying positions such as CD may accelerate or decelerate from lower Vo than players in other positions (De Hoyo et al., 2018). Since soccer players perform actions which start at different Vo (M. Varley & Aughey, 2012), previous studies assumed that different Vo may result in different neuromuscular preload, body inclines and, therefore, different muscle group activation (Sonderegger et al., 2016; Young et al., 2001). Furthermore, the players experience a massive metabolic load every time the acceleration is increased, even when speed is low (Osgnach et al., 2010). Thus, when designing effective match-based drills, these profiles and positional differences may be considered for a more accurate approach to players' performance (De Hoyo et al., 2018). In addition, an individualized approach to performance is needed, since these results lead to the hypothesis that, for example, a faster CD may have more ability to perform high-intensity accelerations and high-intensity decelerations than a slower player in the same position.

There are some limitations that need to be considered when interpreting the findings of this research. The data were collected using GPS technology. Only one professional soccer team was assessed over 13 official matches from a Spanish competition. In addition, not all the players could participate in all the matches. Another limitation of the study is that the effect of different variables such as team formation, competitive standard, or style of play on the acceleration and sprint profiles was not analyzed. Future studies may consider these variables since these variables may affect match running performance (Aquino, Vieira, et al., 2017; Bradley et al., 2011; Yi et al., 2019). For example, a previous study showed that teams which were characterized by possession-play covered greater distance in high-intensity running actions (Yi et al., 2019). Also, although speed and acceleration bands/thresholds were selected according to previous studies (Andrzejewski et al., 2015; Mark Russell et al., 2016), it is worth noting that this issue has not yet been standardized in the literature (Sweeting et al., 2017).

6.7. Conclusion

The findings of this longitudinal study provide meaningful information related to the sprint and acceleration profiles of Spanish professional soccer match-play. This study found that positional differences exist across playing positions in both profiles, which should be considered by strength and conditioning coaches when designing effective match-based drills in training sessions. Also, special focus should be given to WMF since this position was the most demanding of the acceleration and sprint profiles. In addition, only a few studies have analyzed the acceleration-velocity relationship, which is deemed important when designing training drills. Despite strength and conditioning coaches still focusing on training sprint actions starting at zero speed, most of these actions are performed at 5-6 km/h in match-play. In addition, different Vo were observed between high-intensity and low-intensity accelerations as well as high-intensity and low-intensity decelerations. This may potentially affect the neuromuscular load of the players and coaching strategies are necessary in order to maximize players' performance. Finally, these data could also serve as a comparison source for future researchers or sports scientists and coaches from professional soccer teams. For example, if players decelerate at high-intensity more than they accelerate at high-intensity, coaches who choose to put more emphasis on acceleration capacity than deceleration capacity in training sessions should understand that match-play may require the opposite.

CHAPTER 7

Study V. The first, second, and third most demanding passages of play in professional soccer: a longitudinal study

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7. THE FIRST, SECOND, AND THIRD MOST DEMANDING PASSAGES OF PLAY IN PROFESSIONAL SOCCER: A LONGITUDINAL STUDY

7.1. Abstract

The study aimed to compare the physical demands required during the first, second, and third most demanding passages (MDP) of play considering the effect of playing position, type of passage, and passage duration. A longitudinal study for three mesocycles was conducted in a professional soccer team competing in *LaLiga123*. Tracking systems collected total distance covered (DIS), high-speed running distance (HSRD), sprinting distance (SPD), total of high-intensity accelerations (ACC_{HIGH}), and total of high-intensity decelerations (DEC_{HIGH}). The results confirmed that a significant effect of the type of passage (first, second or third MDP of play) on DIS ($F_{(1.24, 178.89)} = 115.53$; $p = 0.01$; $\eta p^2 = 0.45$), HSRD ($F_{(1.35, 195.36)} = 422.82$; $p = 0.01$; $\eta p^2 = 0.75$), SPD ($F_{(1.43, 206.59)} = 299.99$; $p = 0.01$; $\eta p^2 = 0.68$), ACC_{HIGH} ($F_{(1.45, 209.38)} = 268.59$; $p = 0.01$; $\eta p^2 = 0.65$), and DEC_{HIGH} ($F_{(1.45, 209.38)} = 324.88$; $p = 0.01$; $\eta p^2 = 0.69$) was found. In addition, a significant interaction between playing position, type and duration of the passage was observed in DIS ($F_{(12.60, 453.47)} = 1.98$; $p = 0.02$; $\eta p^2 = 0.05$) and ACC_{HIGH} ($F_{(13.99, 503.78)} = 1.92$; $p = 0.03$; $\eta p^2 = 0.06$). In conclusion, significant differences in physical demands between the first, second, and third MDP of play were observed. However, there were some cases (DIS and ACC_{HIGH}) in which no significant differences were found between these passages. Therefore, coaches should consider not only the magnitude of these peak intensity periods (e.g., distance covered per minute) but also the number of passages that players may experience during match play.

7.2. Keywords

Game Analysis, Team Sport, Competition, Performance, Football

7.3. Introduction

Soccer is characterized in its physical nature by an intermittent activity profile, mainly based on continuous changes of direction and speed (e.g., walking, jogging, high-speed running) (Aquino, Munhoz-Martins, et al., 2017; Granero-Gil et al., 2020; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Rago, Brito, Figueiredo, Krustrup, et al., 2020). This activity profile leads to the contribution of both aerobic and anaerobic energy system and hence, its training is a determining factor in performance and injury prevention (Hunter et al., 2015). Many studies have reported that the knowledge of the physical demands of competition is necessary to prescribe the optimum training load, especially in teams competing on leagues with uncongested schedules (i.e., one match per week) (Bangsbo et al., 2006; Clemente, Owen, et al., 2019; Harper et al., 2019). In this sense, previous studies have reported the average physical demands of competition to provide information to strength and conditioning coaches who may replicate the external load demands of competition in training (Bangsbo et al., 2006; Clemente, Rabbani, et al., 2019). However, training tasks aimed at replicating average demands may underestimate match demands (Martín-García, Casamichana, et al., 2018; Martín-García, Gómez Díaz, et al., 2018).

Recent studies suggest that it is important to consider not only the general demands but also the peak demands that the player faces in certain phases of the match (Delaney et al., 2018; Martín-García, Casamichana, et al., 2018). These phases are known as the most demanding passages of play (MDP), which may be also referred as worst-case scenarios (Castellano et al., 2020; Fereday et al., 2020; Martín-García, Casamichana, et al., 2018; Martin-Garcia et al., 2019). These MDP may be set at different durations (e.g., 1, 3, 5, 10 minutes) because a player may cover ~190 meters per minute given a 1-minute passage but a decrease to ~135 meters per minute is observed in 10-minutes passages (Martín-García, Casamichana, et al., 2018).

Currently, there is relatively little evidence published on the MDP in professional soccer. The investigations which are available within the literature show that: i) the MDP are specific periods in which the players are exposed to the greatest physical demands (Fereday et al., 2020; Martín-García, Casamichana, et al., 2018; Martin-Garcia et al., 2019); ii) positional differences exist in different variables of the MDP; iii) the longer the duration of the MDP, the lower the intensity (Delaney et al., 2018; Doncaster et al., 2020; Lacome et al., 2018; Martín-García, Casamichana, et al., 2018); and, iv) differences may exist based on contextual variables such as match half (Casamichana et al., 2019).

However, from a practical perspective, it would be of interest to understand if these MDP of play have any similarity to other highly demanding passages, which may happen during official matches. To the best of the authors' knowledge, there are no investigations available concerning this research question. Taking the first MDP as a reference of peak match demands may lead to misleading conclusions about the MDP of play. Hence, the analysis of successive passages in official matches is considered necessary in order to prescribe the training load considering the match's physical demands. Therefore, the aim of this study was to compare the physical demands required during the first, second, and third most demanding passages (MDP) of play in professional soccer matches considering the effect and interaction of playing position, type of passage, and passage duration.

7.4. Methods

Study design

A longitudinal study for three mesocycles was conducted in a professional soccer team. A total of thirteen consecutive matches from *LaLiga 123* were registered. The research was conducted on a non-congested schedule which consisted of one match per week. The MDP of play were collected by electronic performance tracking systems (RealTrack Systems, Almeria, Spain) based on four passage durations (1, 3, 5 and 10 minutes) (Martín-García, Casamichana, et al., 2018), type of passage (first, second and third) and playing position (central defender, CD: n = 3; full-back, FB: n = 4; midfielder, MF: n = 4; wide-midfielder, WMF: n = 4; forward, FW: n = 5).

Participants

Data was collected from a total of 20 players (age: 26.8 ± 3.8 years old; body mass index: 23.1 ± 0.2) for thirteen consecutive matches. Full-match participation was considered as inclusion criteria. However, goalkeepers were excluded from the study since this playing position has a different activity-profile (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a; White et al., 2018). Informed consent was obtained by the club in order to use the data of the participants once the season finished. This study was approved by the University of Almeria's Ethics Board.

Procedures

The physical demands of the MDP of play were analyzed from the total distance covered (DIS), high-speed running distance (HSRD, above 19.8 km/h), sprinting distance (SPD, above 25.2 km/h), total of high-intensity accelerations (ACC_{HIGH}, above 3 m/s^2) and total of high-intensity decelerations (DEC_{HIGH}, below -3 m/s^2). These variables were reported related to the duration of the passage (i.e., per minute) and each passage was calculated using rolling averages. This procedure was set based on previous investigations on the MDP of play in professional soccer (Martín-García, Casamichana, et al., 2018; Martin-Garcia et al., 2019).

These variables were reported at the end of each match by the software SPro (RealTrack Systems, Almería, Spain) since the data was collected using WIMU Pro (RealTrack Systems, Almería, Spain). These electronic performance tracking systems had Global Positioning Systems (GPS), which allowed the collection of the variables included in this study at 10 Hz sampling frequency. Furthermore, these systems are considered as valid (bias in mean velocity: 1.18-1.32 km/h; bias in distance: 2.32-4.32 m) and reliable (intraclass correlation coefficients: above 0.93) instruments for time-motion analysis in soccer (Bastida Castillo et al., 2018). Each player wore the same tracking system over the data collection period to avoid inter-unit error (Martín-García, Casamichana, et al., 2018). The tracking system was placed in a vertical position in the upper back pocket of a chest vest (Rasán, Valencia, Spain). The data was transferred to SPro software at the end of each match through Smart Station (RealTrack Systems, Almería, Spain). In addition, the number of satellites connected to the device was obtained from "SATCOUNT" channel on SPro software (RealTrack Systems, Almería, Spain) in order to ensure that the data collection was carried out with an adequate connection in every match (Match 1: 7.88 ± 0.75 satellites; Match 2: 8.36 ± 0.93 satellites; Match 3: 7.48 ± 0.97 satellites; Match 4: 7.81 ± 0.59 satellites; Match 5: 8.09 ± 0.99 satellites; Match 6: 9.89 ± 0.72 satellites; Match 7: 8.41 ± 1.04 satellites; Match 8: 8.73 ± 1.49 satellites; Match 9: 9.01 ± 1.11 satellites; Match 10: 8.39 ± 0.73 satellites; Match 11: 8.69 ± 0.73 satellites; Match 12: 9.96 ± 0.87 satellites; Match 13: 10.89 ± 0.83 satellites) (Malone et al., 2017).

Statistical analysis

Descriptive statistics were calculated for all variables based on playing position and passages. The normality of data was obtained using the Shapiro-Wilk test. Besides, Levene's test was used to assess the equality of variances while sphericity was assessed using Mauchly's test (p < 0.05 in all within-subjects variables). A linear model with a mixed-design analysis of variance (ANOVA) for repeated measures was analyzed. DIS, HSRD, SPD, ACC_{HIGH} and DEC_{HIGH} were considered dependent variables. Duration (1, 3, 5 or 10 minutes) and type of passage (first, second or third MDP) were set as within-subjects variables while playing position was set as between-subjects variable. Bonferroni post hoc tests were conducted for the comparison between type of passage. In addition, effect sizes were reported using partial eta-squared (ηp^2). The level of significance was set at alpha 0.05 ($p \leq 0.05$) and the statistical analysis was performed with SPSS Statistics for Windows version 25 (IBM Corp., Armonk, NY, USA).

7.5. Results

Distance covered

Figure 11 shows the comparisons between the types of passage based on the duration of the passage and playing position. The type of passage had a significant effect on the DIS covered in the MDP of play ($F_{(1.24,\ 178.89)} = 115.53$; $p = 0.01$; $\eta p^2 = 0.45$). In addition, a significant interaction between playing position, type and duration of the passage was found for DIS variable ($F_{(12.60,\ 453.47)} = 1.98$; $p = 0.02$; $\eta p^2 = 0.05$).

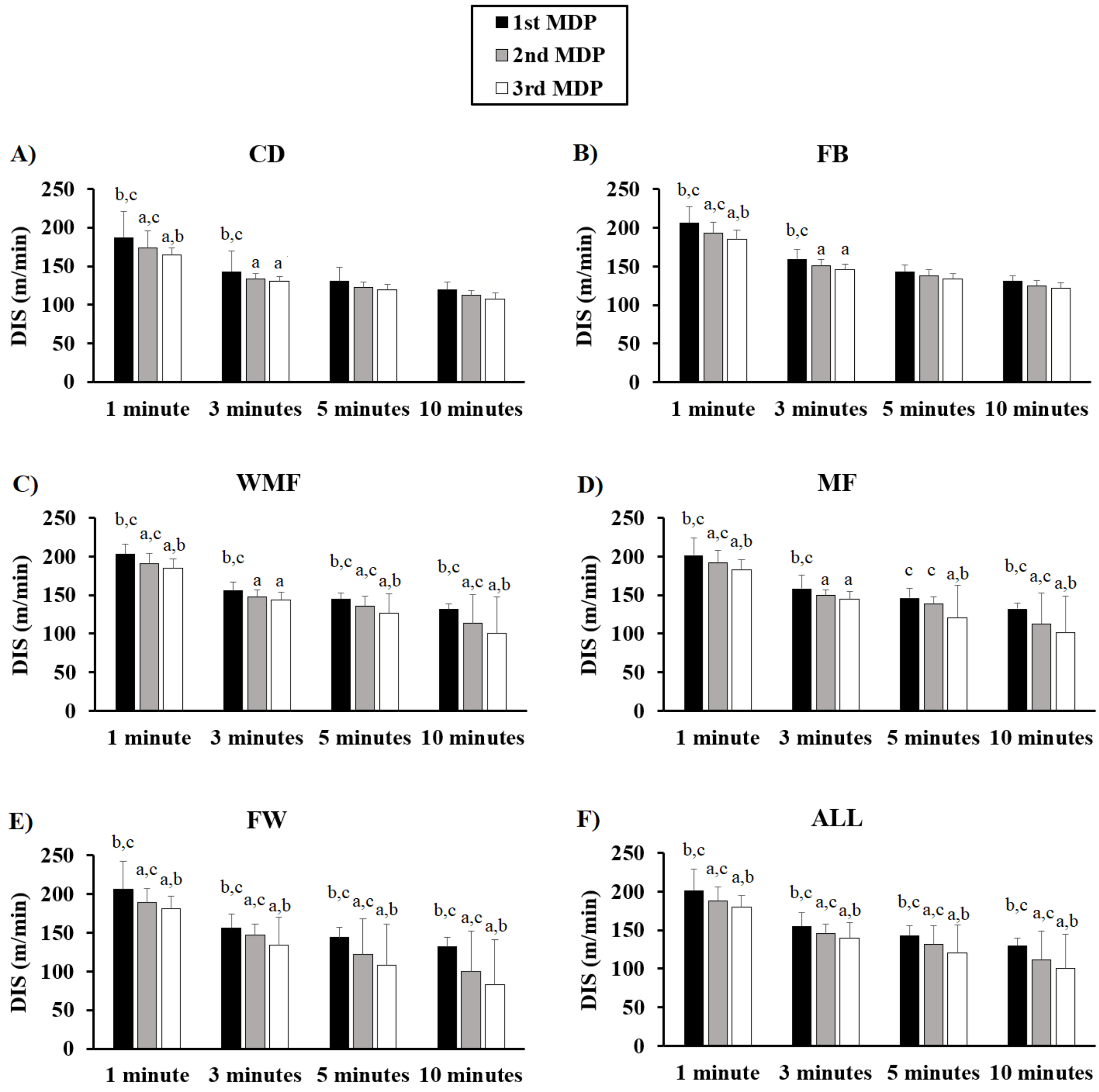

Figure 11. Differences in distance covered (DIS) in meters per minute (m/min) between the first, second and third most demanding passages of play based on the duration of the passage (1, 3, 5 and 10 minutes) and playing position (CD, central defender in Figure 11a; FB, full-back in Figure 11b; WMF, wide-midfielder in Figure 11c; MF, midfielder in Figure 11d; FW, forward in Figure 11e; ALL, team in Figure 11f). Significant differences ($p < 0.05$) compared to the first (a), second (b), and third (c) MDP.

Although significant differences ($p < 0.05$) were found when comparing DIS covered between the types of passage in most MDP, this comparison was not significant in specific cases. For instance, Figure 11a shows that no significant differences were found between the first and second MDP in DIS covered by CD in 5-minutes passages (mean difference: ~8.01 m; p =

0.23), and 10-minutes passages (mean difference: ~7.26 m; p = 0.87); between the first and third MPD in 5-minutes passages (mean difference: ~10.78 m; p = 0.32), and 10-minutes passages (mean difference: ~11.77 m; p = 0.46); and between the second and third MDP in 3-minutes passages (mean difference: ~3.09 m; p = 0.87), 5-minutes passages (mean difference: ~2.77 m; p = 0.99), and 10-minutes passages (mean difference: 4.51 m; p = 0.99).

Figure 11b shows that no significant differences were found between the first and second MDP in DIS covered by FB in 5-minutes passages (mean difference: ~4.73 m; p = 0.88) and 10-minutes passages (mean difference: ~5.29 m; p = 0.99); between the first and third MPD in 5-minutes passages (mean difference: ~8.89 m; p = 0.55) and 10-minutes passages (mean difference: ~8.93 m; p = 0.83); and between the second and third MPD in 5-minutes passages (mean difference: ~4.15 m; p = 0.99) and 10-minutes passages (mean difference: ~3.63 m; p = 0.99).

Figure 11c shows that no significant differences were found between the second and third MPD in DIS covered by WMF in 3-minutes passages (mean difference: ~4.36 m; p = 0.23) and 5-minutes passages (mean difference: ~8.57 m; p = 0.13).

Figure 11d shows that no significant differences were found between the first and second MPD in DIS covered by MF in 5-minutes passages (mean difference: ~7.98 m; p = 0.13); and between the second and third MPD in 3-minutes passages (mean difference: ~4.73 m; p = 0.20).

High-speed running distance covered

When it comes to HSRD covered (Figure 12), the type of passage had a significant effect on the MDP of play ($F_{(1.35,\ 195.36)}$ = 422.82; p = 0.01; ηp^2 = 0.75). However, the interaction between playing position, type and duration of the passage was not significant in this variable ($F_{(9.69,\ 348.66)}$ = 0.64; p = 0.77; ηp^2 = 0.02). Figure 12 shows the comparisons between the types of passage, which were always significant (p < 0.05) based on the duration of the passage and playing position.

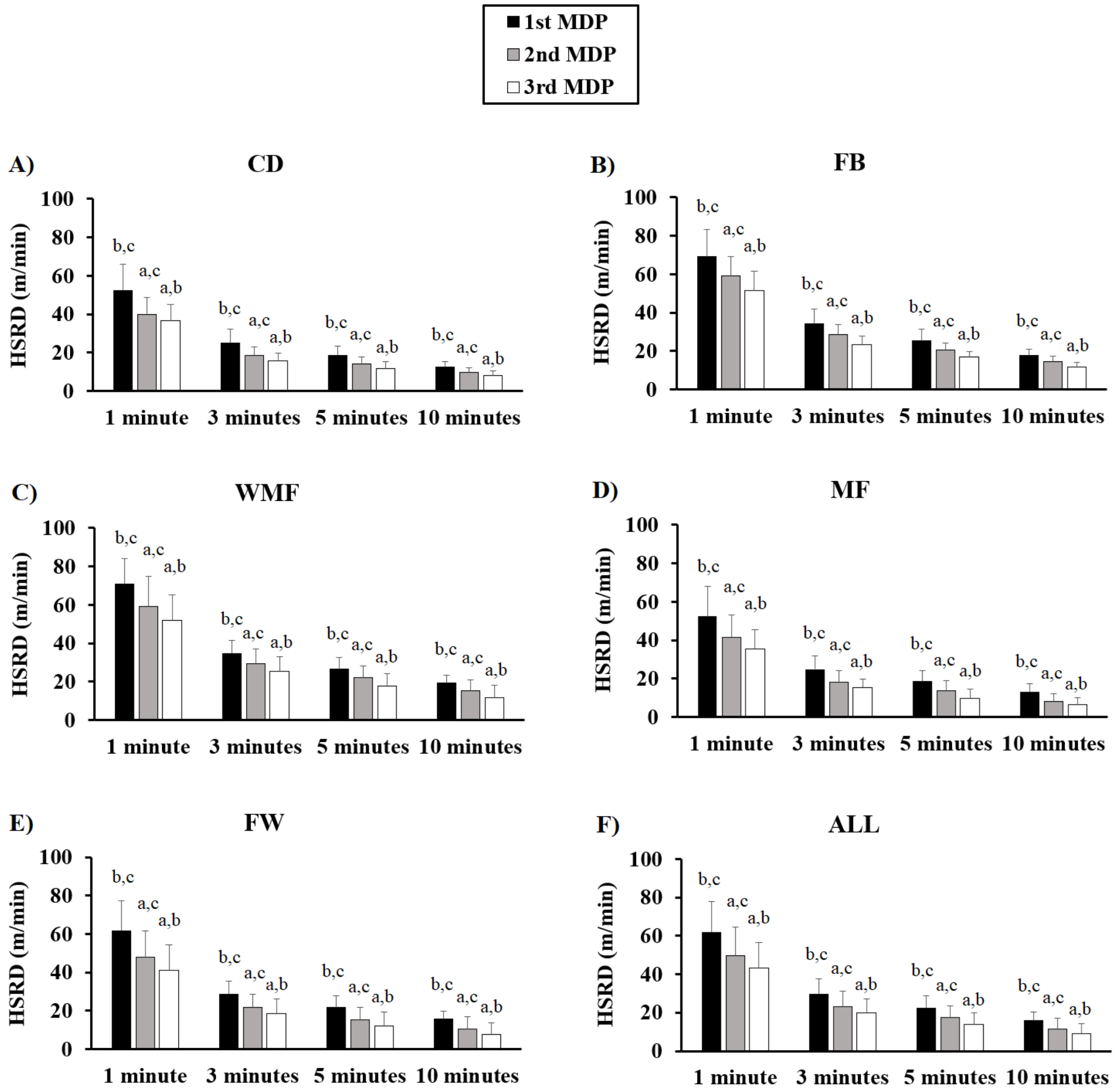

Figure 12. Differences in high-speed running distance covered (HSRD) in meters per minute (m/min) between the first, second and third most demanding passages of play based on the duration of the passage (1, 3, 5 and 10 minutes) and playing position (CD, central defender in Figure 12a; FB, full-back in Figure 12b; WMF, wide-midfielder in Figure 12c; MF, midfielder in Figure 12d; FW, forward in Figure 12e; ALL, team in Figure 12f). Significant differences ($p < 0.05$) compared to the first (a), second (b), and third (c) MDP.

Sprinting distance covered

Figure 13 shows the descriptive statistics of SPD covered by the type of passage, playing position, and duration of the passage. In addition, the type of passage had a significant effect on the SPD covered in the MDP of play ($F_{(1.43, 206.59)} = 299.99$; $p = 0.01$; $\eta p^2 = 0.68$). Regarding the interaction between playing position, type and duration of the passage, it was not significant for SPD ($F_{(7.41, 266.71)} = 1.23$; $p = 0.28$; $\eta p^2 = 0.03$). However, the comparisons between the types of passage were always significant ($p < 0.05$) based on the duration of the passage and playing position (Figure 13).

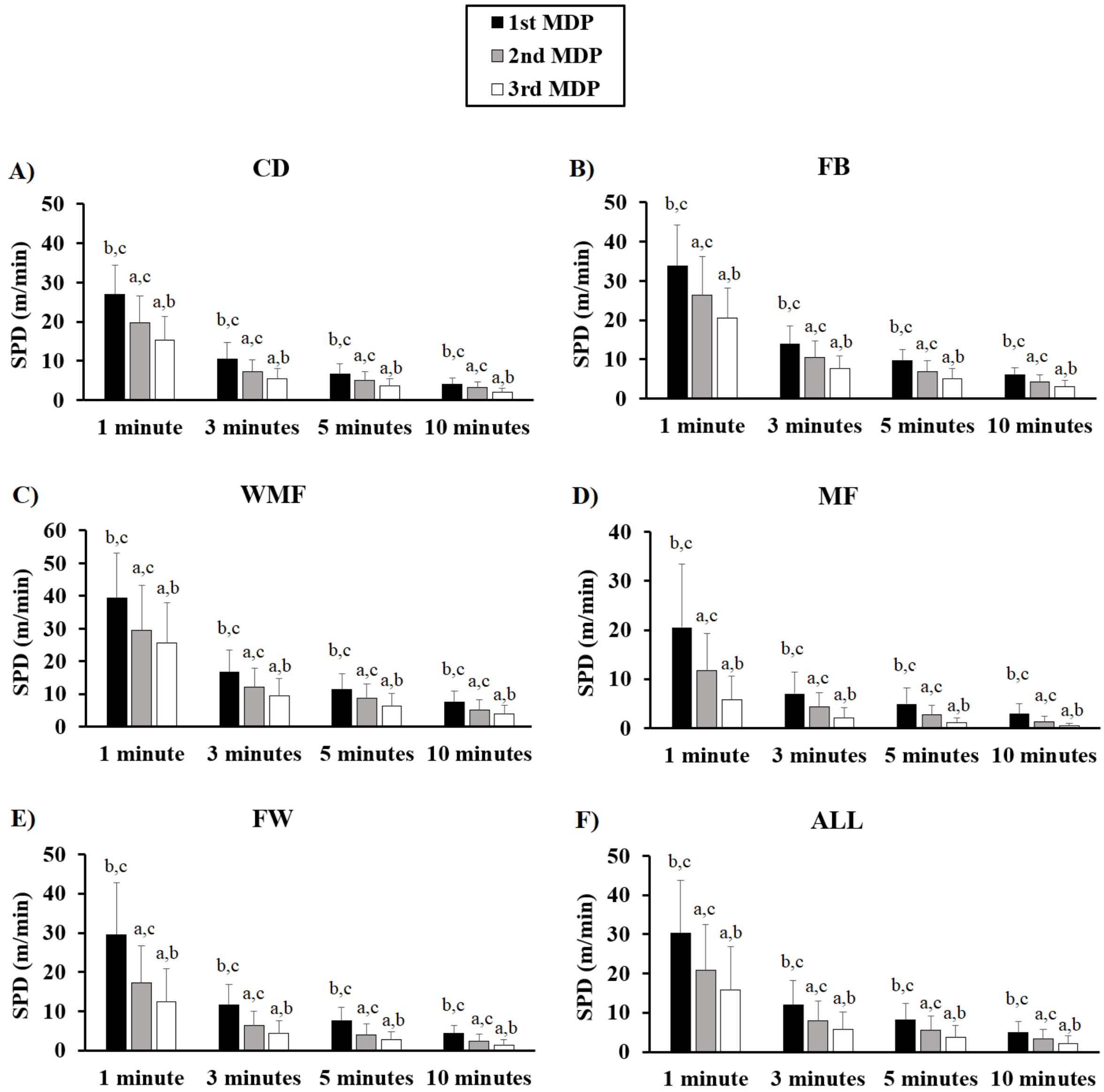

Figure 13. Differences in sprinting distance covered (SPD) in meters per minute (m/min) between the first, second and third most demanding passages of play based on the duration of the passage (1, 3, 5 and 10 minutes) and playing position (CD, central defender in Figure 13a; FB, full-back in Figure 13b; WMF, wide-midfielder in Figure 13c; MF, midfielder in Figure 13d; FW, forward in Figure 13e; ALL, team in Figure 13f). Significant differences ($p < 0.05$) compared to the first (a), second (b), and third (c) MDP.

Total of high-intensity accelerations

When it comes to the total of ACC_{HIGH} (Figure 14), the type of passage had a significant effect on the MDP of play ($F_{(1.45,\ 209.38)} = 268.59$; $p = 0.01$; $\eta p^2 = 0.65$). In addition, there was a significant interaction between playing position, type and duration of the passage for ACC_{HIGH} ($F_{(13.99,\ 503.78)} = 1.92$; $p = 0.03$; $\eta p^2 = 0.06$). The comparisons of ACC_{HIGH} between the types of passage were always significant ($p < 0.05$) based on the duration of the passage and playing position (Figure 14), except for the comparison between the first and second 1-minute passage in CD (mean difference: ~0.25; $p = 0.18$) and 10-minutes passage (mean difference: ~0.14; $p = 0.11$); between the second and third 1-minute passage in FW (mean difference: ~0.19; $p = 0.12$) and 3-minutes passage in CD (mean difference: ~0.11; $p = 0.07$).

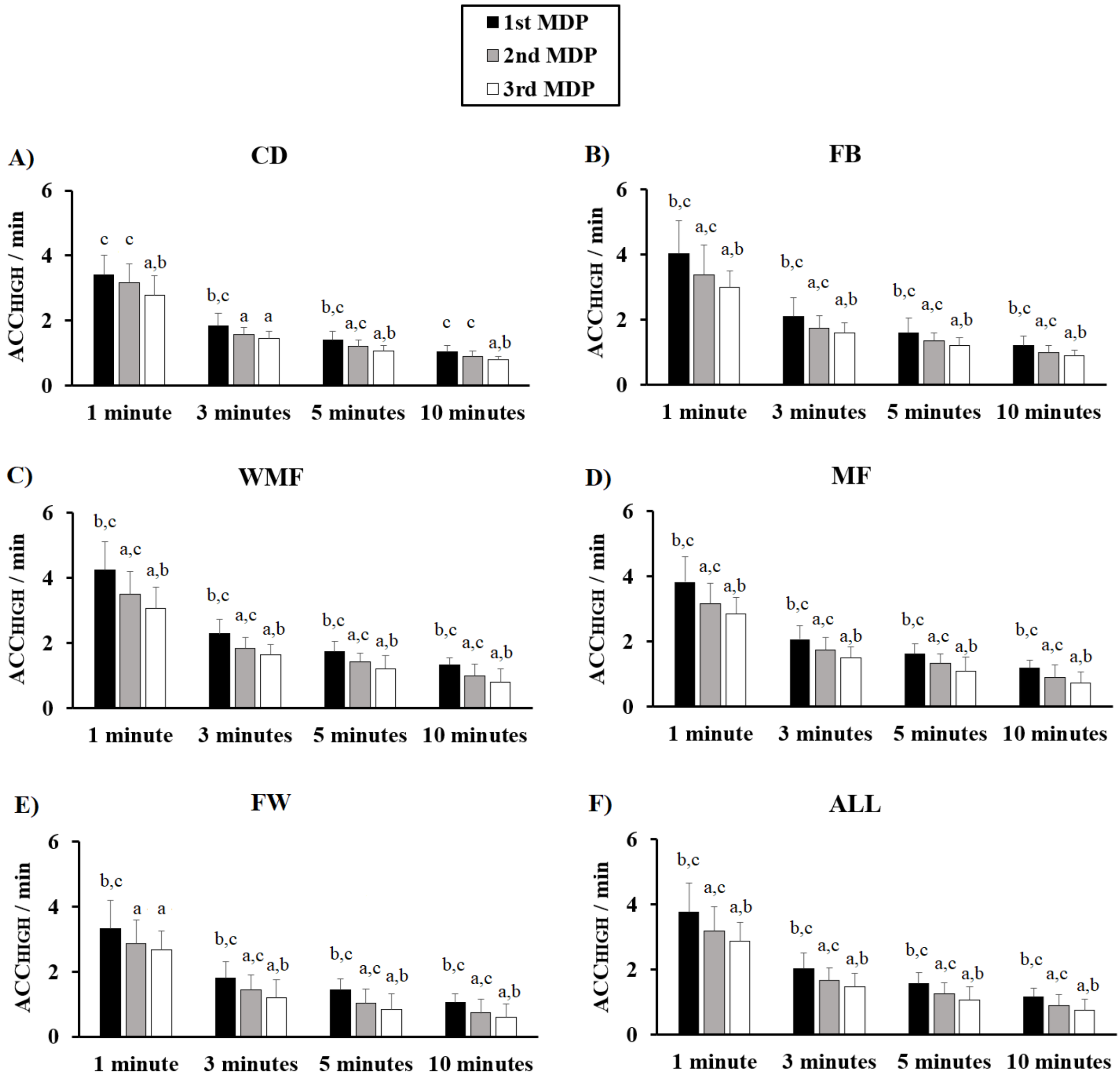

Figure 14. Differences in the total of high-intensity accelerations (ACC_{HIGH}) per minute between the first, second and third most demanding passages of play based on the duration of the passage (1, 3, 5 and 10 minutes) and playing position (CD, central defender in Figure 14a; FB, full-back in Figure 14b; WMF, wide-midfielder in Figure 14c; MF, midfielder in Figure 14d; FW, forward in Figure 14e; ALL, team in Figure 14f). Significant differences ($p < 0.05$) compared to the first (a), second (b), and third (c) MDP.

Total of high-intensity decelerations

Finally, figure 15 shows the descriptive statistics of DEC_{HIGH} by type of passage, playing position, and duration of the passage. The type of passage had a significant effect on the total of DEC_{HIGH} in the MDP of play ($F_{(1.45, 209.38)} = 324.88$; $p = 0.01$; $\eta p^2 = 0.69$). However, the interaction between playing position, type and duration of the passage was not significant in DEC_{HIGH} ($F_{(10.79, 388.55)} = 0.73$; $p = 0.28$; $\eta p^2 = 0.03$). Besides, the comparisons between DEC_{HIGH} based on the type of passage were always significant ($p < 0.05$) based on the duration of the passage and playing position (Figure 15).

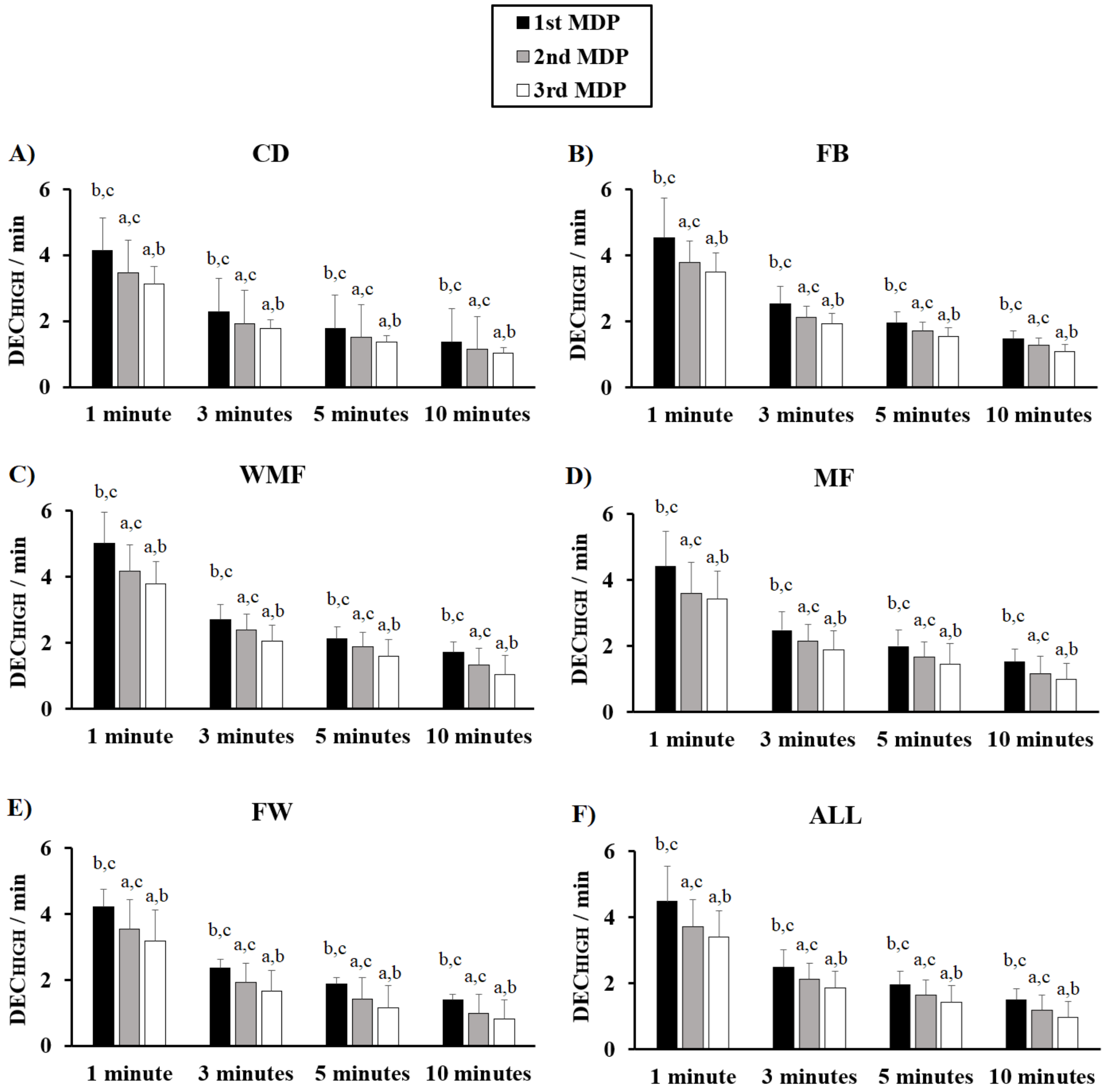

Figure 15. Differences in the total of high-intensity decelerations (DEC_{HIGH}) per minute between the first, second and third most demanding passages of play based on the duration of the passage (1, 3, 5 and 10 minutes) and playing position (CD, central defender in Figure 15a; FB, full-back in Figure 15b; WMF, wide-midfielder in Figure 15c; MF, midfielder in Figure 15d; FW, forward in Figure 15e; ALL, team in Figure 15f). Significant differences ($p < 0.05$) compared to the first (a), second (b), and third (c) MDP.

7.6. Discussion

To the best of the authors' knowledge, this was the first study to investigate if there was any similarity between the first, second and third MDP of play in professional soccer matches. The aim of this study was to compare the physical demands required during the first, second, and

MDP of play considering the effect of playing position, type of passage, and passage duration. One of the main findings of the study was the observed significant effect of the type of passage on all the variables included in the study. The results confirmed that significant differences in physical demands existed between the first, second, and third MDP of play in all playing positions and passage durations. However, a further novel finding was that there were some cases (e.g., DIS and ACC_{HIGH}) in which no significant differences were found between these passages, which implies that coaches should consider not only the magnitude of the MDP but also the number of passages that players may experience in match-play.

Although significant differences ($p < 0.05$) were found when comparing DIS covered between the types of passage in most MDP, this comparison was not significant in specific cases. For example, FB and CD did not show any significant differences in DIS covered between passages for 5-minutes and 10-minutes MDP. This finding reveals that the first MDP cannot be considered as a "unique" period in terms of intensity since the second and third passages are similar to the first one. This may be explained by the fact that the intensity in distance covered per minute decreases in longer passages (Delaney et al., 2018; Fereday et al., 2020; Lacome et al., 2018; Martín-García, Casamichana, et al., 2018) because significant differences between the first, second, and third passages were always observed in 1 minute. In consequence, it is important to consider not only the magnitude (e.g., distance covered per minute) of the peak intensity periods (Bradley & Noakes, 2013; Delaney et al., 2018; Fereday et al., 2020; Fransson et al., 2017; Martín-García, Casamichana, et al., 2018) but also the amount of passages (i.e., how many passages at peak intensity) when analyzing the MDP of play. Specifically, defensive positions such as CD and FB need to be considered since the DIS covered in the first, second and third passages are similar.

When it comes to HSRD, a significant effect from the type of passage on the HSRD covered during the MDP of play was found and significant differences ($p < 0.05$) between the first, second, and third passages were observed in all playing positions and passage durations. This may be an important finding in the understanding of the MDP since the professional soccer players analyzed in this investigation were unable to cover during second or third passages similar HSRD in comparison with the MDP of play. Since HSRD represents the distance covered above 19.8 km/h (Martín-García, Casamichana, et al., 2018; Martín-García, Gómez Díaz, et al., 2018), this high-speed threshold may explain why it is difficult to experience successive peak intensity periods. In this regard, future investigations should be designed in order to explain these results. For example, it would be of interest to analyze the inter-player variability in the MDP of play because a previous investigation found that the greater the speed threshold, the greater the variability (Fransson et al., 2017), which means that there may be players experiencing second or third passages similar to the MDP.

Regarding SPD covered, similar findings to HSRD were found. The SPD covered was significantly different ($p < 0.05$) when comparing between the first, second, and third passages in all passage durations and playing positions. Although the speed threshold, which is set at 25.2 km/h for SPD (Martín-García, Casamichana, et al., 2018; Martín-García, Gómez Díaz, et al., 2018), may be a potential factor for decreasing the ability to reach a high-intensity period as mentioned above, it does not necessarily imply a relationship with physical fitness (M. Buchheit et al., 2012). A previous study observed that match contextual variables related to tactical or strategic requirements were likely to modulate on-field activity patterns (e.g., repeated-sprint activity) independently of the players' fitness (M. Buchheit et al., 2012). Likewise, a recent study found that not all the training tasks (e.g., small-, medium- or large-sided games) were suitable to achieve the SPD from the MDP of play, which suggests that more research is necessary to understand what drills may be designed to train the MDP of play (Martin-Garcia et al., 2019).

In addition, this study included the analysis of acceleration-based variables, whose results were in line with the distance-related variables. A significant effect on the total of ACC_{HIGH} in the MDP of play was found and differences were observed between the first, second, and third passages in most playing positions and passage durations. However, a further novel finding of this study was that no significant differences were observed for CD between the first and second 1-minute passage in CD (mean difference: ~0.25; $p = 0.18$); and between the second and third 1-minute passage in FW (mean difference: ~0.19; $p = 0.12$) or 3-minutes passage in CD (mean difference: ~0.11; $p = 0.07$). Contrary to the findings of our study, DIS covered by CD and FB, in which no significant differences were observed in longer passages (i.e., 5 or 10 minutes), the variable of ACC_{HIGH} did not report significant differences in shorter passages (i.e., 1 or 3 minutes). These results imply that strength and conditioning coaches need to consider the design of training tasks that stimulate the total of ACC_{HIGH} in short periods (Martín-García, Casamichana, et al., 2018; Martin-Garcia et al., 2019). However, these tasks should be aimed at reaching not only the ACC_{HIGH} of the MDP of play but also performing several passages (two or more, from one to three minutes). In this regard, a recent investigation reported an interesting practical implication for this variable since it was observed that training tasks involving a smaller number of players elicited greater ACC_{HIGH} than others with more players (Martin-Garcia et al., 2019). For instance, small-sided games with five or six players may be a good strategy to adapt players for the MDP of play (Castellano & Casamichana, 2013; Martin-Garcia et al., 2019).

When it comes to $DEC_{HIGH,}$ a significant effect of the type of passage was found on the total of DEC_{HIGH} in the MDP of play and significant differences were observed between the first, second, and third passages in all playing positions and passage durations. These results suggest that professional soccer players may experience several peak intensity periods with a high number of DEC_{HIGH}, but the intensity required in the first passage is significantly greater than the second MDP, which was also significantly more demanding than the third passage. Previous investigations on DEC_{HIGH} concluded that the damaging consequences of frequent and intense decelerations require specific loading strategies in order to mechanically protect the players from such consequences (Harper et al., 2019; Harper & Kiely, 2018). DEC_{HIGH} usually last less than one second (Bloomfield et al., 2007a; Harper et al., 2019) and require a high magnitude of mechanical load per meter (Dalen et al., 2016; Harper et al., 2019). Since the mechanical load demands players to repeatedly suffer from high-intensity eccentric actions, the muscle damage and asymmetry in hamstring isometric strength increase (Harper et al., 2019; M. Russell et al., 2016). In consequence, future investigations may analyze if the above-mentioned reasons, which are related to the neuromuscular fatigue of the player, explain why the in DEC_{HIGH} from the first, second, and third MDP are significantly different.

However, this study presents several limitations. Although each player wore the same tracking system over the data collection period to avoid inter-unit error (Martín-García, Casamichana, et al., 2018), the data was collected with GPS technology (Martin Buchheit & Simpson, 2017; Grünbichler et al., 2019). Then, the accuracy of variables such as ACC_{HIGH} and DEC_{HIGH} may be highly dependent on the devices used in this study (Martín-García, Casamichana, et al., 2018) or the satellite connection from each match (Malone et al., 2017). Future research may be conducted using local positioning systems which may increase the accuracy of the data (Bastida Castillo et al., 2018). Also, more variables (e.g., total of high-speed running actions or total of sprints) from the MDP of play could be analyzed since these represent the external load profile in professional soccer (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). Besides, absolute speed and acceleration thresholds were used for the calculation of HSRD, SPD, ACC_{HIGH}, and DEC_{HIGH}. In this regard, recent studies suggest that adding individualized thresholds (e.g., based on the player's maximal acceleration or sprinting speed) are advisable to detect individual differences (Abbott et al., 2018; Rago, Brito, Figueiredo, Krustrup, et al., 2020; Sonderegger et al., 2016).

The findings from this study have several practical applications for strength and conditioning coaches. For example, the magnitude of the MDP of match play from professional soccer players were provided based on playing position, which may serve as a reference for the design of training drills in order to adapt the players from each position to their specific competitive demands. Also, these training drills may be designed for different durations since the data was reported based on typical durations of the training drills (i.e., 1, 3, 5 and 10 minutes). Finally, the results imply that training drills should be designed considering not only the magnitude (e.g., distance covered per minute) of the MDP of play but also the successive passages (e.g., first, second, or third MDP) that players may experience in a match given the effect on the performance variables included in the study.

7.7. Conclusion

The results from this longitudinal study, which was conducted on professional soccer players for thirteen matches, confirmed that a significant effect of the type of passage (first, second or third MDP of play) was found on all the variables included in the study (DIS, HSRD, SPD, ACC_{HIGH}, DEC_{HIGH}). Significant differences in the physical demands existed between the first, second, and third MDP of play in all playing positions and passage durations. However, there were some cases (e.g., DIS and ACC_{HIGH}) in which no significant differences were found between the first, second, and third MDP of play.

CHAPTER 8

Study VI. When do soccer players experience the most demanding passages of match play? A longitudinal study in a professional team

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8. WHEN DO SOCCER PLAYERS EXPERIENCE THE MOST DEMANDING PASSAGES OF MATCH PLAY? A LONGITUDINAL STUDY IN A PROFESSIONAL TEAM

8.1. Abstract

This study analyzed the periods in which the most demanding passages (MDP) of play occurred during professional soccer matches, considering different criterion variables and investigating the effect that the playing position had on the MDP-of-play occurrence for each criterion variable. The MDP of play were calculated based on five criterion variables: distance covered (DIS), sprinting distance covered (SPD), high-metabolic load distance (HMLD), and the total of high-intensity accelerations and decelerations (ACC_{HIGH} and DEC_{HIGH}). The results showed that the first period of the match (0'-15') was the interval with the highest frequency (i.e., the greatest % of cases) in which the players achieved the MDP of play for all the variables (DIS = 38.9%; SPD = 28.4 %; HMLD = 37.7 %; ACC_{HIGH} = 54.3 %; DEC_{HIGH} = 48.8 %). The playing position had no significant effect on MDP-of-play occurrence in any variable (likelihood ratio, LR = 15.88 - 32.05; $p > 0.05$; effect size, ES = 0.01 - 0.04), except for the DIS covered (LR = 32.05; $p = 0.04$; ES = 0.05), in which the most frequent MDP for the full back position occurred within the second period of the match (15'-30'). In conclusion, the study presents novel findings with significant practical implications for strength and conditioning coaches since the first periods of the matches usually elicited the MDP of play and these periods need to be trained to prevent injuries and optimize performance.

8.2. Keywords

Game analysis, worst-case scenario, performance, team sport.

8.3. Introduction

The MDP of play have been studied using different criterion variables (e.g., distance, sprinting distance, and high-intensity accelerations and decelerations) (Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Oliva-Lozano, Fortes, & Muyor, 2020). For example, professional soccer players might perform 3 high-intensity accelerations per minute, 4 high-intensity decelerations per minute or cover 192 meters per minute in the MDP of match play (Martín-García, Casamichana, et al., 2018). In addition, contextual variables such as playing position (Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Oliva-Lozano, Fortes, & Muyor, 2020), match half (Casamichana et al., 2019; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e), playing formation, ball in play or ball possession (Riboli, Semeria, et al., 2021) may have a significant influence on the MDP of play.

However, one of the limitations of these studies is that they usually analyze the load or magnitude of the MDP of play (e.g., the distance covered, the total of accelerations/decelerations or the time spent at different percentages of the MDP) (Casamichana et al., 2019; Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Fortes, & Muyor, 2020; Oliva-Lozano, Gómez-Carmona, Rojas-Valverde, et al., 2021; Riboli, Esposito, et al., 2021) but no information is available regarding the specific period of the match when these passages occur. From a practical perspective, this information would allow coaches to design specific training strategies to prepare the players for the MDP of play. It is assumed that experiencing the MDP of play in the first 15 minutes of the match or in the last 15 minutes of the match might influence the design of training drills.

Therefore, the aims of this study were to: 1) analyze the periods in which the most demanding passages of play occurred during professional soccer matches based on different criterion variables; and 2) investigate the effect that the playing position had on MDP-of-play occurrence for each criterion variable.

8.4. Methods

Study design

Data were collected during 13 consecutive microcycles from a professional soccer team competing in LaLiga 123. The team played one match per microcycle and a total of 13 matches were registered. Since this study aimed to analyze the period in which the MDP occurred, the match was divided into 6 periods, each with a duration of 15 minutes: period 1 (1’-15’), period 2 (15’-30’), period 3 (30’-45’), period 4 (45’-60’), period 5 (60’-75’), and period 6 (75’-90’). Five criterion variables were selected for the MDP of play: distance covered (DIS), sprinting distance covered (SPD, above 25.2 km/h), high-metabolic load distance (HMLD, distance covered when the metabolic power was above 25.5 W/kg), total of high-intensity accelerations (ACC_{HIGH}, above 3 m/s^2), and total of high-intensity decelerations (DEC_{HIGH}, below -3 m/s^2) (Martín-García, Casamichana, et al., 2018).

Participants

Twenty professional soccer players (age: 26.8 ± 3.8 years old; body mass index: 23.1 ± 0.2) took part in the study. The players were categorized by playing position: central defenders (CD, *n* = 3), forwards (FW, *n* = 5), midfielders (MF, *n* = 4), wide midfielders (WMF, *n* = 4) and full backs (FB, *n* = 4). Only players that completed the entire duration of the match were included in the study (total match observations = 161; matches per player = 8.53 ± 3.42). Goalkeepers were not included given the differences in the activity profile for this position (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). The club gave its informed consent to collect the data for this study and approval was also obtained from the institutional ethics board (UALBIO2020/032).

Procedures

Data were collected using WIMU Pro units (RealTrack Systems, Almería, Spain) during 13 official matches. These electronic performance tracking systems, which contain inertial sensors and Global Positioning System (GPS) technology, are frequently used for collecting data on the physical demands in professional soccer (Granero-Gil et al., 2020; Oliva-Lozano, Maraver, Fortes, et al., 2020b; Oliva-Lozano, Fortes, Krustrup, et al., 2020; Rago, Rebelo, et al., 2019). In addition, these tracking systems have been considered as accurate for physical performance analysis (Bastida Castillo et al., 2018; FIFA, 2020). Before the match, the units were calibrated following the manufacturer's instructions (Oliva-Lozano, Maraver, Fortes, et al., 2020b). Then, a member of the research team placed the units in the back pocket of each player's vest (Rasán, Valencia, Spain) 15 minutes before kick-off. The players always wore the same tracking system to avoid inter-unit error (Martín-García, Casamichana, et al., 2018).

Once the match had finished, the data were transferred to SPro (RealTrack Systems, Almería, Spain) via Smart Station (RealTrack Systems, Almería, Spain). The performance report for the MDP of play was obtained on SPro, which used a 1-minute rolling average technique for MDP detection in the five criterion variables (DIS, SPD, HMLD, ACC_{HIGH}, and DEC_{HIGH}) (Oliva-Lozano, Martín-Fuentes, Fortes, et al., 2021). Therefore, the physical demands from the MDP of play were reported in relation to the passage length (i.e., per minute).

Statistical analysis

Firstly, descriptive statistics were obtained to show how often the MDP of play occurred within each 15-minute period, considering the different criterion variables (DIS, SPD, HMLD, ACC_{HIGH}, and DEC_{HIGH}) and playing positions (CD, FB, FW, MF, and WMF). Then, the eta correlation ratio (η) was obtained in order to analyze the association between the playing position and the periods in which the MDP of play occurred during the soccer matches. The Likelihood Ratio Chi-Square statistic (LR) was also used to analyze whether a dependency relationship could be inferred from the sample to the population (i.e., analyzing if the relationship were statistically significant). The fact that more than 20% of the categories had expected frequencies lower than 5 was the reason why the LR statistic was selected instead of the Pearson Chi-Square statistic (Koehler & Larntz, 1980). If there was a significant correlation ($p \leq 0.05$) between the playing position and the periods in which the MDP of play occurred during the soccer matches, the null hypothesis was rejected and the alternative hypothesis was accepted (i.e., the playing position and the MDP of play were significantly associated). In the case of there being a significant association between the variables, adjusted standardized residuals were used to determine among which categories there were large differences between the observed and the expected frequencies. In this regard, an adjusted residual with an absolute value greater than 1.96 indicated that the number of cases within that cell was significantly larger, or smaller, than would be expected if the null hypothesis were true, with a significance level of 0.05.

To complete the exploratory association analysis, a simple correspondence analysis was performed, represented through a perceptual map, which allowed us to graphically compare the relative frequencies and establish the relationships between the different categories of the two qualitative variables considered (the playing position and the criterion variable) as well as the similarities between the categories of each variable. Finally, the eta square (η^2) was obtained as a measure of the effect size. The data analysis was performed using IBM SPSS Statistics version 26 (SPSS Inc., Armonk, NY, USA) with the level of significance set at $p \leq 0.05$.

8.5. Results

Figure 16 shows how often the MDP of play occurred within each 15-minute match period for each criterion variable (DIS, SPD, HMLD, ACC_{HIGH}, and DEC_{HIGH}). The first period (0'-15') was the interval with the highest frequency (i.e., having the greatest total or percentage of cases), in which the players achieved the MDP of play for all the variables over the course of the matches. The following period (15'-30') represented the second most frequent interval in which the MDP was achieved for all the variables, except for SPD. In the case of the SPD, the second most frequent period was at the end of the match (75'-90').

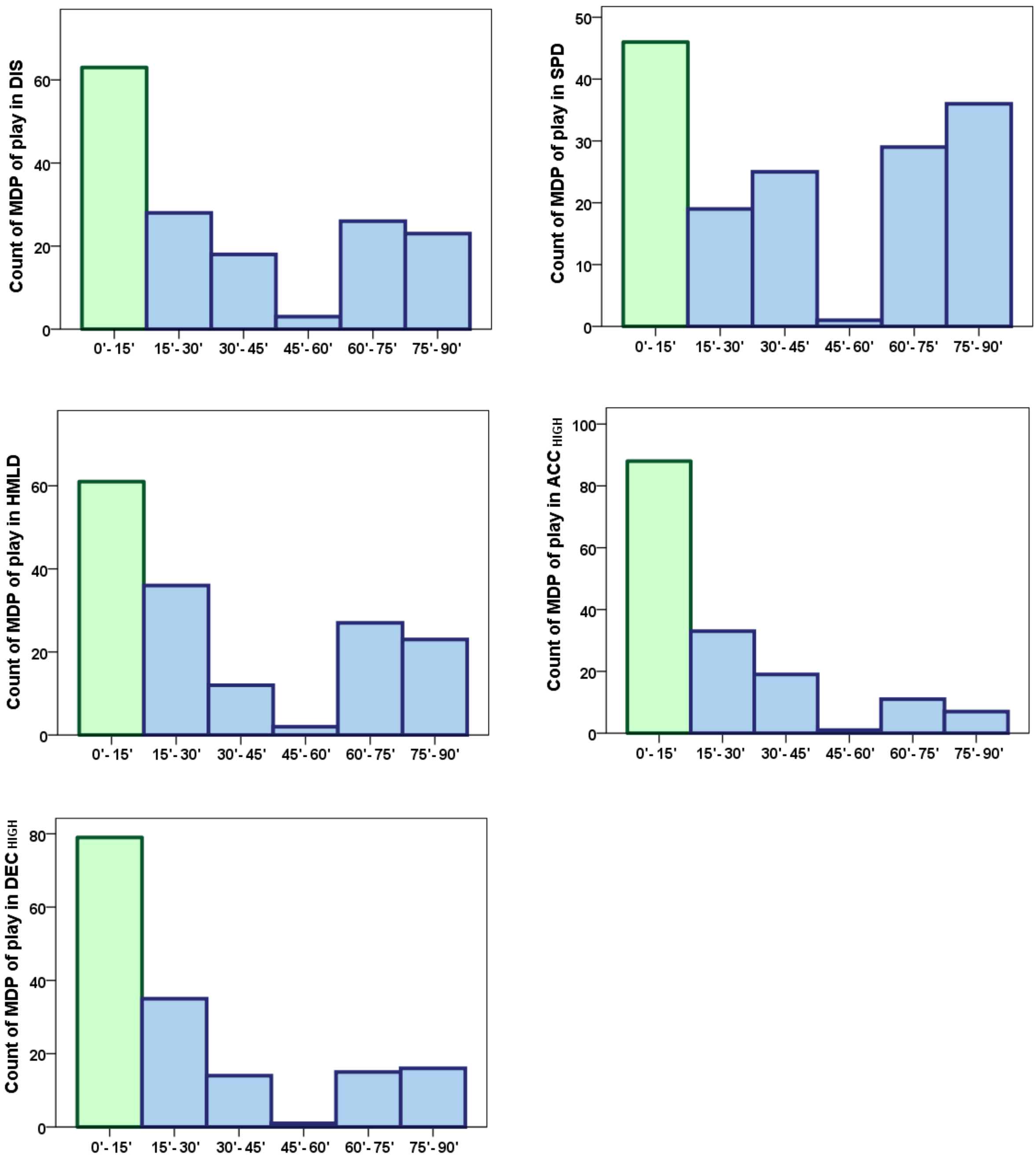

Figure 16. Counts of the most demanding passages (MDP) of play based on the criterion variable and the periods in which the MDP occurred. DIS: distance covered; SPD: sprinting distance covered; HMLD: high-metabolic load distance; ACC_{HIGH}: total of high-intensity accelerations; DEC_{HIGH}: total of high-intensity decelerations.

Table 7 shows the distribution of the MDP of play throughout the match, considering the effect of the playing position for each criterion variable. Regarding the DIS covered, the playing position had a significant effect on the period in which the MDP of DIS occurred (LR = 32.05;

p = 0.04; ES = 0.05); this explains the rejection of the null hypothesis for the independence of the variables at the 95 % confidence level.

Table 7. Distribution of the MDP of play throughout each 15-minute period considering the effect of the playing position for each criterion variable.

Variable	Position	Period						η	LR	*p*	ES
		0'-15'	15'-30'	30'-45'	45'-60'	60'-75'	75'-90'				
DIS	WMF	16 (45.7 %)	6 (17.1 %)	3 (8.6 %)	0 (0 %)	6 (17.1 %)	4 (11.4 %)	0.11	32.05	0.04	0.05
	FW	23 (57.5 %)	3 (7.5 %)	3 (7.5 %)	1 (2.5 %)	5 (12.5 %)	5 (12.5 %)				
	CD	9 (34.6 %)	3 (11.5 %)	5 (19.2 %)	0 (0 %)	4 (15.4 %)	5 (19.2 %)				
	MF	13 (37.1 %)	8 (22.9 %)	3 (8.6 %)	1 (2.9 %)	8 (22.9 %)	2 (5.7 %)				
	FB	2 (7.7 %)	8 (30.8 %)	4 (15.4 %)	1 (3.8 %)	3 (11.5 %)	7 (26.9 %)				
SPD	WMF	7 (20 %)	6 (17.14 %)	7 (20 %)	1 (2.86 %)	7 (20 %)	7 (20 %)	0.11	15.88	0.72	0.01
	FW	15 (37.5 %)	3 (7.5 %)	5 (12.5 %)	0 (0 %)	4 (10 %)	11 (27.5 %)				
	CD	7 (26.9 %)	2 (7.7 %)	5 (19.2 %)	0 (0 %)	4 (15.4 %)	8 (30.8 %)				
	MF	12 (34.4 %)	5 (14.3 %)	3 (8.6 %)	0 (0 %)	8 (22.9 %)	5 (14.3 %)				
	FB	5 (19.2 %)	3 (11.5 %)	5 (19.2 %)	0 (0 %)	6 (23.1 %)	5 (19.2 %)				
HMLD	WMF	10 (28.6 %)	8 (22.9 %)	5 (14.3 %)	1 (2.9 %)	6 (17.1 %)	5 (14.3 %)	0.11	25.13	0.19	0.01
	FW	21 (52.5 %)	4 (10 %)	2 (5 %)	0 (0 %)	5 (12.5 %)	8 (20 %)				
	CD	9 (34.6 %)	6 (23.1 %)	3 (11.5 %)	0 (0 %)	4 (15.4 %)	4 (15.4 %)				
	MF	16 (45.7 %)	8 (22.9 %)	1 (2.9 %)	0 (0 %)	8 (22.9 %)	2 (5.7 %)				
	FB	5 (19.2 %)	10 (38.5 %)	1 (3.8 %)	1 (3.8 %)	4 (15.4 %)	4 (15.4 %)				
ACC	WMF	19 (54.3 %)	7 (20 %)	5 (14.3 %)	0 (0 %)	3 (8.6 %)	1 (2.86 %)	0.15	32.05	0.18	0.02
	FW	30 (75 %)	4 (10 %)	1 (2.5 %)	0 (0 %)	2 (5 %)	2 (5 %)				
	CD	11 (42.3 %)	8 (30.8 %)	5 (19.2 %)	0 (0 %)	0 (0 %)	2 (7.7 %)				
	MF	17 (48.6 %)	7 (20 %)	4 (11.4 %)	0 (0%)	5 (14.3 %)	1 (2.9 %)				
	FB	11 (42.3%)	7 (26.9 %)	4 (15.4 %)	1 (3.8 %)	1 (3.8 %)	1 (3.8 %)				
DEC	WMF	22 (62.9 %)	8 (22.9 %)	1 (2.9 %)	0 (0 %)	1 (2.9 %)	3 (8.6 %)	0.20	21.29	0.38	0.04
	FW	24 (60 %)	7 (17.5 %)	2 (5 %)	0 (0 %)	4 (10 %)	3 (7.5 %)				
	CD	10 (38.5 %)	6 (23.1 %)	4 (15.4 %)	0 (0 %)	5 (19.2 %)	1 (3.8 %)				
	MF	14 (40 %)	8 (22.9 %)	5 (14.3 %)	0 (0 %)	2 (5.7 %)	5 (14.3 %)				
	FB	9 (34.6 %)	6 (23.1 %)	2 (7.7 %)	1 (3.8 %)	3 (11.5 %)	4 (15.4 %)				

Note: η = eta; LR = likelihood ratio; ES = effect size; FW = forward; MF = midfielder; WMF = wide midfielder; FB = full back; CD = central defender.

To further explain this association regarding the MDP of DIS covered, it was necessary to identify which category combinations presented the largest differences between the observed and the expected frequencies. In this regard, Table 8 shows the adjusted standardized residuals. The association between period 1 (0'-15') and the FW position was also significant (adjusted standardized residual = 2.7), as it was between the FB position and period 2 (15’-30’) and period 6 (75’-90’) (adjusted standardized residuals = 2.1). However, the residual was negative (adjusted standardized residual = -3.5) for the association between period 1 (0’-15’) and the FB position, which indicates that fewer players than expected performed the MDP of play within this period.

Table 8. Adjusted standardized residuals for the most demanding passages (MDP) of play in distance covered.

Position	Period					
	0’-15’	**15’-30’**	**30’-45’**	**45’-60’**	**60’-75’**	**75’-90’**
WMF	0.9	0	-0.6	-0.9	0.2	-0.5
FW	2.7	-1.9	-0.9	0.3	-0.7	-0.4
CD	-0.5	-0.9	1.4	-0.8	-0.1	0.8
MF	-0.3	1	-0.6	0.5	1.2	-1.6
FB	-3.5	2.1	0.8	0.9	-0.6	2.1

Furthermore, a simple correspondence analysis was performed and represented through a perceptual map in order to complete the exploratory association analysis between the playing position and the period in which the MDP of DIS occurred (Figure 17). Period 1 (0’-15’) differed most from the other periods, this difference being greater when compared to period 2 (15’-30’) and period 6 (75’-90’). These periods also showed similar behavior compared to period 4 (45’-60’) and period 3 (30’-45’), respectively. In addition, the greatest playing position differences were found between FW (57.5 % of the MDP of play occurred in period 1) and FB (7.7 % of the MDP of play occurred in period 1).

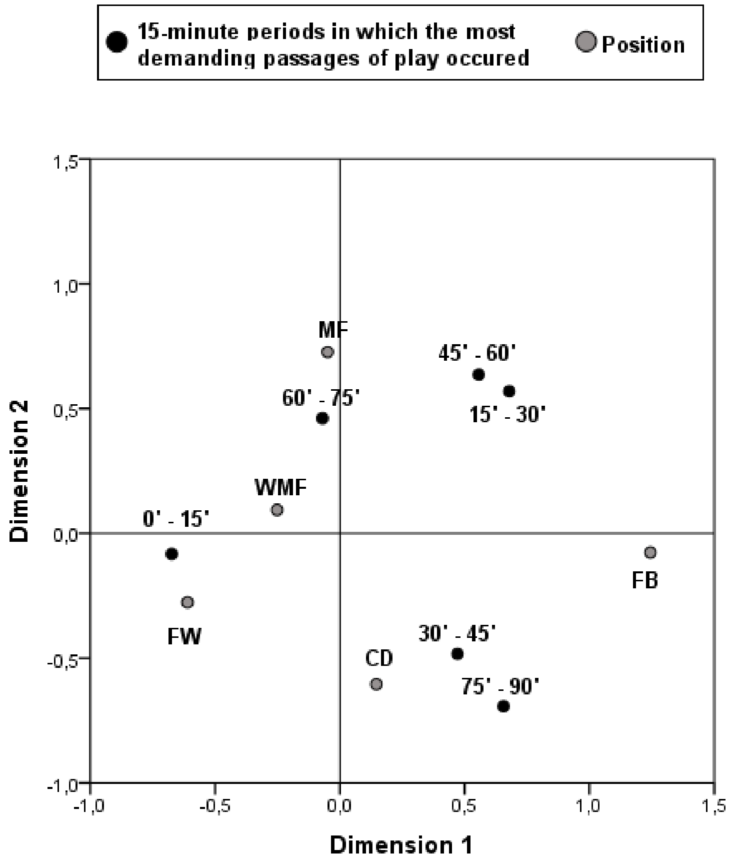

Figure 17. Simple correspondence analysis represented through a perceptual map, showing the relationships between the different categories of playing position (FW, forward; MF, midfielder; WMF, wide midfielder; FB, full back; CD, central defender) and the periods in which the most demanding passage of play for distance occurred. Note: The distance between any row dots or column dots serves as a measure of their similarity (or dissimilarity).

When it comes to the SPD, most of the MDP occurred in period 1 for FW (37.5 %), MF (34.4 %), CD (26.9 %), WMF (20 %), and FB (19.2 %). The results showed that the playing position had no significant effect on the period in which the MDP of SPD occurred (LR = 15.88; p = 0.72; ES = 0.01) so the null hypothesis was accepted for the independence of the variables.

Regarding the HMLD, the most frequent MDP of play occurred during the first period, again for WMF (52.5 %), MF (45.7 %), CD (34.6 %), FW (28.6 %), and FB (19.2 %). In addition, the results showed that the playing position and the period in which the MDP of HMLD occurred presented a low correlation (η = 0.11), and that these variables were not significantly associated (LR = 25.13; p = 0.19; ES = 0.01). In consequence, the null hypothesis was accepted for the independence of the variables.

Finally, similar results were observed for the MDP of play relating to the ACC_{HIGH} and DEC_{HIGH}. The first period reported the most MDP of play for FW (ACC_{HIGH}: 75 %; DEC_{HIGH}: 60 %), WMF (ACC_{HIGH}: 54.3 %; DEC_{HIGH}: 62.9 %), MF (ACC_{HIGH}: 48.6 %; DEC_{HIGH}: 40 %), CD (ACC_{HIGH}: 42.3 %; DEC_{HIGH}: 38.5 %) and FB (ACC_{HIGH}: 42.3 %; DEC_{HIGH}: 34.6 %). The playing position had no significant effect (η = 0.15 – 0.20) on the period in which the MDP of ACC_{HIGH} or DEC_{HIGH} occurred since the null hypothesis was accepted for the independence of the ACC_{HIGH} (LR = 32.05; p = 0.18; ES = 0.02) and DEC_{HIGH} (LR = 21.29; p = 0.38; ES = 0.04) variables.

8.6. Discussion

This study analyzed the periods in which the MDP of play occurred during professional soccer matches, considering different criterion variables and investigating the effect that the playing position had on MDP-of-play occurrence for each of the variables. This innovative approach to the analysis of the MDP of play has significant practical implications for strength and conditioning coaches. For instance, the current study found that the first 15-minute period of the matches (0'-15') elicited the MDP of play for all the variables. In addition, the playing position had no significant effect on MDP-of-play occurrence in any variable, except for the DIS covered, in which the most frequent MDP for FB occurred in the second period of the match (15'-30').

Although the results showed that the MDP of play in DIS are usually experienced during the first match period, a significant dependence relationship was observed between the playing position and the period in which the MDP of DIS occurred. For example, the greatest differences between the playing positions were found between FW (57.5 % of the MDP of play occurred in period 1) and FB (7.7 % of the MDP of play occurred in period 1). In line with previous research, these results suggest that the tactical role of each playing position (e.g., attacking vs defensive positions) (Dellal et al., 2011; Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Oliva-Lozano, Fortes, & Muyor, 2021) might influence MDP-of-play performance. For example, the DIS covered by FB (~195.3 m/min) may be significantly greater than FW (~180.9 m/min) (Martín-García, Casamichana, et al., 2018). However, this interpretation should be viewed with caution because the playing position only explained 4.6 % of the variance in the period in which the MDP of DIS occurred (η^2 = 0.05). Moreover, all the playing positions usually experienced the MDP of

DIS covered during the first 30 minutes of the matches. Therefore, strength and conditioning coaches should take this into consideration when designing training drills aimed at preparing the players for the MDP of play.

When it comes to the MDP of play in the SPD and HMLD covered, similar results were found - the most frequent MDP of play occurred during the first period of the match (0'-15'). This finding agrees with a recent study which observed that the first period of the match (0'-15') elicited most maximum speed actions (Oliva-Lozano, Fortes, & Muyor, 2021). In fact, these results are consistent with previous research, which observed that fatigue decreased the ability to perform physical work as the soccer match progressed (Casamichana et al., 2019; Mohr et al., 2003; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Rampinini et al., 2007, 2009). Moreover, the playing position had no significant effect on the period in which the MDP of SPD or HMLD occurred. Recent studies have also observed declines in the SPD and HMLD covered in the MDP of play during the second half of the match regardless of the playing position (Casamichana et al., 2019; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e). These findings were in line with other research works, which concluded that the high-intensity running distance covered (above 18 km/h, 19.8 km/h, and 30 km/h) by professional soccer players took place within the first 15 minutes of the match (Mohr et al., 2003; Mark Russell et al., 2016). Consequently, these results suggest that soccer players tend to face the greatest demands during the first period of the match.

Regarding the ACC_{HIGH} and DEC_{HIGH}, all the playing positions showed the most frequent MDP of play during the first 15-minute period (0'-15'). Thus, the playing position was not significantly associated with the period in which the MDP of ACC_{HIGH} and DEC_{HIGH} occurred. These results lend support to previous findings in the literature which also observed a decline in the acceleration and deceleration capacity as the match progressed (Akenhead et al., 2013; Dalen et al., 2016; Harper et al., 2019; Mark Russell et al., 2016). For instance, one study found the greatest amount of ACC_{HIGH} (~5) and DEC_{HIGH} (~9) during the first 15-minute period of the match (Mark Russell et al., 2016). This change in the acceleration and deceleration capacity towards the end of the match suggests that these actions are vulnerable to neuromuscular fatigue and, therefore, to an exacerbated risk of injury (Harper et al., 2019).

There are several limitations which should be taken into account when interpreting this study's findings. Firstly, the study sample was limited to one professional soccer team and no training data were included (Oliva-Lozano, Gómez-Carmona, Rojas-Valverde, et al., 2021). Furthermore, the MDP of play were calculated for 1-minute intervals. Futures studies might include longer passages as well (e.g., 3, 5 or 10 minutes) (Oliva-Lozano, Martín-Fuentes, Fortes, et al., 2021). In addition, the effect of match-to-match variability was not considered (Oliva-Lozano, Muyor, Fortes, et al., 2021). Also, it would be of interest to analyze the context of the MDP of play by investigating if these MDP are linked to offensive or defensive actions, running with or without the ball, different playing formations, etc. Lastly, it is important to highlight that individualization of the data (e.g., considering player's maximum speed) and the combination with internal load parameters are necessary for an accurate load monitoring (Oliva-Lozano, Gómez-Carmona, Rojas-Valverde, et al., 2021).

8.7. Conclusion

This study presents novel findings with significant practical implications for strength and conditioning coaches since the first 15-minute period of the matches (0'-15') elicited the MDP of play for DIS, SPD, HMLD, ACC_{HIGH} and DEC_{HIGH}. Apart from the technical and tactical skills required in soccer match play, the MDP of play need to be trained for, considering not only the magnitude of these passages of play (e.g., DIS covered per minute) but also when these passages occur over the course of the game. Given the observed decline in physical performance during the MDP of play as the matches progressed, strength and conditioning coaches should design specific training drills (e.g., from 1-minute to 10-minute passages considering area per player) in order to prepare the players for match's high intensity periods. Repeated sprints and high-intensity interval training may be among the appropriate strategies for developing proficient physical and physiological capabilities in professional soccer players (Turner & Stewart, 2014).

CHAPTER 9

Study VII. When and how do professional soccer players sprint in match play?

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9. WHEN AND HOW DO PROFESSIONAL SOCCER PLAYERS SPRINT IN MATCH PLAY?

9.1. Abstract

The aims of this study were to examine the periods in which the maximum speed actions occurred during professional soccer matches and analyze these actions considering the effect of playing position and different contextual variables. The study was conducted for three mesocycles in LaLiga123 matches. Performance-related variables (V_{MAX}: maximum speed; Vo: starting speed; SPD: sprinting distance; ACC_{MAX}: maximum acceleration; DEC_{MAX}: maximum deceleration) and sprint-related contextual variables (trajectory, ball possession, role, field area in which the action occurred) from each maximum speed action were collected. The first 15 minutes of each match half elicited the greatest amount of maximum speed actions (44.6% of cases), regardless of playing position (likelihood ratio, LR=13.95; p=0.95; effect size, ES=0.16). However, the playing position had a significant effect on the role of the action (Chi-Squared, χ^2=50.68; p=0.001; ES=0.63) and the field area in which the sprint occurred (χ^2=26.54; p=0.001; ES=0.46). Regarding the effect of different contextual variables on the sprint-related performance variables, no significant effect from any contextual variable on ACC_{MAX}, DEC_{MAX} or Vo was found (p>0.05). Nevertheless, the contextual variables had a significant effect on SPD (from ball possession: sprints without the ball > sprints with the ball; trajectory: non-linear sprints > linear sprints; role: offensive sprints > defensive sprints) and V_{MAX} (from ball possession: sprints without the ball > sprints with the ball; playing position: midfielders < other positions). Considering match demands, training drills should be designed to maximize performance in the first 15-minute periods of each half with special focus on non-linear sprints and V_{MAX} (>30 km/h), Vo (7-10 km/h), SPD (>30 m), ACC_{MAX} (>3m/s^2), and DEC_{MAX} (< -4 m/s^2).

9.2. Keywords

Sprint Profile, Game Analysis, Team Sport, Competition, Performance

9.3. Introduction

The selection, testing, and training of soccer players should emphasize the acquisition of sprinting skills (Haugen et al., 2013; Oliva-Lozano, Fortes, Krustrup, et al., 2020). A recent study concluded that professional soccer players need to perform ~10 sprints per match, which require speeds above ~30 km/h (Oliva-Lozano, Fortes, Krustrup, et al., 2020), even though significant performance differences between playing positions may exist (Chmura et al., 2018; Konefał et al., 2019; Oliva-Lozano, Fortes, Krustrup, et al., 2020). This is key for the design of specific training drills and recovery strategies since, for instance, wide-midfielders may perform ~16 sprints per match while central midfielders may perform ~5 sprints (Oliva-Lozano, Fortes, Krustrup, et al., 2020).

Nevertheless, the analysis of the sprint profile of professional soccer players in competitive match play is limited to date (Ingebrigtsen et al., 2015; Oliva-Lozano, Fortes, Krustrup, et al., 2020). Different components of the sprint profile such as the period in which the maximum running speed actions occur or how the players reach their maximum speed (e.g., with or without the ball, linearly or non-linearly, attacking or defending, sprinting in own team's field, or sprinting in opponent team's field) need to be studied considering that the sprinting ability is regulated by a complex interaction of multiple factors (Haugen et al., 2014). Specifically, a better understanding of maximum running sprints considering not only playing position and contextual variables (e.g., ball possession, sprint trajectory, role of the sprint) but also performance-related variables (e.g., distance covered, starting speed, acceleration, and deceleration) is necessary since these are unique actions that occur in the course of the game (Oliva-Lozano, Fortes, Krustrup, et al., 2020).

Furthermore, another limitation of previous research is that there is no information regarding the period in which these sprints occur during professional soccer matches. From a practical standpoint, this is important information given that experiencing the maximum speed actions in the first or last minutes of the match may significantly influence the training drills design. Therefore, the aims of this study were to: 1) examine the periods in which the maximum speed actions occurred during professional soccer matches; and 2) analyze the maximum speed actions registered in match play considering the effect of playing position and different contextual variables.

9.4. Methods

Study design

This study was conducted for three mesocycles in a non-congested schedule, which involved a total of 13 official matches (i.e., one match per week) in LaLiga 123. Sprint-related performance variables were collected using electronic performance and tracking systems. In addition, each match was recorded on video in order to synchronize it with the data collected by the electronic performance and tracking systems.

Participants

A total of 19 male professional soccer players (age: 26.8 ± 3.8 years old; body mass: 23.1 ± 0.2) participated in the study. Each player was categorized according to its playing position (central defenders, CD; full backs, FB; midfielders, MF; wide midfielders, WMF; and forwards, FW). Overall, a total of 127 match observations were available (WMF, *n* = 27; MF, *n* = 27; FW, *n* = 25; FB, *n* = 25; CD, *n* = 24). Only the players who completed the full match were included in the study while goalkeepers could not be included given the different nature of their activity-profile (Oliva-Lozano, Fortes, & Muyor, 2020; White et al., 2018). Informed consent was obtained for the use of data from the participants once the season was completed. Moreover, the study was approved the Bioethics Board of the university.

Procedures

Each player worn a WIMU Pro device (RealTrack Systems, Almeria, Spain) in a chest vest (Rasán, Valencia, Spain) during the matches. These tracking systems contain inertial sensors (four 3D accelerometers, three 3D gyroscopes, one 3D magnetometer, one barometer) and global positioning system (GPS) technology. These devices were selected since previous investigations considered them as valid and reliable instruments for the collection of physical performance parameters (Bastida Castillo et al., 2018) in addition to the approval from the FIFA Quality Programme (FIFA, 2020). Each tracking system was calibrated before the start of the match following the manufacturer's instructions (Oliva-Lozano, Maraver, Fortes, et al., 2020b).

The data were transferred to the SPro software (RealTrack Systems, Almeria, Spain) in order to synchronize each match with the video recorded by 4K-HDR cameras (Sony Corp., Tokyo, Japan). The start of the first and second half was used as a reference for the start and end of the synchronization. Then, the Intervals Pro report from SPro (RealTrack Systems, Almeria, Spain), which showed the sprint-related performance variables (V_{MAX}: maximum velocity in km/h; Vo: starting velocity in km/h; SPD: sprinting distance covered in meters; ACC_{MAX}: maximum acceleration in m/s^2; DEC_{MAX}: maximum deceleration in m/s^2) collected at 10 Hz, was obtained. This allowed the selection of the maximum speed action reached by each player and the observational analysis considering the sprint-related performance variables (i.e., V_{MAX}, Vo, SPD, ACC_{MAX}, and DEC_{MAX} from the maximum speed actions registered in the match) and the following contextual variables: ball possession (i.e., sprint with or without the ball), trajectory (i.e., linear or non-linear sprint), role of the sprint (i.e., offensive or defensive sprint) and field area in which the sprint occurred (i.e., sprint in own team's field area or sprint in opponent team's field area). In addition, each maximum speed action was categorized according to 15 minutes: period 1 (1'-15'), period 2 (15'-30'), period 3 (30'-45'), period 4 (45'-60'), period 5 (60'-75'), and period 6 (75'-90') since the first aim of the study was to this study aimed to examine the periods in which the maximum speed actions occurred.

Statistical analysis

Regarding the first aim of the study, descriptive statistics were obtained to show the periods in which the maximum speed actions occurred during the matches. Then, Chi-Squared test was calculated to analyze the association between the periods in which the maximum speed actions occurred and the playing position. Pearson Chi-Squared statistic (χ^2) was selected unless 20% of the categories had expected frequencies lower than 5 and in this case, the likelihood ratio (LR) statistic was used (Koehler & Larntz, 1980). If the association was not significant between the periods in which the maximum speed actions occurred and the playing position, the null hypothesis for the independence of the variables was accepted at the 95% confidence level. However, if the association between the variables was significant, the null hypothesis was rejected and adjusted standardized residuals were obtained to determine among which categories the differences were large. An adjusted residual with an absolute value higher than 1.96 showed that the number of cases within that cell was significantly greater or lower than would be expected if the null hypothesis were true. Additionally, Crammer's V was reported as a measure of effect size (ES) for chi-squared test (Cohen, 1988).

Regarding the analysis of the association between contextual variables and the maximum speed actions registered by each position for the second aim of the study, Chi-Squared test was applied again with the same criteria than the first aim. However, a multi-factor analysis of variance (ANOVA) through a general linear model was also conducted in order to investigate the effect that playing position (i.e., CD, FB, MF, WMF, and FW) and contextual variables (i.e., ball possession, sprint trajectory, role of the sprint, and field area in which the sprint occurred) had on the sprint-related performance variables (i.e., V_{MAX}, Vo, SPD, ACC_{MAX}, and DEC_{MAX}). Playing position and contextual variables were set as the independent variables while the sprint-related performance variables were set as the dependent variables. Then, Bonferroni post hoc tests were carried out to compare between independent variables. In this case, the effect sizes were reported using partial eta-squared (ηp^2) (Cohen, 1988). The statistical analysis was performed on SPSS Statistics for Windows version 25 (IBM Corp., Armonk, NY, USA) and the level of significance was set at $p \leq 0.05$. However, the statistical power, which was greater than 0.85 in all the variables analyzed for the sample size of the study, was calculated on G*Power software (Heinrich-Heine-Universität Düsseldorf, Düsseldorf, Germany) (Faul et al., 2007).

9.5. Results

Figure 18 shows the distribution of the maximum speed actions throughout each 15-minute period of match play. The period 1 (0'-15': 22.7 % of cases) and the period 4 (45'-60': 21.9 % of cases) reported the greatest amount of maximum speed actions. Also, the results showed that the playing position had no significant effect on the period in which the maximum speed actions occurred (LR = 13.95; p = 0.95; ES = 0.16), which explains the acceptance of the null hypothesis for the independence of the variables at the 95% confidence level.

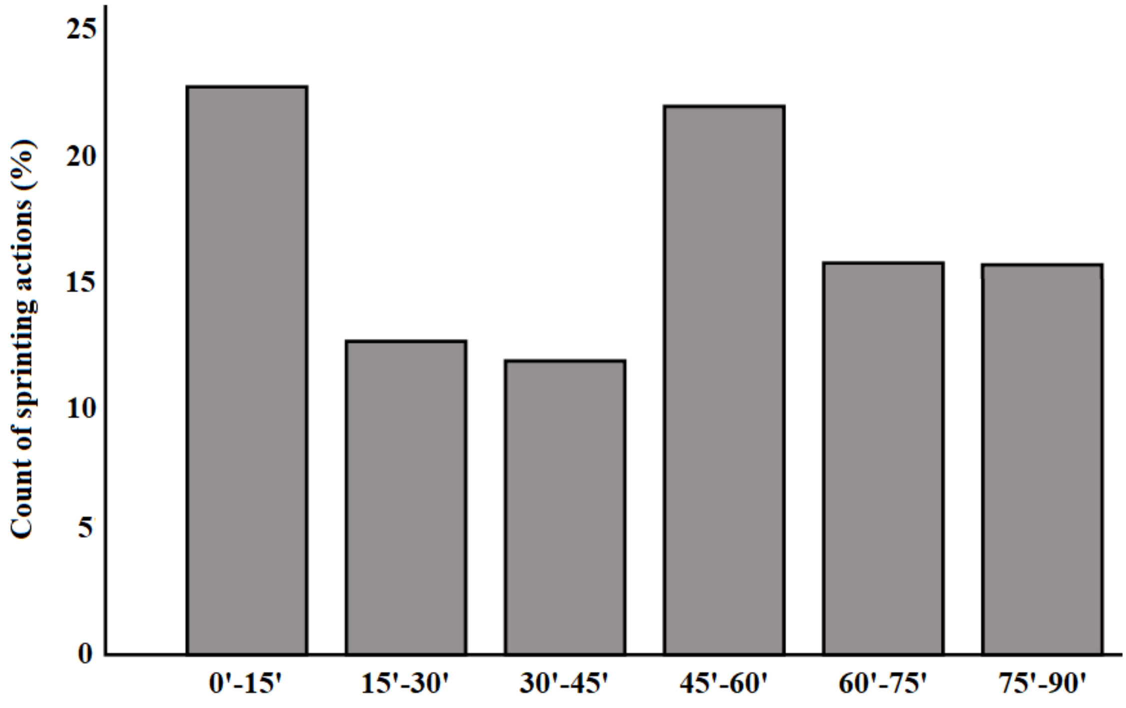

Figure 18. Count of maximum speed actions throughout each 15-minute period of match play.

Table 9 shows the total of maximum speed actions registered in match play considering each contextual variable and playing position. The playing position had no significant effect on sprints with/without the ball (sprints without the ball = 94.5%; sprints with the ball = 5.5% of cases; LR = 2.13; p = 0.71; ES = 0.14) or sprint trajectory (non-linear sprints = 70.3 % of cases; linear sprints = 29.7 % of cases; χ^2 = 5.48; p = 0.24; ES = 0.21).

Table 9. Descriptive statistics for maximum speed actions registered in match play considering each contextual variable and playing position

Variables		**CD**	**FW**	**WMF**	**FB**	**MF**	**ALL**	χ^2	***p***	**ES**
Ball possession	Yes	1 (4.2 %)	3 (12 %)	1 (3.7 %)	1 (4 %)	1 (3.7 %)	7 (5.5 %)	2.13*	0.71	0.14
	No	23 (95.8 %)	22 (88 %)	26 (96.3 %)	24 (96 %)	26 (96.3 %)	121 (94.5 %)			
Trajectory	Linear	11 (45.8 %)	4 (16 %)	7 (25.9 %)	8 (32 %)	8 (29.6 %)	38 (29.7 %)	5.48	0.24	0.21
	Non-linear	13 (54.2 %)	21 (84 %)	20 (74.1 %)	17 (68 %)	19 (70.4 %)	90 (70.3 %)			
Role	Offensive	1 (4.2 %)	23 (92 %)	19 (70.4 %)	11 (44 %)	6 (22.2 %)	60 (46.9 %)	50.68	0.001	0.63
	Defensive	23 (95.8 %)	2 (8 %)	8 (29.6 %)	14 (56 %)	21 (77.8 %)	68 (53.1 %)			
Field area	Own team	22 (91.7%)	6 (24 %)	11 (40.7 %)	16 (64 %)	17 (63 %)	72 (56.3 %)	26.54	0.001	0.46
	Opponent team	2 (8.3 %)	19 (76 %)	16 (59. 3%)	9 (36 %)	10 (37 %)	56 (43.8 %)			

Note: χ^2 = chi squared; *Chi squared statistic represented as the likelihood ratio (LR) given that at least 20% of the categories had expected frequencies lower than 5; ES = effect size; FW = forward; MF = midfielder; WMF = wide midfielder; FB = full back; CD = central defender.

However, the playing position had a significant effect on the role of the sprint action (χ^2 = 50.68; p = 0.001; ES = 0.63). Specifically, a significant association between the role of the sprint action and FW (offensive sprints = 92 %; defensive sprints = 8 %; adjusted standardized residual = 5), WMF (offensive sprints = 70.4 %; defensive sprints = 29.6 %; adjusted standardized residual = 2.8), CD (offensive sprints = 4.2 %; defensive sprints = 95.8 %; adjusted standardized residual = 4.7), and MF (offensive sprints = 22.2 %; defensive sprints = 77.8 %; adjusted standardized residual = 2.9), while the association was not significant between the role of the sprint and FB (offensive sprints = 44 % of cases; defensive sprints = 56 % of cases; adjusted standardized residual = 0.3).

In addition, a significant effect of the playing position on the field area in which the sprint occurred was observed (χ^2 = 26.54; p = 0.001; ES = 0.46), which explains the rejection of the null hypothesis for the independence of the variables at the 95% confidence level. Specifically, the association was significant between the field area in which the sprint occurred and CD (sprints in own team's area = 91.7%; sprints in opponent team's area = 8.3%; adjusted standardized residual = 3.9), and FW (sprints in own team's area = 24 %; sprints in opponent team's area = 76 %; adjusted standardized residual = 3.6).

Figure 19 shows the effect of different contextual variables on the sprint performance. When it comes to the SPD covered, a significant effect from ball possession (sprints without the ball: ~33.81 m > sprints with the ball: ~30.20 m; $F_{(1, 91)}$ = 6.15; p = 0.02; ηp^2 = 0.06), sprint trajectory (non-linear sprints: ~35.45 m > linear sprints: ~29.28 m; $F_{(1, 91)}$ = 6.89; p = 0.01; ηp^2 = 0.07), and role of the sprint action (offensive sprints: ~37.79 m > defensive sprints: ~29.94 m; $F_{(1, 91)}$ = 10.52; p = 0.002; ηp^2 = 0.10) was observed.

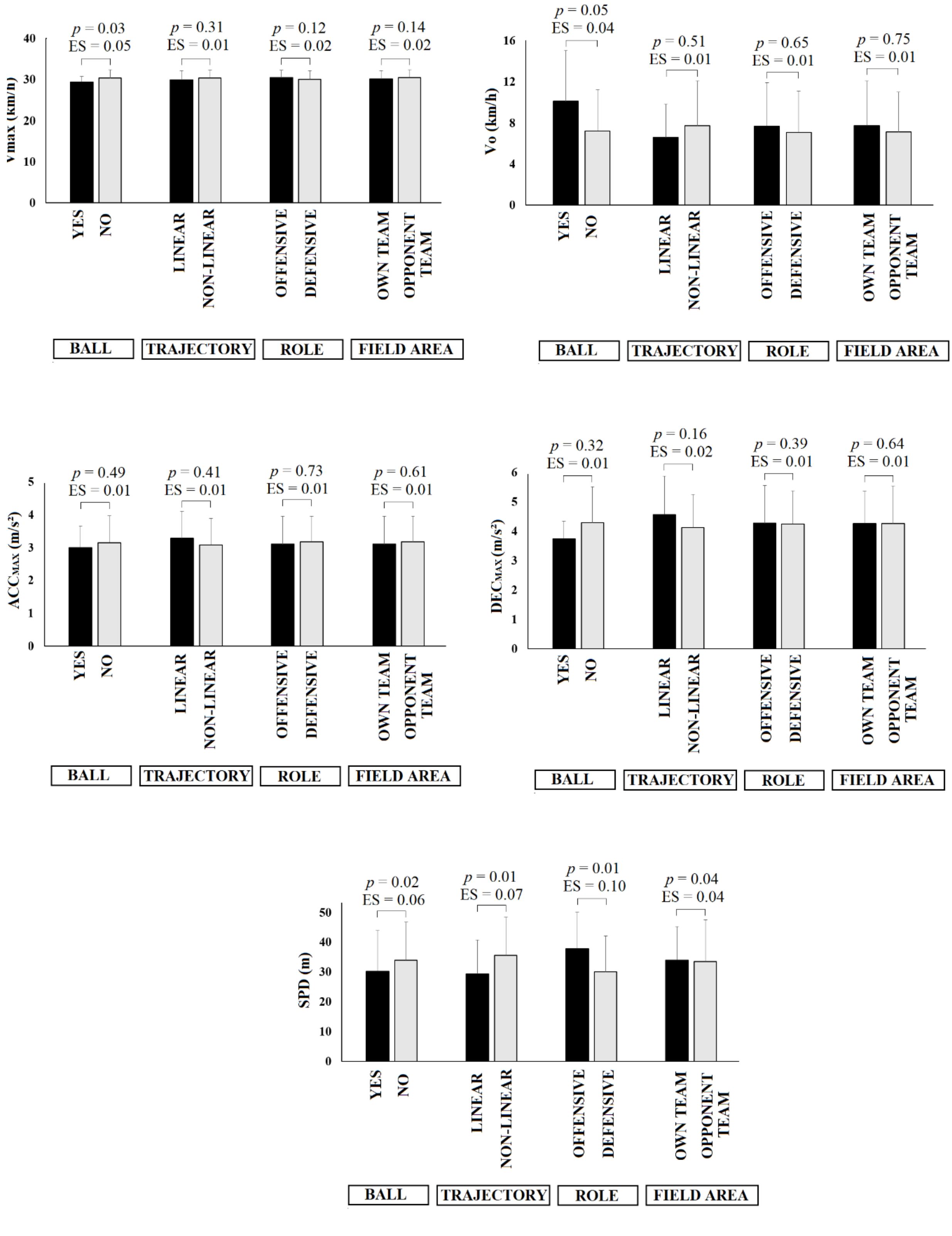

Figure 19. Effect of different contextual variables on the sprint-related performance variables.

Regarding the V_{MAX}, a significant effect from ball possession (sprints with the ball: ~29.43 km/h; sprints without the ball: ~30.33 km/h; $F_{(1, 91)} = 4.98$; $p = 0.03$; $\eta p^2 = 0.05$) was found. In addition, playing position had a significant effect on the sprint performance ($F_{(4, 91)} = 5.79$; $p = 0.001$; $\eta p^2 = 0.20$), being the V_{MAX} from MF (~28.34 km/h) significantly lower than the rest of playing positions (FW = ~30.13 km/h; CD = ~30.41 km/h; FB = ~30.57 km/h; WMF = ~31.94 km/h). However, no significant effect from any contextual variable on ACC_{MAX}, DEC_{MAX} or Vo was observed ($p > 0.05$).

9.6. Discussion

The main purpose of this study was to analyze when and how professional soccer players sprint in match play. One of the novel findings of this study was that the first period of each match half (i.e., period 1 and period 4) elicited the greatest amount of maximum speed actions in competitive match play, regardless of playing position. However, the playing position had a significant effect on the role of the sprint action and the field area in which the sprint occurred. Regarding the effect of different contextual variables on the sprint-related performance variables, no significant effect from any contextual variable on ACC_{MAX}, DEC_{MAX} or Vo was observed. Nevertheless, the contextual variables had a significant effect on SPD (from ball possession, sprint trajectory, and role of the sprint action) and V_{MAX} (from ball possession and playing position).

This study found that the maximum speed actions were more frequent in the beginning period of each match half compared to the rest of periods, regardless of the playing position. To the best of the authors' knowledge, this is the first study to report this findings. However, this goes in line with previous studies, which concluded that the sprint performance was reduced temporarily during and towards the end of each match half (Krustrup et al., 2006; Mohr et al., 2003; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e). Overall, it may be concluded that professional soccer players tend to decrease their physical performance in the second half compared to the first half (Carling & Dupont, 2011; Mohr et al., 2003; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Mark Russell et al., 2016). Specifically, one of these studies also showed that the high-intensity running distance was greater in the first period of each match half compared to the rest of periods (Mohr et al., 2003). Although the reasons why performance is decreased towards the end of the match are unclear, this may be explained by the effect of fatigue associated with reduced glycogen levels (Krustrup et al., 2006; Reilly et al., 2008).

In addition, contextual variables such as the role of the sprint action and the field area in which the sprint occurred were significantly associated with the playing position. For example, offensive positions such as FW and WMF perform significantly greater number of sprints in opponent team's field area and offensive sprints compared to the total of sprints in own team's field area and defensive sprints. These results are consistent with a previous investigation, which showed that FW and WMF performed more offensive sprints (FW = ~20.6 sprints; WMF = ~15.9 sprints) than defensive sprints (FW = ~4.9 sprints; WMF = ~8.7 sprints) (Andrzejewski et al., 2015). On the contrary, the same study found that defensive players such as FB and CD performed more defensive sprints (FB = ~13.2 sprints; CD = ~11.7 sprints) than offensive sprints (FB = ~9.7 sprints; CD = ~1.4 sprints) (Andrzejewski et al., 2015). These differences might be explained by the technical and tactical role of these playing positions (Andrzejewski et al., 2015; Dellal et al., 2011; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e). For example, CD usually perform defensive actions aimed to secure the team's goal area (Andrzejewski et al., 2015) while FW are rarely involved in team's defensive tasks but continually try to receive orthogonal and diagonal passes, reaching the opponent's penalty area and sprinting for taking a shot on goal (Andrzejewski et al., 2014). However, the playing position had no effect on the sprint trajectory or sprints with/without the ball. This is justified by the results which show that most maximum speed actions are non-linear and without the ball. In this regard, a recent study recommended strength and conditioning coaches to implement training strategies that enhance the mechanical efficiency of the players when sprinting in non-linear actions (e.g., curvilinear sprints) (Fílter et al., 2020).

Additionally, although no significant effect from any contextual variable on ACC_{MAX}, DEC_{MAX} or Vo was observed, some contextual variables had an effect on SPD covered and V_{MAX}. For instance, running ball possession in the maximum speed actions decreased the SPD covered and V_{MAX} since running with the ball is not only technically more demanding but also ~10 % more energy-demanding than running without the ball (Piras et al., 2017). Thus, specific training drills need to be designed to improve general running with the ball and dribbling technique at speeds above 25 km/h (Carling, 2010). In addition, these training drills should also consider the offensive and defensive roles of the sprint because the results showed that the players covered greater SPD in offensive sprints compared to defensive sprints. Finally, playing position should also be considered given that the V_{MAX} from MF (~28.34 km/h) was significantly lower than the rest of playing positions (FW = ~30.13 km/h; CD = ~30.41 km/h; FB = ~30.57 km/h; WMF = ~31.94 km/h). This is explained by the fact that the technical-tactical role of MF requires continuous offensive and defensive actions mainly in central zones of the soccer pitch, where the density of players increase (Fradua et al., 2013; Oliva-Lozano, Fortes, Krustrup, et al., 2020). In consequence, training drills need to be designed based on the effect of contextual variables but also considering the demands of match-play. For example, players should be prepared for sprints longer than 30 m, achieving speeds above 30 km/h as well as high intensity accelerations and decelerations (accelerations above 3 m/s^2 and decelerations below -4 m/s^2) (Oliva-Lozano, Fortes, Krustrup, et al., 2020). In addition, the sprinting actions need to include starting speeds about 7-10 km/h despite the fact that fitness coaches still focus on sprinting actions from stationary conditions (Oliva-Lozano, Fortes, Krustrup, et al., 2020).

Nonetheless, it is to mention that this study presents some limitations. For instance, GPS technology was used for the data collection in the matches. However, future investigations may consider the addition of local positioning systems in order to improve the accuracy of the data (Bastida Castillo et al., 2018). Also, this study was focused on sprint-related contextual variables while other match-related contextual variables (e.g., style of play, team formation, match location, match outcome, opponent level) were not analyzed. Future research may consider these limitations to have a better understanding of the impact of match-related contextual variables on sprint performance.

9.7. Conclusion

This study showed that the first period of each match half (i.e., period 1 and period 4) elicited the greatest amount of maximum speed actions in competitive match play, regardless of playing position. Nevertheless, the playing position had a significant effect on the role of the sprint action and the field area in which the sprint occurred. When it comes to the effect of different contextual variables on the sprint-related performance variables, no significant effect from any contextual variable on ACC_{MAX}, DEC_{MAX} or Vo was observed. However, the contextual variables had a significant effect on SPD (from ball possession, sprint trajectory, and role of the sprint action) and V_{MAX} (from ball possession and playing position).

This study presents a novel approach to the literature with results that imply significant practical applications for strength and conditioning coaches. Considering that the first 15-minute periods of each match half elicited the greatest amount of maximum speed actions, training drills should be designed with the aim of maximizing performance in these periods of the match. However, training the resistance to fatigue is also important since situational factors may elicit maximum speed actions at any time of the match. In addition, although non-linear sprints are the most frequent maximum speed actions and special focus should be put on sprints with different trajectories, linear sprint training is also positive since it may lead to improvements in non-linear sprints too (Fílter et al., 2020). Overall, the training drills should be based on the demands of match-play. For instance, players need to be prepared for sprints longer than 30 m, achieving speeds above 30 km/h as well as high intensity accelerations and decelerations (accelerations above 3 m/s^2 and decelerations below -4 m/s^2. Furthermore, the sprints need to be trained with starting speeds about 7-10 km/h.

CHAPTER 10

Study VIII. Exploring the use of player load in professional soccer players

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10. EXPLORING THE USE OF PLAYER LOAD IN PROFESSIONAL SOCCER PLAYERS

10.1. Abstract

The aims of this study were to (1) analyze the distribution of the player load (PL_{TOTAL}) in three axis of movement (PL_{AP}: anterior-posterior; PL_{ML}: medial-lateral; PL_{V}: vertical) during professional soccer matches, (2) investigate the effect of playing position on PL-related variables, and (3) explore the association between PL_{TOTAL} and distance covered by the players.

Data were collected from professional soccer players using WIMU Pro tracking systems (RealTrack Systems, Almeria, Spain), which included inertial sensors. The axis of movement had a significant effect on the distribution of the load ($p < 0.001$; conditional $R^2 = 0.91$), with the greatest contribution from the PL_{V} ($p < 0.001$; $d = 5.41$-5.86). Moreover, no effect of playing position on PL_{TOTAL}, PL_{V}, PL_{ML}, or PL_{AP} was observed ($p > 0.05$). Finally, a large correlation was found between PL_{TOTAL} and distance covered, and the linear mixed model showed that distance may be predicted by the PL_{TOTAL} (conditional $R^2 = 0.81$; $p < 0.001$). Differences in load distribution were based on the axis of movement, although playing position had no effect on any variable. The selection of either distance covered, which is representative of a 2-dimensional analysis, or PL_{TOTAL}, which is representative of a 3-dimensional analysis, may be adequate for monitoring locomotor demands or accelerometer-derived load. Training strategies which focus on the vertical component of match-play should be adopted. In addition, given that PL_{TOTAL} is an accelerometry-based metric which combines the accelerations in anterior-posterior, medial-lateral, and vertical planes, strength and conditioning coaches may use this parameter as a measure of total body load.

10.2. Keywords

External Load, Body Load, Football, Match Analysis, Team Sports.

10.3. Introduction

Current EPTS allow the collection of performance-related variables such as total distance covered, total of high-speed actions, maximum speed, acceleration, and deceleration (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). In addition, most available tracking systems encompass inertial sensors (e.g., accelerometers, gyroscopes, and magnetometers) to understand the three-dimensional (3-D) nature of soccer (Barrett, Midgley, Reeves, et al., 2016). Previously, triaxial accelerometers have been used to quantify external load through specific metrics such as Player Load (PL_{TOTAL}), which is measured in arbitrary units (a.u.) and combines the accelerations in anterior-posterior (PL_{AP}), medial-lateral (PL_{ML}), and vertical (PL_{V}) planes (Boyd et al., 2011; Chambers et al., 2015; Gómez-Carmona et al., 2020; Hulin et al., 2018). Soccer strength and conditioning coaches and practitioners frequently adopt PL_{TOTAL} as a useful load monitoring tool (Gómez-Carmona et al., 2020). For instance, body impacts, which lead to a rise in PL_{TOTAL} (Gómez-Carmona et al., 2020), may increase perceived exertion, upper body neuromuscular fatigue, and plasma creatine kinase (Hulin et al., 2018; Johnston et al., 2014). Thus, although previous literature has focused mainly on positioning-related metrics (e.g., distance covered, total of sprints, accelerations, etc.) (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Palucci-Vieira et al., 2018), the use of PL_{TOTAL} has been extensively used in a wide variety of team sports (Gómez-Carmona et al., 2020).

However, little is known about the distribution of the load for each axis of movement and this might be important for a better understanding of the development of fatigue (Barrett, Midgley, Reeves, et al., 2016). For example, changes of direction, which are frequent actions performed by soccer players, require high mechanical load (Besier et al., 2001; Merks et al., 2021), but repetitive loading of musculoskeletal tissues illustrates damage accumulation consistent with a mechanical fatigue process (Edwards, 2018). Consequently, given the biomechanical nature of changes of direction, PL_{ML} might be a representative variable of these actions regarding the fatigue and muscle damage of the player. Likewise, accelerations and decelerations, which are key load indicators of performance (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d), might be significant contributors to PL_{AP}, as well as tackles or jumps, which might increase PL_{V}.

Also, from a practical standpoint, it is of interest to understand the position-specific workload profiles of match-play in order to prescribe adequate recovery strategies and adapt the training stimulus to the competitive demands (Oliva-Lozano, Gómez-Carmona, Rojas-Valverde, et al., 2021). For example, a recent study showed that midfielders performed more high intensity changes of direction than other playing positions (Granero-Gil et al., 2020). Thus, the match demands may have a direct impact on muscle damage indicators (e.g., increased creatine kinase concentrations) (M. Russell et al., 2016; Souglis et al., 2018). In this regard, a previous investigation found that playing position had a significant effect on the time-course of specific muscle damage, oxidative stress, and inflammation markers following an official soccer match (Souglis et al., 2018). For instance, midfielders showed greater peaks than defenders in all biochemical markers (Souglis et al., 2018). However, research is conflicting with some studies observing that the match demands are also position-dependent (Dalen et al., 2016; Martín-García, Casamichana, et al., 2018) while others concluded that the variance of variables such as PL_{TOTAL} was not significantly explained by the positional role during professional soccer match play (Barrett, Midgley, Reeves, et al., 2016). Further investigations on the PL_{TOTAL} experienced by each position in professional soccer is needed given this variable has received little attention. (Dalen et al., 2016) This analysis might help to understand the post-match fatigue response of professional soccer players (Souglis et al., 2018).

The potential use of PL-related variables for load monitoring purposes in team sports has been suggested by previous investigations (Dalen et al., 2016; Gómez-Carmona et al., 2020). Specifically, PL_{TOTAL} is a key variable for strength and conditioning coaches given that this may be representative of a 3-D performance. Conversely, distance covered or high-speed running actions only represent 2D movements and are frequently investigated in soccer research (Dalen et al., 2016; Gómez-Carmona et al., 2020). However, previous research has found strong associations between PL_{TOTAL} and distance covered in semiprofessional soccer players (Casamichana et al., 2013; Casamichana & Castellano, 2015).

Based on the aforementioned studies, PL_{TOTAL} may be a useful workload parameter (Gómez-Carmona et al., 2020); studies exploring the use of this parameter in professional soccer are necessary. We hypothesized that despite different load distribution between axes of movement, PL_{TOTAL} might be used as a body load indicator for all playing positions. Therefore, the aims of this study were to analyze (1) the distribution of the PL_{TOTAL} in three axes of movement (PL_{AP}, PL_{ML}, PL_{V}) during professional soccer matches, (2) the effect of playing position on PL-related variables, and (3) the association between PL_{TOTAL} and distance covered by professional soccer players.

10.4. Methods

Study design

A longitudinal study was conducted in a professional soccer team, which competed in Spanish LaLiga123. A total of 13 consecutive matches that belonged to the last period of the league were registered. All matches were played in open stadiums (i.e., non-covered stadiums) so wearable tracking systems, which included global positioning system (GPS) and inertial measurement units (e.g., accelerometers, gyroscopes, or magnetometer), were used for the data collection. The data collection was authorized by the club and the Bioethics Committee of the university approved the study (UALBIO2020/032).

Participants

A total of 19 professional soccer players (age: 26.8 ± 3.8 years old; height: 1.79 ± 0.08 m; body mass: 73.6 ± 6.4 kg) were analyzed. Only players completing the total duration of the match were included in the analysis for a final sample size of 12 players, who were categorized according to their playing position (i.e., central defender, full-back, midfielder, wide-midfielder, and forward). Goalkeepers were not included in the study given their different match activity-demands (Oliva-Lozano, Gómez-Carmona, Rojas-Valverde, et al., 2021).

Procedures

Every player was provided with a WIMU Pro tracking system (RealTrack Systems, Almería, Spain), which was placed in the back pocket of the same tight-fitted chest vest (Rasán, Valencia, Spain) in every match. This tracking system consists of 3D accelerometers, gyroscopes, and magnetometers collecting data at 100 Hz as well as 10 Hz GPS (using differential Doppler to obtain velocity). Previous research showed good criterion validity (bias in mean velocity: 1.2-1.3 km/h; bias in distance: 2.3-4.3 m) and reliability (intraclass correlation coefficients: above 0.93) for the collection of physical performance variables in soccer (Bastida Castillo et al., 2018). Also, these tracking systems have the FIFA Quality Programme certificate for the collection of position and velocity metrics (FIFA, 2020). In addition, each tracking system was calibrated before the start of the match following manufacturer's instructions (Oliva-Lozano, Gómez-Carmona, Rojas-Valverde, et al., 2021). For this purpose, one member of the research group placed the tracking systems on a flat surface without surrounding magnetic devices and turned them on. Thirty seconds later, the units were placed in the chest vest.

Data collected by the tracking systems were visualized on SPro software (RealTrack Systems, Almería, Spain) and the following variables were downloaded for each player and match half at the end of the match: player load (PL_{TOTAL}, a.u.), anterior-posterior player load (PL_{AP}, a.u.), medial-lateral player load (PL_{ML}, a.u.), vertical player load (PL_{V}, a.u.), and distance covered in meters (Gómez-Carmona et al., 2020). Also, the total of satellites connected to the device were downloaded from SPro in order to ensure that GPS data collection was carried out with an adequate connection (8.77 ± 1.30 satellites) in all matches (Malone et al., 2017). One member of the research team ensured that the GPS had satellite connection before the start of the matches (Rico-González et al., 2020).

Statistical analysis

Firstly, outliers from the dependent variables were eliminated from the analysis. Specifically, a total of 600 match observations including first and second half data points were included considering each playing position (central defenders, n = 144; full-backs, n = 120; midfielders, n = 123; wide-midfielders, n = 110; forwards, n = 103). Regarding the first aim of the study, the differences between PL_{TOTAL} across the three axes were evaluated via linear mixed models (LMM) with the axes (i.e., PL_{V}, PL_{AP}, PL_{ML}) as fixed effect and half, and player as random effects. In case of statistically significant differences, a post-hoc analysis was calculated using Bonferroni correction. Moreover, for pairwise comparisons with statistically significant differences, effect sizes were calculated via Cohen's d and interpreted as < 0.2 (trivial), 0.20 – 0.59 (small), 0.60 – 1.19 (moderate), 1.2 – 1.19 (large), and ≥ 2.0 (very large) (Hopkins et al., 2009). Regarding the second aim of the study, the difference between playing positions in PL_{TOTAL}, PL_{V}, PL_{AP}, and PL_{ML} were assessed vial LMM with playing position as fixed effect, and half and player as random effects. For the third aim of our study, a LMM was adopted with PL_{TOTAL} as the dependent variable, distance as a fixed effect and half, and player as random effects. All the analyses were conducted on RStudio (version 3.5.2) and significance was set at $p < 0.05$. Based on the sample size of 12 players, the statistical power was greater than 0.8 for all analyzed variables.

10.5. Results

Regarding the first aim of the study, Figure 20 shows the distribution of the PL_{TOTAL} in the three axes of movement (PL_{AP}, PL_{ML}, PL_{V}) during professional soccer matches. Specifically, the axis of movement had a significant effect on the distribution of the PL_{TOTAL} ($p < 0.001$; conditional $R^2 = 0.912$) with significant differences between PL_{V} and PL_{ML} (22.58 ± 0.54 a.u; $p < 0.001$; $d = 5.86$; very large), PL_{V} and PL_{AP} (19.24 ± 0.49 a.u; $p < 0.001$; $d = 5.41$; very large), as well as PL_{AP} and PL_{ML} (3.35 ± 0.41 a.u; $p < 0.001$; $d = 1.13$; moderate).

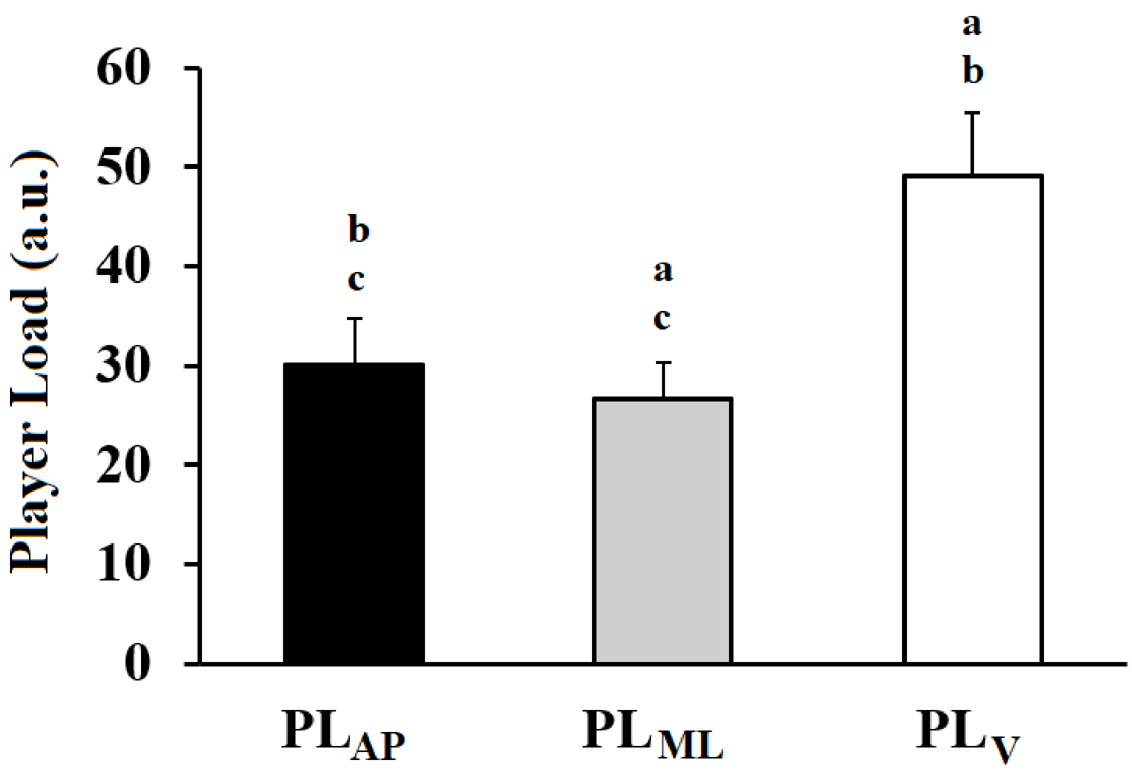

Figure 20. Differences in the triaxial distribution of player load (PL_{AP}: anterior-posterior; PL_{ML}: medial-lateral; PL_{V}: vertical). [a]Statistical difference ($p < 0.001$) to PL_{AP}; [b]Statistical difference ($p < 0.001$) to PL_{ML}; [c]Statistical difference ($p < 0.001$) to PL_{V}.

Moreover, no significant effect of playing position was observed for PL_{TOTAL}, PL_{V}, PL_{ML}, and PL_{AP} (Table 10).

Table 10. Outcomes of linear mixed models with playing position as fixed effect and half and player as random effects

Dependent variable	Fixed effect	Estimate	Std. Error	df	t-value	*p*	R^2	Model Fit
PL_{TOTAL}	*Intercept*	65.0	3.8	12.8	17.0	<0.001	Conditional = 0.646 Marginal = 0.179	AIC = 1305 BIC = 1332
	Forwards	7.7	5.7	11.8	1.3	0.206		
	Full Backs	7.4	5.7	11.8	1.3	0.221		
	Midfielders	8.6	5.2	12.2	1.7	0.119		
	Wide Midfielders	10.9	5.7	11.8	1.9	0.080		
PL_{AP}	*Intercept*	27.1	1.9	12.6	14.3	<0.001	Conditional = 0.612 Marginal = 0.125	AIC = 1037 BIC = 1064
	Forwards	3.8	2.9	11.8	1.3	0.216		
	Full Backs	1.3	2.9	11.7	0.4	0.668		
	Midfielders	3.6	2.6	12.1	1.4	0.190		
	Wide Midfielders	3.6	2.9	11.7	1.2	0.237		
PL_{ML}	*Intercept*	24.1	1.6	13.0	15.3	<0.001	Conditional = 0.717 Marginal = 0.206	AIC = 896 BIC = 922
	Forwards	3.9	2.4	12.0	1.7	0.130		
	Full Backs	2.0	2.4	11.9	0.8	0.411		
	Midfielders	2.5	2.1	12.2	1.2	0.254		
	Wide Midfielders	4.7	2.4	11.9	2.0	0.071		
PL_{V}	*Intercept*	44.1	2.5	12.7	17.8	<0.001	Conditional= 0.621 Marginal= 0.207	AIC = 1164 BIC = 1190
	Forwards	4.0	3.7	11.7	1.1	0.302		
	Full Backs	7.0	3.7	11.6	1.9	0.083		
	Midfielders	6.3	3.3	12.1	1.9	0.082		
	Wide Midfielders	7.4	3.7	11.6	2.0	0.068		

Individual descriptive relationships between PL_{TOTAL} and distance are shown in Figure 21. The LMM analysis showed that PL_{TOTAL} was significantly associated with distance covered (conditional $R^2 = 0.809$; $p < 0.001$ – Table 11).

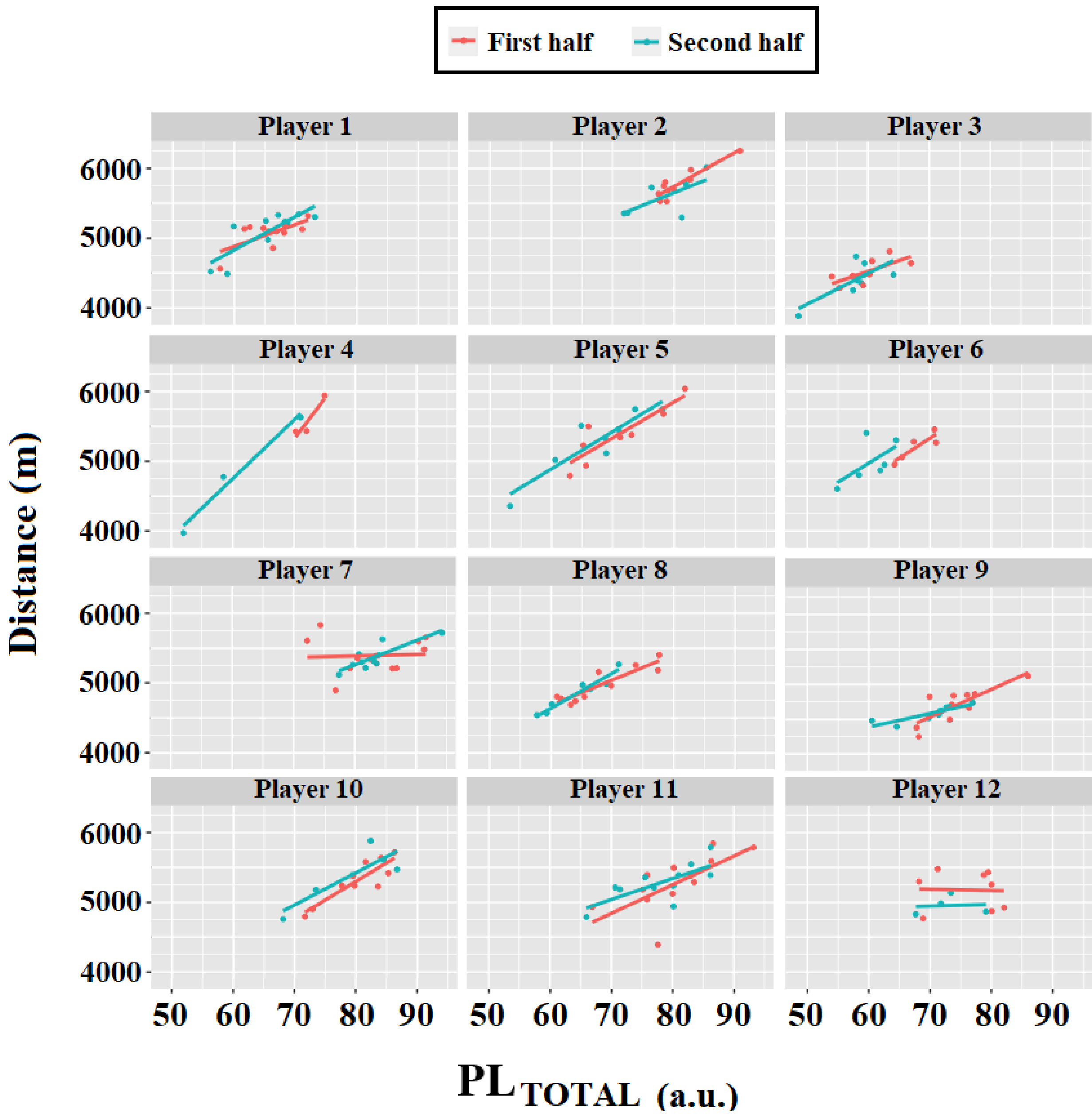

Figure 21. Individual descriptive relationships between distance covered (m) and PL_{TOTAL} (a.u.) in the first and second halves of the matches.

Table 11. Outcomes of linear mixed model with PL_{TOTAL} as dependent variable, distance as fixed effect, and half, and player as random effects.

Dependent variable	Fixed effect	Estimate	Std. Error	df	t-value	*p*	R^2	Model Fit
PL_{TOTAL}	*Intercept*	71.4	1.7	11.7	42	<0.001	Conditional = 0.809	AIC = 1165
	Distance	0.01	<0.001	190	14.2	<0.001	Marginal = 0.435	BIC = 1181

10.6. Discussion

The main purpose of this study was to explore the use of player load in professional soccer by analyzing the distribution of the PL_{TOTAL} in three axis of movement, investigating the effect of playing position on PL-related variables, and analyzing the association between PL_{TOTAL} and distance covered during match-play. The results, which were in line with our hypothesis, showed that the axis of movement had a significant effect on the distribution of the PL, with PL_{V} demonstrating the greatest load. In addition, no effect of playing position on any PL-related variable was observed. Finally, a significant association between PL_{TOTAL} and distance covered was observed, suggesting that strength and conditioning coaches may not need to analyze both volume parameters in their daily monitoring.

Regarding the first aim of the study, the results are consistent with previous studies that analyzed the relative contribution of each axis to the PL_{TOTAL} (Barrett, Midgley, Reeves, et al., 2016; Barrett, Midgley, Towlson, et al., 2016; Page et al., 2015). Specifically, PL_{V} was greater than PL_{AP} and PL_{ML} (Barrett, Midgley, Reeves, et al., 2016; Barrett, Midgley, Towlson, et al., 2016; Page et al., 2015), and PL_{AP} greater than PL_{ML} (Page et al., 2015). These findings demonstrate that each axis of movement contributes to PL_{TOTAL} but in different ways. This might be explained by previous research on soccer players, which showed that players spent ~48.7 % of time moving in a directly forward direction, ~20.6 % of time not moving in any direction and the rest of time moving lateral, backward, diagonal and arced directions (Bloomfield et al., 2007b). Moreover, there are specific actions of match-play such as the sprint, which may require greater PL_{V} and PL_{AP} than PL_{ML}. However, strength and conditioning coaches need to consider that most sprints are non-linear actions (e.g., curve sprints) (Oliva-Lozano, Fortes, & Muyor, 2021), so this might lead to an increase in PL_{ML}. Specifically, curve sprints require the player to generate centripetal forces and lead to different mechanical and neuromuscular behaviors compared to linear sprints (Filter et al., 2020). Given that the PL_{V} contributed most to PL_{TOTAL}, this implies that vertical force production is a critical component of soccer players performance (Loturco et al., 2020). Thus, it is recommended that professional soccer players perform both ballistic and non-ballistic vertically directed exercises (Loturco et al., 2015, 2020) in addition to core exercises for an effective kinetic chains transfer to upper and lower body extremities (Oliva-Lozano & Muyor, 2020). A previous study observed that the first 15 minutes of the match elicited the highest PL_{TOTAL}, PL_{V}, PL_{ML}, and PL_{AP}, and each 15 min period were progressively reduced during the second half (Barrett, Midgley, Reeves, et al., 2016). These previous findings suggest that the individual axes should be monitored as a measure of external load given that this decrease in performance might be associated with the development of fatigue during the match (Barrett, Midgley, Reeves, et al., 2016).

Another finding of this study was that playing position had no significant effect on any PL-related variable. In this regard, a recent study observed that the pattern of development of the PL_{TOTAL}, PL_{V}, PL_{ML}, and PL_{AP} throughout match time was very similar in all playing positions, which implies that physical pacing patterns might be employed by soccer players (Dalen et al., 2020). However, this pattern was not observed for other external load variables such as distance covered, sprinting distance, total of accelerations or total of decelerations (Dalen et al., 2020). This is also consistent with other investigations, which observed that playing position had no significant effect on the locomotor efficiency (i.e., PL_{TOTAL} per meter covered) (Oliva-Lozano, Maraver, Fortes, et al., 2020b) and that the variance in the PL_{TOTAL} was not significantly explained by the positional role during professional soccer match play (Barrett, Midgley, Reeves, et al., 2016). Nevertheless, other researchers also showed that positional differences in PL_{TOTAL} may exist across playing positions (Dalen et al., 2016). For instance, central defenders, midfielders, and wide-midfielders showed 12 %, 18 %, and 26 % greater PL_{TOTAL}, respectively, than full-back players, which may be explained by the technical-tactical role of each playing position in each team (Dalen et al., 2016). These conflicting findings between studies suggest that more research is required to determine the effect of additional contextual factors such as team playing style, playing formation, or league/competition levels on PL variables (Brito Souza et al., 2020; Palucci-Vieira et al., 2018). Although playing position had no significant effect on any PL-related variable in our study, it is also recommended that team performance analysts examine the physical demands for each playing position in order to perform a context-specific analysis.

Finally, a significant relationship between PL_{TOTAL} and distance covered was observed, which is in line with previous research assessing the relationship between training load indicators(Casamichana et al., 2013; Casamichana & Castellano, 2015) ($r > 0.7$ and $p < 0.01$). Although this implies the potential use of PL_{TOTAL} as a significant workload parameter, soccer practitioners should consider if it is necessary to daily analyze both parameters. Given the large number of variables provided by electronic performance tracking systems, one of the greatest challenges is the selection of key performance parameters (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Rojas-Valverde et al., 2020). The results from this study do not mean that PL_{TOTAL} and distance covered are interchangeable variables, but both parameters are strongly correlated. Therefore, the selection of one of them may be enough for load monitoring purposes.

Although this study presents novel findings, some limitations need to be acknowledged. For instance, only competition data were included from only one team. Future studies may include several teams and training data. Also, the tracking systems were placed at the scapulae, but it has been suggested that the center of mass may be a better location to acquire accelerometer data (Barrett, Midgley, Towlson, et al., 2016).

10.7. Conclusion

PL_{TOTAL} and the triaxial data provided by performance tracking systems (i.e., PL_V, PL_{AP}, PL_{ML}) may be used for load monitoring purposes in training sessions and matches. Given the differences observed between each axis of movement, training strategies need to be adopted in order to tolerate the load experienced by professional soccer players. However, given the large contribution of PL_V to PL_{TOTAL}, special focus should be placed on the vertical component. Thus, both ballistic and non-ballistic vertically directed strength and conditioning exercises are recommended. Although playing position had no significant effect on any PL-related variable in our study, it is recommended that team performance analysts examine the physical, technical and tactical demands for each playing position in order to understand context-specific factors influencing PL. In addition, given the relationship between distance covered and PL_{TOTAL}, and that PL_{TOTAL} is a triaxial accelerometry-based metric which combines the accelerations in anterior-posterior, medial-lateral, and vertical movements, strength and conditioning coaches are encouraged to use this parameter as a measure of total body load. For instance, PL_{TOTAL} could be used as a surrogate measure of total distance in stadiums with por satellite coverage.

CHAPTER 11

Study IX. Kinematic analysis of the postural demands in professional soccer match play using inertial measurement units

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11. KINEMATIC ANALYSIS OF THE POSTURAL DEMANDS IN PROFESSIONAL SOCCER MATCH PLAY USING INERTIAL MEASUREMENT UNITS

11.1. Abstract

The development of wearable sensors has allowed the analysis of trunk kinematics in match play, which is necessary for a better understanding of the postural demands of the players. The aims of this study were to analyze the postural demands of professional soccer players by playing position. A longitudinal study for 13 consecutive microcycles, which included one match per microcycle, was conducted. Wearable sensors with inertial measurement units were used to collect the percentage (%) of playing time spent and G-forces experienced in different trunk inclinations, and the inclination required for different speeds thresholds. The inclination zone had a significant effect on the time percentage spent on each zone (p<0.001, ηp^2=0.85) and the G-forces experienced by the players (p<0.001, ηp^2=0.24). Also, a significant effect of the speed variable on the trunk inclination zones was found since trunk flexion increased with greater speeds (p<0.001; ηp^2=0.73), except for midfielders. The players spent most of the time in trunk flexion between 20° and 40°, the greatest G-forces were observed in trunk extension zones between 0° and 30°, and a linear relationship between trunk inclination and speed was found. This study presents a new approach for the analysis of players' performance. Given the large volumes of trunk flexion and the interaction of playing position, coaches are recommended to incorporate position-specific training drills aimed to properly prepare the players for the perception-action demands (i.e., visual exploration and decision making) of the match as well as trunk strength exercises and other compensatory strategies before and after the match.

11.2. Keywords

Football, Posture, Game Analysis, Load, Team Sports, Tracking Systems

11.3. Introduction

Soccer is a team sport which is played in a dynamic environment with considerable demands on the perceptual-motor skills of the players (Vaeyens et al., 2007; Vänttinen et al., 2010; Ward & Williams, 2003). Then, as in other team sports in which the ball, teammates, referees, or opposition players are continually in motion, it is suggested that the understanding of the postural demands met by the players when performing sports-specific skills would provide coaches and performance analysts with meaningful information about the performance in perception and action (Warman et al., 2019). For example, the downward orientation of the head and the trunk may restrict the ability to perform in the field of regard (Lim et al., 2017; Warman et al., 2019). However, soccer players usually play the ball with the feet, which may increase the trunk flexion and move the field of regard down (Warman et al., 2019). Also, the increase in trunk flexion is a natural movement given the increase in speed (Souza, 2016), which suggests that the analysis of the trunk inclination required for different speeds thresholds is necessary.

In addition, the trunk kinematics have a significant effect on knee and hip energetics in running (Teng & Powers, 2014a), hamstring injury (Schuermans et al., 2017), patellofemoral joint stress (Teng & Powers, 2014b), and low back pain in professional soccer players (Grosdent et al., 2016). For instance, a previous study found that upright trunk posture in running was associated with greater patellofemoral joint stress than running with forward trunk flexion (Teng & Powers, 2014b). In this regard, another study concluded that running with an upright trunk posture increased knee extensors' energy generation and absorption while incorporating ~10 degrees trunk flexion decreased such energy generation and absorption (Teng & Powers, 2014a).

Moreover, soccer is a sport which involves different high-intensity actions such as accelerations, decelerations, sprints, changes of directions, jumps, collisions, or landings (Granero-Gil et al., 2020; Oliva-Lozano, Fortes, & Muyor, 2020; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Riboli, Semeria, et al., 2021). In this context, the ankles, knees and hip chained to the spine play a crucial role as shock absorbers since the magnitude and total of shocks on the musculoskeletal system lead to chronic injury risks in recreational runners (Lindsay et al., 2014; Simoni et al., 2020). For instance, the trunk acceleration magnitude (i.e., G-force) is highly correlated to the forces lending to the mechanics of injury (Lindsay et al., 2014). These accelerations, which are measured by inertial measurement units that register triaxial movements (x, y, and z), are considered as an important external workload indicator (Gómez-Carmona et al., 2020; Oliva-Lozano, Maraver, Fortes, et al., 2020b). In consequence, the understanding of the G-forces placed on the trunk when performing activities involving running actions is considered necessary in order to maximize running economy and injury prevention (Oliva-Lozano, Maraver, Fortes, et al., 2020b).

However, there are limited data available to date concerning the postural demands of professional soccer players in match play (Oliva-Lozano, Maraver, Fortes, et al., 2020b). A recent investigation, which was conducted on soccer players (Oliva-Lozano, Maraver, Fortes, et al., 2020b), suggested that practitioners should consider this information for the design of training drills given the postural demands observed during match play. In addition, this investigation concluded that strength and conditioning coaches should also consider the impact that contextual variables such as playing position may have on the trunk inclination and G-forces experienced by the players (Oliva-Lozano, Maraver, Fortes, et al., 2020b). Nevertheless, more studies on the postural demands of professional soccer players during match play are necessary because it is the only study published to date (Oliva-Lozano, Maraver, Fortes, et al., 2020b). Perhaps, one of the reasons for the lack of research on this topic is explained by the methodological difficulties associated with the instruments used for measuring trunk kinematics (Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b). Although the gold standard instruments for this aim are the motion capture systems, these are limited to laboratory settings (Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b; Poitras et al., 2019). In recent years, wearable inertial measurement units have been considered as alternative instruments for motion capture since these may give insight into how soccer players use their trunk to perform the sport-specific skills in match play (Warman et al., 2018, 2019).

Therefore, the aims of this study were to: 1) analyze the percentage (%) of playing time that soccer players spend in different trunk inclinations in match play; 2) analyze the G-forces that soccer players experience in different trunk inclinations; 3) analyze the trunk inclination required for different speeds thresholds; 4) analyze the effect of playing position on the time percentage that soccer players spend in different trunk inclinations, G-forces that the players experience in different trunk inclinations, and trunk inclination required for different speeds thresholds. Based on the results observed from a recent study on professional soccer players (Oliva-Lozano, Maraver, Fortes, et al., 2020b), it is hypothesized that the players may spend most of the time in trunk flexion. Then, the greatest G-forces may be observed in similar trunk flexion ranges and a linear relationship between trunk inclination and speed should be found.

11.4. Methods

Study design

A longitudinal study for 13 consecutive microcycles, which included one match per microcycle, was conducted in LaLiga 123. This study was carried out between March 17th, 2019 (first match) and June 6th, 2019 (last match). Wearable sensors with inertial measurement units were used to obtain time-, acceleration- and velocity-based variables considering different trunk inclination angles. The study was designed according to the Ethical Standards in Sports and Exercise Science Research (Harriss & Atkinson, 2015) and the club authorized the data collection during the competitive season. In addition, the institutional bioethics committee's approval was obtained.

Participants

A total of 15 professional soccer players (27.14 ± 3.94 years; 1.82 ± 0.06 cm; 75.57 ± 5.64 kg) participated in the study. The players were categorized into different playing positions: central defenders (CD), full-backs (FB), forwards (FW), midfielders (MF), and wide-midfielders (WMF). Only players who completed the total duration of the match were included in the analysis. However, goalkeepers were not considered for the study given the different nature of their activity-profile (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a).

Procedures

The data were collected by WIMU Pro devices (RealTrack Systems, Almería, Spain) in match play (Figure 21). These are wireless inertial measurement units composed of four triaxial accelerometers, three triaxial gyroscopes, one triaxial magnetometer, and one barometer. In addition, these devices are Global Positioning Systems (GPS). Based on previous studies which used the same tracking devices (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e, 2020d), these were calibrated before the start of the match following the manufacturer's instructions (RealTrack Systems, Almería, Spain). The data collected by the device was visualized on SPro (RealTrack Systems, Almería, Spain) at the end of each match and the raw data from “ATTITUDE EULER Z”, “ACELT”, and “GPS Speed” channels was downloaded for the analysis.

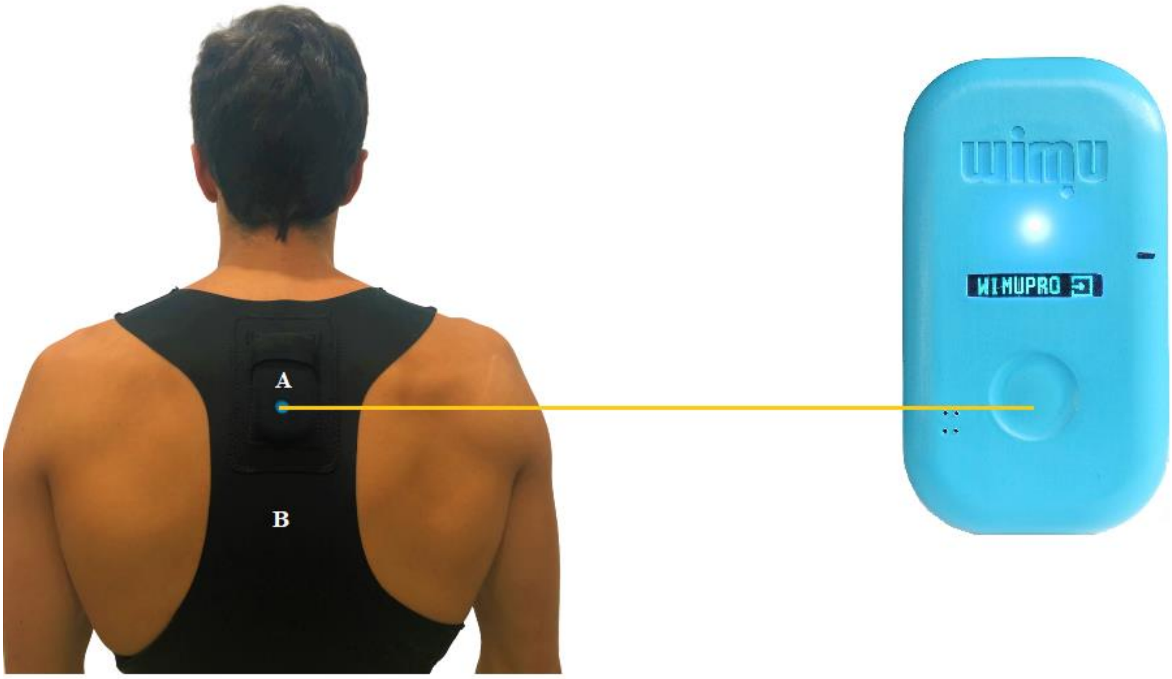

Figure 21. Tracking system (A) placed in the back pocket of a chest vest (B).

Since each player wore a WIMU Pro device, which was vertically placed in the back pocket of a chest vest, the “ATTITUDE EULER Z” represented the orientation of the device (in degrees, °) for movements within the Z-axis (i.e., trunk flexion and extension movements) (Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b). This device has been considered as a reliable instrument for measuring the inclination for movements within the Z-axis (mean bias: ~1.2°; intraclass correlation coefficients > 0.97; coefficient of variation < 7%) (Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b). Then, these data, which were collected at 100Hz, were used to calculate the trunk inclination zones based on a recent protocol (Warman et al., 2019). Considering that the upright position represented the 0° position and the “ATTITUDE EULER Z” reported -90° for this position, the authors applied a formula (i.e., value from ATTITUDE EULER Z + 90) in order to obtain the upright position at 0°. Therefore, the trunk flexion zones were: 0° - 10°, 10° - 20°, 20° - 30°, 30° - 40°, 40° - 50°, 50° - 60°, 60° - 70°, 70° - 80°, 80° - 90°, and > 90° while the trunk extension zones were: 0° - -10°, -10° - -20°, -20° - -30°, -30° - -40°, and < -40°. In addition, the time that soccer players spent in different trunk inclinations were calculated as time percentage (e.g. total of values in 10°-20° zone ÷ total duration $\times 100$) since the matches had different durations (i.e., 90 minutes + match-related stoppage time).

The "ACELT" is defined as the resultant vector of the G-forces registered by the triaxial accelerometers (x, y z), which measures the combination of gravity and changes in vertical and horizontal movements of the device (ACELT formula = $\sqrt{x^2 + y^2 + z^2}$) (Gómez-Carmona, Bastida-Castillo, García-Rubio, et al., 2019) (Figure 22A). The accelerometers from WIMU Pro (RealTrack Systems, Almería, Spain) have been tested and considered as good instruments given the accuracy to calculate accelerometry-based variables (mean bias: ~0.01 G; coefficient of variation < 0.6%) (Gómez-Carmona, Bastida-Castillo, García-Rubio, et al., 2019).

Finally, the "GPS Speed" data were collected at 10 Hz. The speed data collected by WIMU Pro is considered as valid (bias: 1.2 – 1.3 km/h) and reliable (intraclass correlation coefficients: > 0.93) (Bastida Castillo et al., 2018). The GPS data collected were synchronized with "EULER Z" data in order to calculate the players' average trunk inclination required for different speeds thresholds (0 - 7 km/h, 7 – 14 km/h, 14 – 21 km/h, >21 km/h) (Figure 22B).

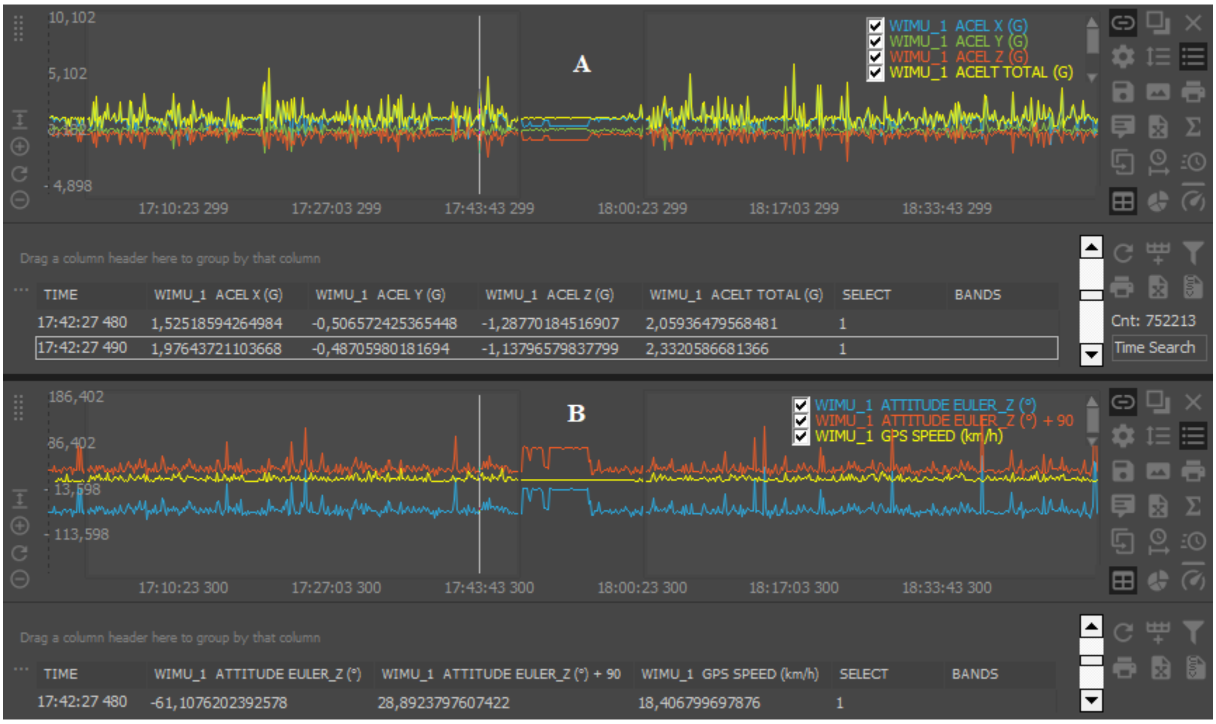

Figure 22. Raw data collected by the tracking system from the "ACELT" channel (A) and the "ATTITUDE EULER Z plus 90" (i.e., upright position) synchronized with GPS Speed (B).

Statistical analysis

The descriptive statistics were obtained for the time percentage that soccer players spent in each zone of trunk inclination, the G-forces that the players experienced in each zone of trunk inclination, and the trunk inclination required for each speed threshold. Shapiro-Wilk test was used to test the normality of the data and Levene's test was performed to assess the equality of variances. The sphericity was obtained through Mauchly's test ($p < 0.05$ in all variables). A linear model with mixed-design analysis of variance for repeated measures was performed. Playing position was considered a between-subject variable for this analysis. The comparisons between the time percentage that the soccer players spent in each zone of trunk inclination, the G-forces that the players experienced in each zone of trunk inclination, and the trunk inclination required for each speed threshold were obtained through Bonferroni post hoc. Also, the effect sizes were reported through partial eta-squared (ηp^2). The statistical analysis was run on SPSS Statistics for Windows (IBM Corp., Armonk, NY, USA) with the level of significance set at $p \leq 0.05$.

11.5. Results

Table 11 shows the descriptive statistics with the time percentage that the soccer players from each playing position spent on different inclination zones during match play as well as the differences between zones. The inclination zone variable had a significant effect on the time percentage spent on each zone ($F_{(1.18, 154.06)} = 510.11$, $p < 0.001$, $\eta p^2 = 0.85$). Specifically, the soccer players spent most of the time in trunk flexion between 20° and 30° (WMF: ~50%; CD: ~46%; MF: ~45%; FB: ~42%; FW: ~36%) followed by the zone between 30° and 40° (FW: ~37%; CD: ~36%; FB: ~26%; MF: ~24%; WMF: 21%). In addition, a significant interaction between playing position and the time percentage spent in different trunk inclination zone was observed ($F_{(7.37, 154.06)} = 5.74$; $p < 0.001$; $\eta p^2 = 0.21$).

Table 11. Time percentage (%) spent on each trunk flexion and extension zone (Mean ± Standard deviation).

	Inclination zones (°)	Central defenders	Full-backs	Forwards	Midfielders	Wide-midfielders
Trunk flexion	0°-10°	0.17 ± 0.18 c, d, e, f, j	1.05 ± 1.25 b, c, d, e, h, i, k, l, m, n, o	0.47 ± 0.80 c, d, e, f, g, j	0.58 ± 0.60 b, c, d, e, f	0.95 ± 0.50 b, c, d, e, f, k, l, m, n, o
	10°-20°	3.29 ± 3.43 c, d	18.95 ± 18.10 a, c, f, g, h, i, j, k, l, m, n, o	7.08 ± 8.79 c, d	17.31 ± 13.58 a, c, f, g, h, i, j, k, l, m, n, o	13.41 ± 4.09 a, c, f, g, h, i, j, k, l, m, n, o
	20°-30°	46.09 ± 11.52 a, b, e, f, g, h, i, j, k, l, m, n, o	42.16 ± 13.31 a, b, e, f, g, h, i, j, k, l, m, n, o	36.16 ± 13.72 a, b, e, f, g, h, i, j, k, l, m, n, o	44.62 ± 12.43 a, b, d, e, f, g, h, i, j, k, l, m, n, o	50.20 ± 4.21 a, b, d, e, f, g, h, i, j, k, l, m, n, o
	30°-40°	35.47 ± 10.40 a, b, e, f, g, h, i, j, k, l, m, n, o	25.59 ± 13.91 a, e, f, g, h, i, j, k, l, m, n, o	36.75 ± 14.36 a, b, e, f, g, h, i, j, k, l, m, n, o	24.23 ± 14.35 a, c, e, f, g, h, i, j, k, l, m, n, o	20.71 ± 4.26 a, c, e, f, g, h, i, j, k, l, m, n, o
	40°-50°	9.47 ± 3.12 a, c, d, f, g, h, i, j, k, l, m, n, o	7.79 ± 5.39 a, c, d, f, g, h, i, j, k, l, m, n, o	10.67 ± 3.89 a, c, d, f, g, h, i, j, k, l, m, n, o	8.59 ± 4.65 a, c, d, f, g, h, i, j, k, l, m, n, o	8.15 ± 1.74 a, c, d, f, g, h, i, j, k, l, m, n, o
	50°-60°	3.05 ± 1.36 a, c, d, e, g, h, i, j, k, l, m, n, o	2.40 ± 1.84 b, c, d, e, g, h, i, j, k, l, m, n, o	3.70 ± 1.04 a, c, d, e, g, h, i, j, k, l, m, n, o	2.76 ± 1.39 a, b, c, d, e, g, h, i, j, k, l, m, n, o	3.08 ± 0.63 a, b, c, d, e, g, h, i, j, k, l, m, n, o
	60°-70°	0.84 ± 0.43 c, d, e, f, g, h, i, k, l, m, n	0.80 ± 0.65 b, c, d, e, f, l, m, n	1.92 ± 2.23 a, c, d, e, f, h, i, k, l, m, n, o	0.79 ± 0.31 b, c, d, e, f	1.08 ± 0.26 b, c, d, e, f, k, l, m, n, o
	70°-80°	0.28 ± 0.14 c, d, e, f, g, j, k, l, m, n	0.31 ± 0.23 a, b, c, d, e, f, g, k, l, m, n	0.64 ± 0.48 c, d, e, f, g, j, k, l, m, n	0.29 ± 0.18 b, c, d, e, f, k, l, m, n, o	0.46 ± 0.19 b, c, d, e, f, j, k, l, m, n, o
	80°-90°	0.16 ± 0.07 c, d, e, f, g, j	0.16 ± 0.09 a, b, c, d, e, f, j	0.47 ± 0.56 c, d, e, f, g, j, k, l, m, n	0.18 ± 0.18 b, c, d, e, f	0.41 ± 0.18 b, c, d, e, f, j, k, l, m, n, o
	>90°	1.01 ± 0.66 a, c, d, e, f, h, i, k, l, m, n, o	0.68 ± 0.28 b, c, d, e, f, i, k, l, m, n, o	1.85 ± 0.90 a, c, d, e, f, h, i, k, l, m, n, o	0.60 ± 0.69 b, c, d, e, f, l, m, n	1.45 ± 0.70 b, c, d, e, f, h, i, k, l, m, n, o
Trunk extension	0°-10°	0.03 ± 0.03 c, d, e, f, g, h, j	0.06 ± 0.06 a, b, c, d, e, f, h, j, l, m, n	0.04 ± 0.01 c, d, e, f, g, h, i, j	0.03 ± 0.02 b, c, d, e, f, h, m, n	0.06 ± 0.03 a, b, c, d, e, f, g, h, i, j, l, m, n
	10°-20°	0.01 ± 0.00 c, d, e, f, g, h, j	0.01 ± 0.01 a, b, c, d, e, f, g, h, i, j, k, m, n	0.02 ± 0.01 c, d, e, f, g, h, i, j, m	0.01 ± 0.01 b, c, d, e, f, h, j, m, n	0.01 ± 0.01 a, b, c, d, e, f, g, h, i, j, k, m, n
	20°-30°	0.00 ± 0.00 c, d, e, f, g, h, j	0.00 ± 0.00 a, b, c, d, e, f, g, h, j, k, l	0.01 ± 0.01 c, d, e, f, g, h, i, j, l	0.00 ± 0.00 b, c, d, e, f, h, j, k, l	0.01 ± 0.01 a, b, c, d, e, f, g, h, i, j, k, l
	30°-40°	0.00 ± 0.00 c, d, e, f, g, h, j	0.00 ± 0.01 a, b, c, d, e, f, g, h, j, k, l	0.02 ± 0.01 c, d, e, f, g, h, i, j	0.00 ± 0.00 b, c, d, e, f, h, j, k, l	0.00 ± 0.00 a, b, c, d, e, f, g, h, i, j, k, l
	>40°	0.15 ± 0.60 c, d, e, f, j	0.05 ± 0.21 a, b, c, d, e, f, j	0.20 ± 0.36 c, d, e, f, g, j	0.01 ± 0.03 b, c, d, e, f	0.02 ± 0.04 a, b, c, d, e, f, g, h, i, j

Note: [a]Statistical difference to 0°-10° (flexion); [b]Statistical difference to 10°-20° (flexion); [c]Statistical difference to 20°-30° (flexion); [d]Statistical difference to 30°-40° (flexion); [e]Statistical difference to 40°-50° (flexion); [f]Statistical difference to 50°-60° (flexion); [g]Statistical difference to 60°-70° (flexion); [h]Statistical difference to 70°-80° (flexion); [i]Statistical difference to 80°-90° (flexion); [j]Statistical difference to >90° (flexion); [k]Statistical difference to 0°-10° (extension); [l]Statistical difference to 10°-20° (extension); [m]Statistical difference to 20°-30° (extension); [n]Statistical difference to 30°-40° (extension); [o]Statistical difference to >40° (extension)

Table 12 shows the descriptive statistics with the G-forces that the soccer players from each playing position experienced in different inclination zones during match play as well as the differences between zones. The inclination zone also had a significant effect on the G-forces that the soccer players experienced in each zone ($F_{(2.85, 247.96)} = 26.78$, $p < 0.001$, $\eta p^2 = 0.24$). Specifically, the greatest G-forces were observed in trunk extension zones for CD (~2.3G between 10° and 20° trunk extension), MF (~2.3G between 0° and 10° trunk extension), WMF (~2.2G between 10° and 20° trunk extension), FW (~1.9G between 20° and 30° trunk extension), and FB (~1.8G between 0° and 10° trunk extension). However, the interaction between playing position and the G-forces experienced in the trunk inclination zones was not significant ($F_{(11.4, 87)} = 0.93$; $p = 0.52$; $\eta p^2 = 0.04$).

Table 12. ACELT (G) for each trunk flexion and extension zone (Mean ± Standard deviation).

	Inclination zones (°)	Central defenders	Full-backs	Forwards	Midfielders	Wide-midfielders
Trunk flexion	0°-10°	2.16 ± 0.45 b, c, d, e, f, g, h, i, j	1.49 ± 0.26 b, c,	1.83 ± 0.32 b, c, d, e, h, i, j	2.12 ± 0.69 b, c, d, e, f, g, h, i, j	1.56 ± 0.15 b, c, i, j, k
	10°-20°	1.48 ± 0.22 a, c, d, e, h, i, j, k, l	1.20 ± 0.12 a, f, g, k	1.30 ± 0.14 a, c, g, k	1.27 ± 0.22 a, c, l, k	1.19 ± 0.04 a, f, g, k, l
	20°-30°	1.09 ± 0.02 a, b, e, f, g, h, i, j, k, l, m	1.12 ± 0.06 a, d, e, f, g, h, i, k	1.10 ± 0.02 a, b, e, f, g, h, i, k	1.10 ± 0.04 a, b, d, e, f, g, h, i, j, k, l, m	1.11 ± 0.02 a, d, e, f, g, h, k, l, m
	30°-40°	1.11 ± 0.05 a, b, e, f, g, h, i, j, k, l, m	1.22 ± 0.08 c, e, f, g, k	1.13 ± 0.06 a, e, f, g, h, i, j, k	1.17 ± 0.05 a, c, d, e, f, g, h, k, l, m	1.22 ± 0.04 c, e, f, g, i, j, k, l
	40°-50°	1.25 ± 0.10 a, b, c, d, f, g, j, k, l, m	1.35 ± 0.09 c, d, f, i, j, k	1.30 ± 0.06 a, c, d, f, g, i, j, k	1.29 ± 0.06 a, c, d, e, k, l	1.32 ± 0.04 c, d, f, g, i, j, k, l
	50°-60°	1.38 ± 0.11 a, c, d, e, g, i, j, k, l, m	1.44 ± 0.06 b, c, d, e, h, i, j	1.45 ± 0.07 c, d, e, i, j	1.33 ± 0.08 a, c, d, e, k	1.43 ± 0.08 b, c, d, e, h, i, j, k, l
	60°-70°	1.44 ± 0.13 a, c, d, f, h, i, j, k, l	1.41 ± 0.07 b, c, d, h, i, j	1.49 ± 0.15 b, c, d, e, i, j	1.33 ± 0.11 a, c, d, k	1.44 ± 0.11 b, c, d, e, h, i, j, k, l
	70°-80°	1.33 ± 0.13 a, b, c, d, g, i, j, k, l, m	1.32 ± 0.08 c, f, g, j, k	1.42 ± 0.19 a, c, d, i, j	1.33 ± 0.12 a, c, d, k	1.30 ± 0.13 c, f, g, i, j, k, l
	80°-90°	1.20 ± 0.11 a, b, c, d, f, g, h, k, l, m	1.23 ± 0.08 c, f, g, j, k	1.27 ± 0.19 a, c, d, f, g, h, j, k	1.26 ± 0.15 a, c, k, l	1.11 ± 0.07 a, d, e, f, g, h, k, l, m
	>90°	1.13 ± 0.09 a, b, e, f, g, h, k, l, m	1.17 ± 0.06 e, f, g, h, i, k	1.12 ± 0.06 a, e, f, g, h, i, k	1.23 ± 0.13 a, c, k	1.08 ± 0.03 a, d, e, f, g, h, k, l, m
Trunk extension	0°-10°	2.14 ± 0.56 b, c, d, e, f, g, h, i, j	1.81 ± 0.45 b, c, d, e, h, i, j	1.90 ± 0.30 b, c, d, e, i, j	2.32 ± 0.71 b, c, d, e, f, g, h, i, j	2.20 ± 0.34 a, b, c, d, e, f, g, h, i, j
	10°-20°	2.34 ± 1.18 b, c, d, e, f, g, h, i, j	1.78 ± 0.70	1.67 ± 0.41	2.09 ± 0.80 b, c, d, e, i, j	2.23 ± 0.63 b, c, d, e, f, g, h, i, j
	20°-30°	2.12 ± 1.21 c, d, e, f, h, i, j	1.77 ± 1.12	1.93 ± 0.82	2.13 ± 1.20 c, d	2.01 ± 0.61 c, i, j
	30°-40°	1.97 ± 1.70	1.63 ± 1.71	1.73 ± 0.43	1.76 ± 1.20	1.91 ± 1.25
	>40°	1.47 ± 1.52	1.44 ± 1.88	1.40 ± 0.60	1.66 ± 1.71	1.19 ± 0.91

Note: [a]Statistical difference to 0°-10° (flexion); [b]Statistical difference to 10°-20° (flexion); [c]Statistical difference to 20°-30° (flexion); [d]Statistical difference to 30°-40° (flexion); [e]Statistical difference to 40°-50° (flexion); [f]Statistical difference to 50°-60° (flexion); [g]Statistical difference to 60°-70° (flexion); [h]Statistical difference to 70°-80° (flexion); [i]Statistical difference to 80°-90° (flexion); [j]Statistical difference to >90° (flexion); [k]Statistical difference to 0°-10° (extension); [l]Statistical difference to 10°-20° (extension); [m]Statistical difference to 20°-30° (extension); [n]Statistical difference to 30°-40° (extension); [o]Statistical difference to >40° (extension)

Regarding the analysis of the trunk inclination required for different speeds thresholds (Figure 23), a significant effect of the speed variable was found since trunk flexion increased with greater speeds ($F_{(1.83,\ 162.85)} = 239.52$; $p < 0.001$; $\eta p^2 = 0.73$). However, the greatest trunk inclination for MF (i.e., 31.84 ± 0.85°) was found between 7 and 14 km/h. In addition, a significant interaction between playing position and the trunk inclination required for the speed zones was observed ($F_{(7.31,\ 89)} = 18.55$; $p < 0.001$; $\eta p^2 = 0.45$).

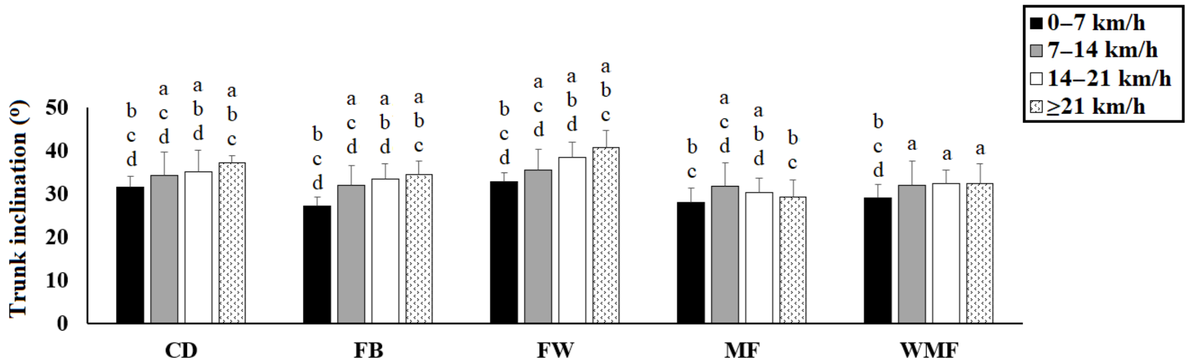

Figure 23. Trunk inclination (in degrees, °) required for different speed thresholds and playing positions

11.6. Discussion

The aims of this study were to analyze the time percentage that soccer players spent in different trunk inclinations in match play, analyze the G-forces experienced in different trunk inclinations, and analyze the trunk inclination required for different speeds thresholds while considering the effect of playing position. This study is one of the first steps in the analysis of the postural demands of professional soccer players. The main findings were that these players spent most of the time in trunk flexion between 20° and 40°, the greatest G-forces were observed in trunk extension zones between 0° and 30°, and a linear relationship between trunk inclination and speed in all playing positions was observed, except for MF. Therefore, the results do not confirm the hypothesis that the greatest G-forces may be observed in trunk flexion zones.

The results showed that the soccer players spent most of the time in trunk flexion between 20° and 40°. A recent investigation on field hockey players observed that these were half of the match in two trunk flexion zones (30°-40°: ~26% of total time; 40°-50°: ~26% of total time) (Warman et al., 2019). This trunk inclination allows the players to perform the sport-specific movements such as running with the ball or passing and controlling the ball, which may move the field of regard down (Lim et al., 2017; Warman et al., 2019). In addition, the results showed that the playing position should be also considered when analyzing the postural demands. WMF was the position with the greatest time percentage (~50%) between 20° and 30° while FW showed the lowest time percentage (~36%) in match play. Although these differences may be due to the positional demands (i.e., WMF tend to run with the ball for longer times than FW) (Ade et al., 2016), these results suggest that these postural demands (e.g., time percentage that the players spend in trunk flexion) need to be considered when designing specific training drills (Oliva-Lozano & Muyor, 2020). This becomes even more important when players report low back pain, which is associated with altered lumbopelvic control (Grosdent et al., 2016), because the players may tend to adopt trunk-flexed postures (Hides et al., 2016; Müller et al., 2015). Hence, trunk strength exercises and lumbopelvic control exercises may be also beneficial for the players (Grosdent et al., 2016; Oliva-Lozano & Muyor, 2020).

When it comes to the G-forces that the soccer players experienced in different inclination zones during match play, a novel finding of the study was that the greatest G-forces were observed in trunk extension zones for all playing positions. Given the short period of time that the players spent in trunk extension zones during the matches (below 2% of the total time), these results might be explained by the fact that the players suffer from very specific collisions, falls, or jumps in these brief periods (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Mark Russell et al., 2016). Nonetheless, the results from this study showed that the average G-forces of soccer players in trunk flexion (~1.32G) during match play are consistent with previous research on running kinematics, which examined the average G-forces experienced by the athletes (1.21G – 1.38G) (Lindsay et al., 2014). However, contrary to the findings on the previous aim, which examined the time percentage that the players spent in each trunk inclination zone, no significant effect of playing position on the G-forces experienced in the trunk inclination zones was found. In this regard, future studies are needed in order to understand if the postural demands are dependent on the playing position or the player itself.

Finally, the results showed that the trunk flexion increased with greater speeds in all playing positions, except for MF. Although the trunk inclination is a variable which has received little attention in the literature, it is to highlight that the increase in trunk flexion is a natural movement given the increase in speed (Souza, 2016). The progression to faster running speeds is associated with increases in electromyographic activity, especially in the multifidus muscle, and kinematic changes (Saunders et al., 2005). However, MF showed different results because the greatest trunk inclination was observed between 7 and 14 km/h, which implies that postural demands of the MF players differ from the rest of playing positions. Considering the importance of the tactical connection between MF and the rest of playing positions in addition to their role as game organizers (e.g., passing the ball and linking the sectors of the team) (Clemente et al., 2015), these results may be explained by the fact that this position requires an upright posture at greater speeds in order to perform in their field of regard (Lim et al., 2017; Warman et al., 2019). From a practical perspective, this is one of the reasons why previous researchers suggested that it is important to understand the postural demands of the players during the sport-specific skills (Jeffreys, 2008; Warman et al., 2018, 2019). For example, if a player tends to increase the trunk flexion when sprinting, this may lead to the downward orientation of the head and restrict the ability to perform in the field of regard (Lim et al., 2017; Warman et al., 2019). In consequence, training drills focused on the visual exploration and decision making are necessary in order to have a successful performance in the field of regard.

It is plausible that some limitations of the study may influence the interpretations of these results. For example, data was collected from only one professional soccer team. This study was focused on the trunk kinematics, but the analysis of the kinematics of the ankles, knees or hip was not conducted. Only players who completed the total duration of the match were included in the analysis as homogenization criteria. In addition, not all the playing positions could be analyzed since goalkeepers were not included. Therefore, future studies should consider these limitations in addition to other variables of interest such as ball possession or player’s fatigue, which may have a significant relationship with the postural demands of soccer players (Oliva-Lozano, Maraver, Fortes, et al., 2020b). For instance, the sagittal trunk inclination and G-forces experienced by professional soccer players in match play are usually reduced during the second half of the match, which suggests that fatigue may lead to changes in the kinematics of the players (Oliva-Lozano, Maraver, Fortes, et al., 2020b).

In addition, the data were collected by inertial measurement units and GPS technology, which have advantages and disadvantages from a practical standpoint. For example, this technology allows the collection of external load (e.g., kinematic parameters such as trunk inclination or speed) and internal load variables (e.g., heart rate) (Kos & Kramberger, 2017; Rojas-Valverde, Gómez-Carmona, et al., 2019). Although these instruments are valid, reliable, and suitable for measuring the inclination in the sagittal plane (Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b), acceleration (G-forces) (Gómez-Carmona, Bastida-Castillo, García-Rubio, et al., 2019) and position-related variables (Bastida Castillo et al., 2018), the gold standard technology for motion capture are optical tracking systems (Poitras et al., 2019). Optical tracking systems are limited to laboratory settings and thus, wearable sensors have been considered as an alternative method for motion capture (Poitras et al., 2019). However, previous investigations suggested that the inertial measurement units should include methods to compensate the drift error and improve the accuracy of the data (Fasel et al., 2018; Fong & Chan, 2010; Guiry et al., 2014). Specifically, the multi-sensor fusion and the placement of multiple sensors on different segments of the body are frequent methods which may increase the accuracy of the data collected (Fasel et al., 2018; Fong & Chan, 2010; Guiry et al., 2014; L. Liu et al., 2020; Marta et al., 2020). Nonetheless, this last method is useful in professional soccer because wearing multiple sensors on the body may be dangerous and uncomfortable for the player (Medina et al., 2017; Oliva-Lozano, Maraver, Fortes, et al., 2020b).

11.7. Conclusion

This study showed how the data collected by inertial measurement units may be used for the analysis of the postural demands of professional soccer players. Since the results showed that match play led to significant postural demands, coaches are recommended to incorporate training drills which consider the match demands. For example, the volume of trunk flexion observed implies that soccer players may unconsciously move the field of regard down and position-specific training drills at different speeds are necessary in order to properly prepare the players for the perception-action demands (i.e., visual exploration and decision making) of the match. In addition, it is suggested that trunk strength exercises are designed with special focus on flexion positions as well as other compensatory exercises for trunk extension muscles, which balance trunk flexors and trunk extensors. Indeed, the trunk strength exercises might add perturbations so as to stimulate trunk accelerations between 2G and 3G in both flexion and extension.

CHAPTER 12

Study X. Effect of playing position, match half, and match day on the trunk inclination, g-forces, and locomotor efficiency experienced by professional soccer players in match play

Oliva-Lozano, J. M., Maraver, E. F., Fortes, V., & Muyor, J. M. (2020). Effect of playing position, match half, and match day on the trunk inclination, g-forces, and locomotor efficiency experienced by elite soccer players in match play. *Sensors*, 20, 1–12. https://doi.org/10.3390/s20205814

12. EFFECT OF PLAYING POSITION, MATCH HALF, AND MATCH DAY ON THE TRUNK INCLINATION, G-FORCES, AND LOCOMOTOR EFFICIENCY EXPERIENCED BY PROFESSIONAL SOCCER PLAYERS IN MATCH PLAY

12.1. Abstract

The rapid growth of wearable sensors has allowed the analysis of trunk kinematics during the match, which is necessary for having a better understanding of the postural demands of soccer players. However, some contextual variables may have an impact on the physical demands of the players. The aim of this study was to analyze the effect of three contextual variables (playing position, match half, and match day) on the sagittal trunk inclination, G-forces, and locomotor efficiency experienced by soccer players in match play. Then, wearable sensors were used to collect the trunk kinematics during 13 matches. Firstly, positional differences were found on the trunk inclination (p=0.01) and the G-forces experienced by the players (p<0.001). For example, the greatest and lowest trunk inclination was found for FW (~34.01°) and FB (~28.85°) while the greatest and lowest G-forces were found for WMF (1.16 G) and CD (1.12 G), respectively. However, there were no positional differences on the locomotor efficiency (p=0.10;). Secondly, the match half had a significant effect on the trunk inclination (p=0.01) and the G-forces experienced by the players (p<0.001) with significant lower values observed during the second half. No differences between halves were found on the locomotor efficiency for any playing position (p=0.41). Finally, no significant effect of match day on any variable was observed. This investigation is one of the first steps towards enhancing the understanding of trunk kinematics from professional soccer players. The positional differences found on the trunk inclination and G-forces imply that the development of position-specific training drills considering the postural demands is necessary so as to prepare the players not only for the physical demands but also for a successful performance in the field of regard. Also, the resistance to fatigue needs to be trained given the differences between halves.

12.2. Keywords

Football, Posture, Match Analysis, Load, Team Sports, Inertial Measurement Units.

12.3. Introduction

One of the variables that gives an insight into the postural demands is the sagittal trunk inclination of the player while running (Warman et al., 2018, 2019). This variable is highly associated with the low back pain (Grosdent et al., 2016), hamstring injury (Schuermans et al., 2017), hip and knee energetics in running (Teng & Powers, 2014a), and patellofemoral joint stress (Teng & Powers, 2014b). For example, running at a controlled speed (e.g., 3.4 m/s) with an excessive upright posture has been associated with greater patellofemoral joint stress compared to running with forward trunk flexion (Teng & Powers, 2014b). In addition, the trunk inclination is not only related to the development of musculoskeletal injuries but it also may explain the performance in the field of regard (Lim et al., 2017; Warman et al., 2019). Then, the trunk inclination may be considered as an important variable since soccer players usually play the ball with the feet and their ability to perform in the field of regard may be affected as well (Warman et al., 2019).

Furthermore, the analysis of the trunk accelerations through the G-forces experienced by the players may provide meaningful information about the players' performance (Gómez-Carmona et al., 2020; Gómez-Carmona, Pino-Ortega, et al., 2019). Soccer is a team sport characterized by high-intensity actions (e.g., intermittent sprints, changes of direction, body impacts, jumps, and landings), which implies that measuring the trunk accelerations is necessary (Granero-Gil et al., 2020; Oliva-Lozano, Fortes, & Muyor, 2020; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d). Since inertial sensors allow the quantification of the trunk accelerations in the three axes of movement, recent investigations have suggested the use of G-forces as an external workload indicator (Gómez-Carmona et al., 2020). The trunk plays an important role as "shock absorber", but the magnitude (i.e., G-forces) and amount of shocks on the musculoskeletal system may increase the risk of injury (Lindsay et al., 2014; Simoni et al., 2020).

Thus, the integration of inertial sensors (e.g., accelerometers) with global positioning systems (GPS) has become a trending method for workload monitoring in team sports (Gómez-Carmona et al., 2020). Many studies support the practical implementation of accelerometry monitoring through variables such as the locomotor efficiency ratio (i.e., player load ÷ total distance covered) (Barrett, Midgley, Reeves, et al., 2016; Gómez-Carmona et al., 2020). This is a very practical variable from a performance standpoint since a player that accumulates more load than another player may be indicative of a reduced locomotor efficiency if both covered the same distance (Barrett, Midgley, Reeves, et al., 2016). Moreover, the locomotor efficiency ratio has been identified as a representative variable of fatigue and injury risk in match play (Barrett, Midgley, Reeves, et al., 2016).

In consequence, the analysis of the postural demands through the trunk inclination, the G-forces experienced by the players and the locomotor efficiency ratio is necessary. In addition, contextual variables such as playing position, match half and match day, which usually have an impact on the physical demands of professional soccer players (Barrett, Midgley, Reeves, et al., 2016; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e, 2020d; Trewin et al., 2018), need to be considered. However, limited data have been published to date. To the best of the authors' knowledge, no studies are available to date regarding the analysis of trunk inclination and the G-forces experienced by the players in competitive match-play. Thus, the aims of this study were to analyze the effect of playing position, match half, and match day on the sagittal trunk inclination, G-forces, and locomotor efficiency ratio of professional soccer players in match play.

12.4. Methods

Study design

This study used a cohort design for 13 microcycles in which one match per microcyle (i.e., weekly periods counting from the day after the match to the following match) was played by an professional soccer team from LaLiga 123. These microcycles belonged to the last phase of the season. Wearable sensors, which contained inertial measurement units and GPS technology, were used in order to collect the trunk kinematics in match play. The data collection was authorized by the club and informed consent for volunteer participation in the study was given. Also, the approval from the institutional bioethics committee was obtained.

Participants

Fifteen professional male soccer players (27.1 ± 3.9 years old; 75.6 ± 5.6 kg; 1.8 ± 0.1 m;) took part in this study. They belonged to specific playing positions: central defenders (CD, 26 match observations), full-backs (FB, 19 match observations), wide-midfielders (WMF, 18 match observations), midfielders (MF, 17 match observations), and forwards (FW, 14 match observations). However, the players who could not participate in the total duration of the match were not included in the study in order to avoid the effect of pacing strategies (Carling & Dupont, 2011; Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Mark Russell et al., 2016). In addition, goalkeepers were excluded from the analysis given the differences in the activity-profile (Oliva-Lozano, Gómez-Carmona, Pino-Ortega, et al., 2020a).

Procedures

WIMU Pro units (RealTrack Systems, Almería, Spain) were used as electronic performance tracking systems in order to collect the data during the matches. These wearable units, which were placed in the back pocket of a chest vest on a vertical position (Figure 24), contain inertial sensors (four 3D accelerometers, three 3D gyroscopes, one 3D magnetometer) recording data at 100Hz and GPS technology recording data at 10Hz. Each unit was calibrated before the start of the match following the manufacturer's instructions (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e). The data collected by the units were transferred to SPro (RealTrack Systems, Almería, Span) at the end of the matches in order to download the "Intervals Pro" report in addition to the raw data from "ATTITUDE EULER Z" and "ACELT" channels.

Figure 24. Tracking system placed in the back pocket of a chest vest

The process to obtain these data was as follows: first, open the session file; second, create the first and second half drills using the “Select mode” on SPro; third, launch “ATTITUDE EULER Z” channel, “ACELT” channel, and “Intervals Pro” to the central panel; forth, click on “Export” to download the data. The “Intervals Pro” report was used to obtain the total distance covered (in meters) and the player load, which is an accelerometer-derived variable that derives from movements registered in the x-, y-, and z-axis (Gómez-Carmona, Bastida-Castillo, González-Custodio, et al., 2019). These variables allowed the calculation of the locomotor efficiency (i.e., locomotor efficiency = player load ÷ total distance covered in meters) (Barrett, Midgley, Towlson, et al., 2016) (Figure 25).

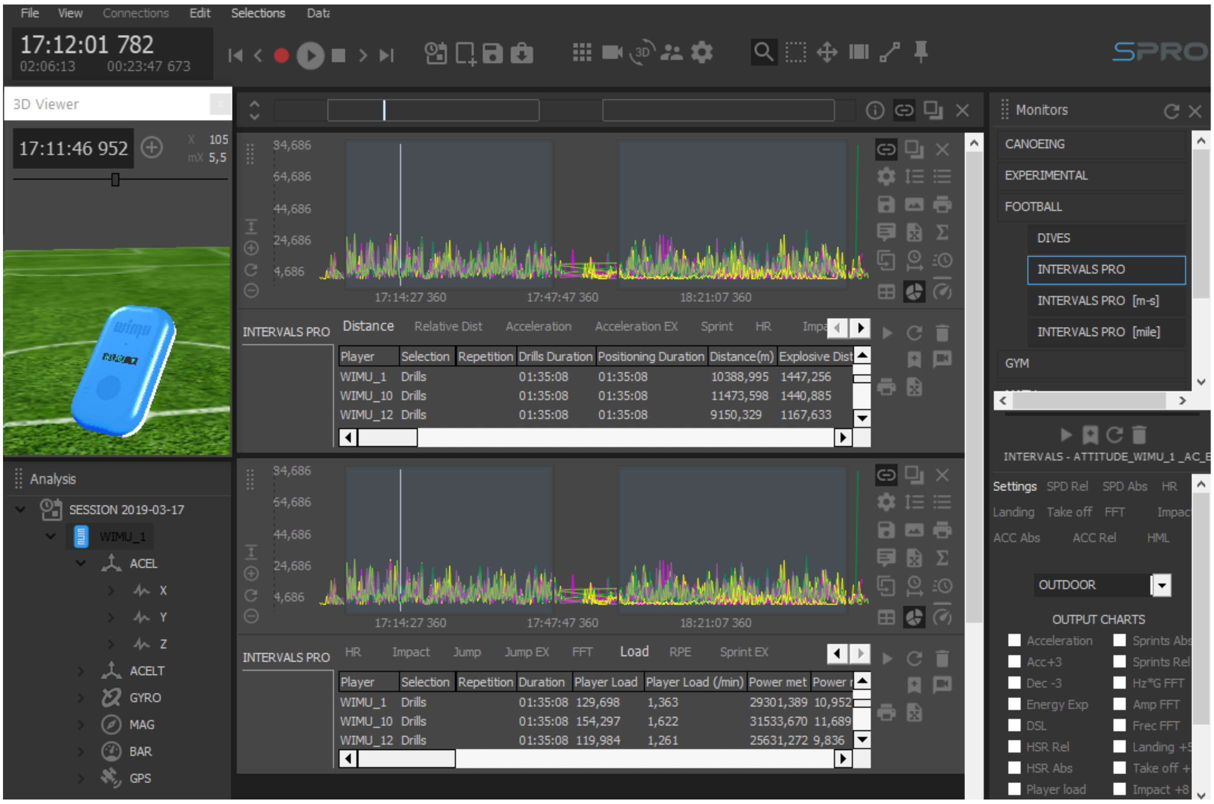

Figure 25. Data collected by the tracking system on the Intervals Pro report (RealTrack Systems, Almería, Spain), which were used to calculate the locomotor efficiency ratio.

The “ATTITUDE EULER Z” was used to analyze the sagittal trunk inclination (in degrees, °) (Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b) (Figure 26a). Since the upright posture equals 0° and the original data collected by the unit reported 90° for the same position, the researchers applied a simple formula, which was the data value from “ATTITUDE EULER Z” plus 90, so as to obtain the right position (Figure 26b). Thirdly, the “ACELT” data, which reported the resultant vector of the G-forces from horizontal and vertical movements registered by the three axis (x, y, z) of the accelerometers (ACELT formula = $\sqrt{x^2 + y^2 + z^2}$) (Gómez-Carmona, Bastida-Castillo, García-Rubio, et al., 2019) (Figure 26c).

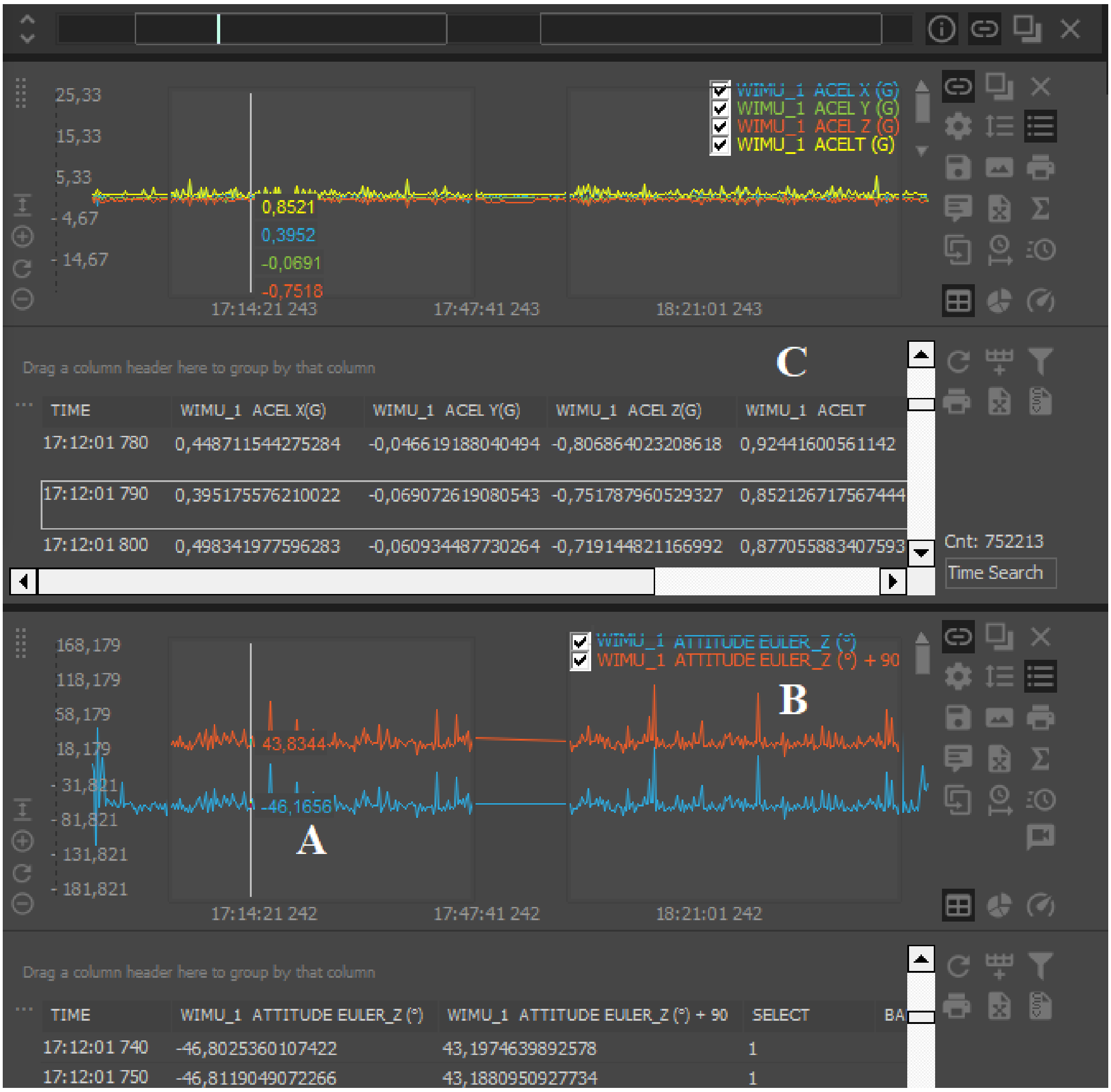

Figure 26. Raw data from “ATTITUDE EULER Z” (A), “ATTITUDE EULER Z plus 90” so as to obtain the right position (B), and “ACELT” (C).

Statistical analysis

First of all, the descriptive statistics for the trunk inclination, G-forces and locomotor efficiency ratio were calculated by playing position, match half, and match day. Then, the equality of variances was calculated through Levene’s test and the sphericity was calculated through Mauchly’s test (p < 0.05 in all variables). A linear model with a mixed-design analysis of variance for repeated measures was run. Trunk inclination, G-forces and locomotor efficiency ratio were set as dependent variables. Then, the Bonferroni post hoc was used in order to compare the results from the dependent variables between playing positions, match halves, and match days. The confidence interval (CI) and Cohen's d were reported for the pairwise comparisons. In addition, the partial eta-squared (ηp^2) was calculated to express the amount of variance accounted for the independent variables. The statistical analysis was performed on SPSS Statistics (IBM Corp., Armonk, NY, USA) with the level of significance set at $p \leq 0.05$.

12.5. Results

Sagittal trunk inclination

Figure 27 shows the mean sagittal trunk inclination and standard deviation by playing position and match half. The playing position had a significant effect on the sagittal trunk inclination ($F_{(4, 32)} = 4.44$; $p = 0.01$; $\eta p^2 = 0.36$). Regarding the match half, it had a significant effect on the trunk inclination ($F_{(1, 32)} = 9.05$; $p = 0.01$; $\eta p^2 = 0.22$). Then, the interaction between match half and playing position was significant too ($F_{(4, 32)} = 3.80$; $p = 0.01$; $\eta p^2 = 0.32$). Specifically, the sagittal trunk inclination during the first half was significantly greater compared to the second half in CD (~1.52°; $p = 0.01$; CI = 0.75 – 2.28; $d = 0.60$) and MF (~1.45°; $p = 0.01$; CI = 0.45 – 2.45; $d = 0.33$).

In addition, FW showed significantly greater sagittal trunk inclination than FB in the first half (~5.09°; $p = 0.04$; CI = 0.13 – 10.05; $d = 1.06$). During the second half, FW also showed significantly greater inclination than FB (~5.49°; $p = 0.02$; CI = 0.74 – 10.25; $d = 1.05$), MF (~6.43°; $p = 0.01$; CI = 1.55 – 11.31; $d = 1.22$), and WMF (~4.99°; $p = 0.04$; CI = 0.18 – 9.80; $d = 1.21$). However, there was no significant effect of match day on the sagittal trunk inclination ($F_{(12, 32)} = 0.81$; $p = 0.64$; $\eta p^2 = 0.23$) so no significant differences in the trunk inclination ($p > 0.05$) were observed between match days for any playing position.

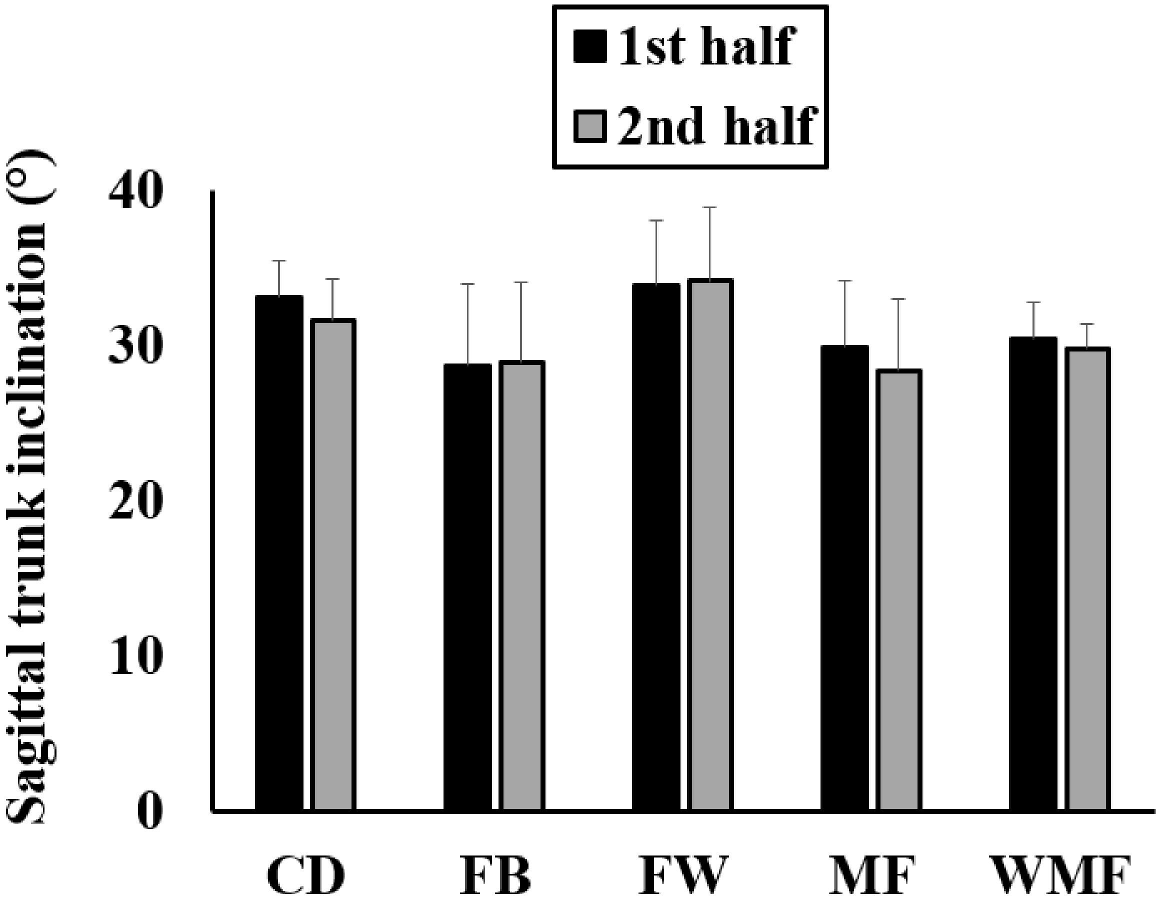

Figure 27. Sagittal trunk inclination of professional soccer players based on playing position and match half. *Significant differences ($p < 0.05$) between halves.

G-forces

The G-forces experienced by the players in match play (Figure 28) were significantly influenced by the match half ($F_{(1, 32)} = 182.58$; $p < 0.001$; $\eta p^2 = 0.85$) and the playing position ($F_{(4, 32)} = 14.56$; $p < 0.001$; $\eta p^2 = 0.65$). The interaction between match half and playing position was also significant ($F_{(4, 32)} = 5.15$; $p = 0.003$; $\eta p^2 = 0.39$). In this regard, the G-forces were lower during the second half of the matches compared to the first half for CD (~0.02 G; p = 0.01; CI = 0.013 – 0.021; d = 0.87), FB (~0.01 G; p = 0.01; CI = 0.002 – 0.012; d = 0.40), FW (~0.02 G; p = 0.01; CI = 0.015 – 0.026; d = 0.93), MF (~0.02 G; p = 0.01; CI = 0.013 – 0.024; d = 1.01), and WMF (~0.01 G; p = 0.01; CI = 0.007 – 0.018; d = 0.41).

During the first half of the matches, CD reported significantly lower G-forces than FB (~0.03 G; p = 0.03; CI = 0.002 – 0.049; d = 1.43), MF (~0.04 G; p = 0.001; CI = 0.014 – 0.063; d =

2.05), WMF (~0.06 G; p = 0.001; CI = 0.029 – 0.078; d = 2.03), and FW (~0.03 G; p = 0.03; CI = 0.002 – 0.054; d = 1.47). In addition, WMF showed significantly greater G-forces than FB (~0.03 G; p = 0.03; CI = 0.002 – 0.055; d = 0.97) in the first half. During the second half of the matches, CD reported significantly lower G-forces than FB (~0.04 G; p = 0.001; CI = 0.013 – 0.058; d = 1.91), MF (~0.04 G; p = 0.001; CI = 0.013 – 0.058; d = 1.57), and WMF (~0.06 G; p = 0.001; CI = 0.035 – 0.080; d = 2.28). Also, WMF showed significantly greater G-forces than FW (~0.03 G; p = 0.01; CI = 0.01 – 0.06; d = 1.12) during the second half. However, the G-forces experienced by the players did not significantly differ between match days ($F_{(12, 32)}$ = 1.41; p = 0.21; ηp^2 = 0.35).

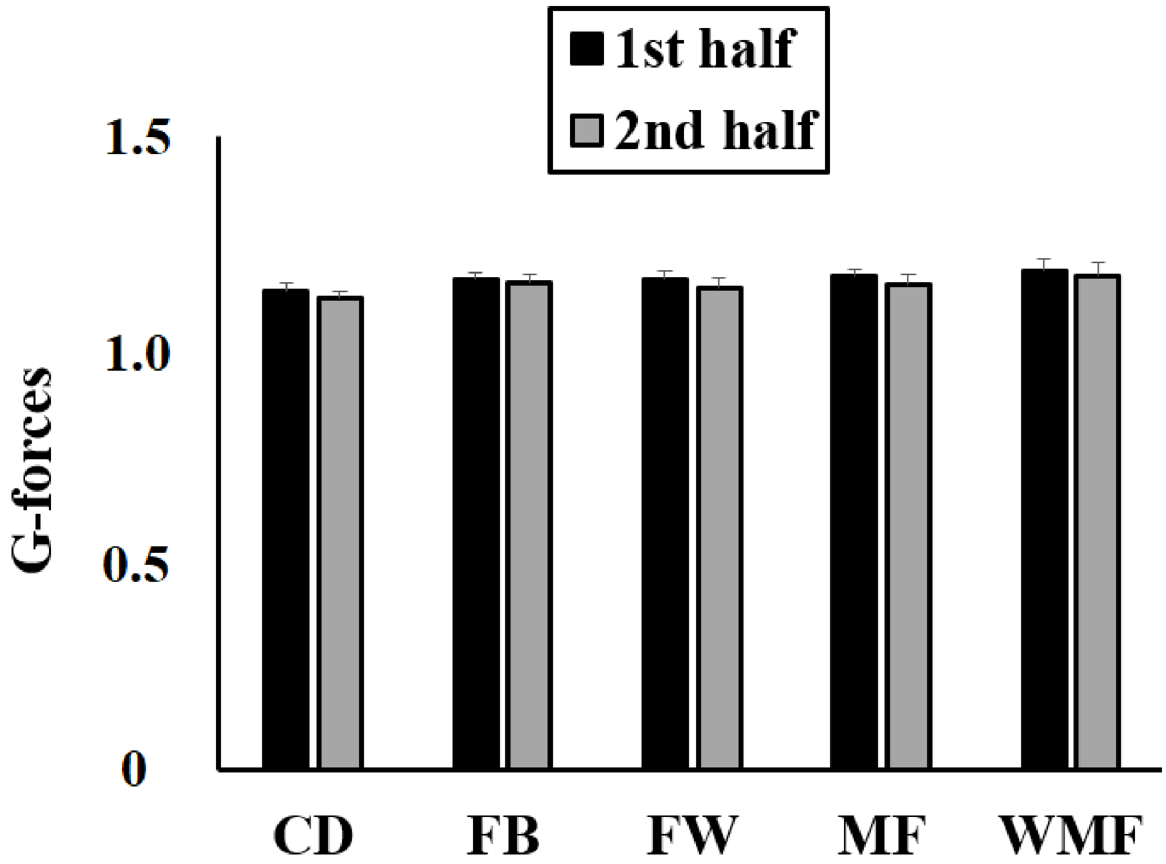

Figure 28. G-forces experienced by professional soccer players based on playing position and match half. *Significant differences (p < 0.05) between halves.

Locomotor efficiency ratio

Figure 29 shows the locomotor efficiency ratio by playing position and match half. Although the match half ($F_{(1, 32)}$ = 9.67; p = 0.004; ηp^2 = 0.23) had a significant effect on the locomotor efficiency ratio, the effect of playing position ($F_{(4, 32)} = 2.12$; $p = 0.10$; $\eta p^2 = 0.21$) and the interaction between match half and playing position was not significant ($F_{(4, 32)} = 1.03$; $p = 0.41$; $\eta p^2 = 0.11$). No differences ($p > 0.05$) were found between playing positions. In addition, match day had no significant effect on the locomotor efficiency ratio experienced by the soccer players ($F_{(12, 32)} = 0.47$; $p = 0.92$; $\eta p^2 = 0.15$).

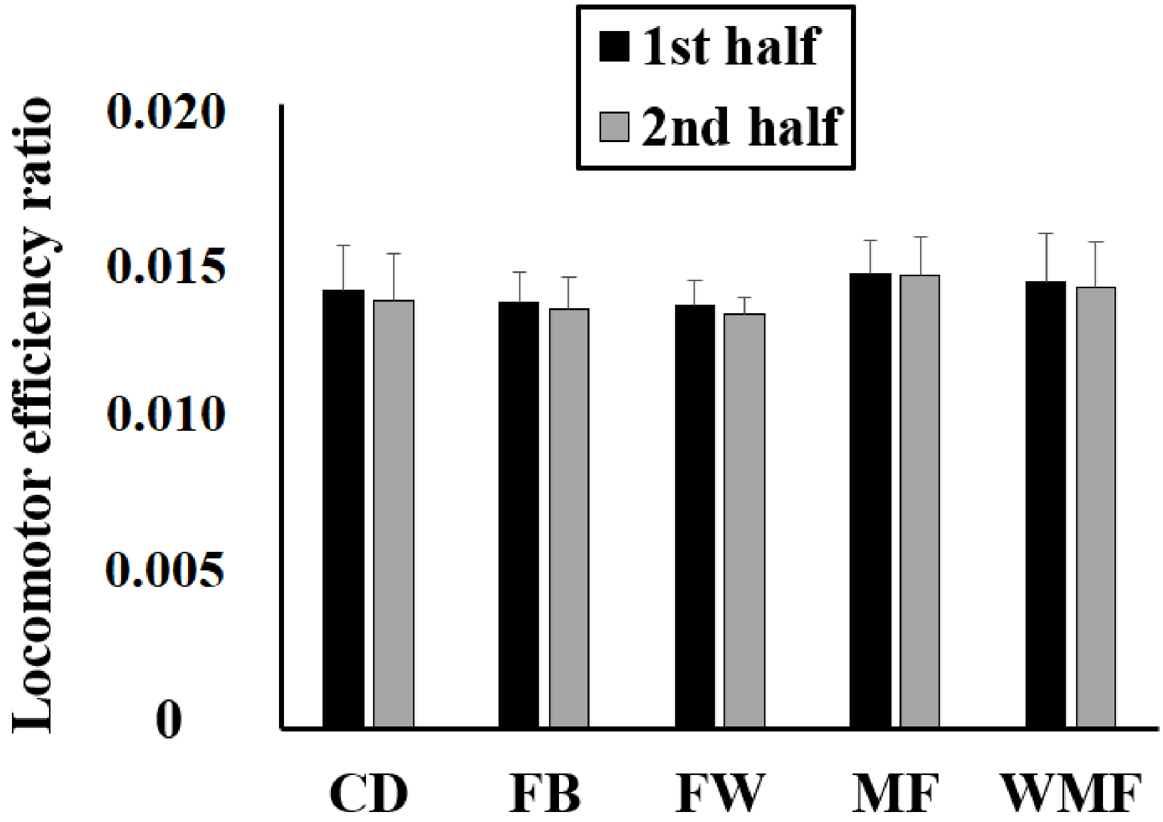

Figure 29. Locomotor efficiency ratio from professional soccer players based on playing position and match half. *Significant differences (p < 0.05) between halves

12.6. Discussion

The main purpose of this investigation was to analyze the effect of playing position, match half, and match day on trunk kinematics of professional soccer players in match play. This investigation, which is one of the first steps towards enhancing the understanding of trunk kinematics from professional soccer players, presents several key findings. Firstly, positional differences were found on the sagittal trunk inclination and the G-forces experienced by the players. However, there were no positional differences on the locomotor efficiency ratio. Secondly, the sagittal trunk inclination and the G-forces experienced by the players were significantly greater during the first half of the matches, while no differences were found for the locomotor efficiency ratio. Finally, no significant differences between matches were observed on the sagittal trunk inclination, G-forces, and locomotor efficiency ratio.

When it comes to the positional differences observed for the trunk inclination and the G-forces experienced by professional soccer players, it is important to mention that soccer is a team sport in which the positional role has a significant influence on the physical demands of the players (Di Salvo et al., 2007; Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Fortes, Krustrup, et al., 2020; Riboli, Semeria, et al., 2021). The results showed trunk inclination values lower (i.e., more upright postures) than other team sports such as field hockey, in which the mean trunk inclination in match play was ~45° and little differences between the playing positions were observed (defenders: ~43.5°; midfielders: ~44.2°; strikers: ~46.4°) (Warman et al., 2019). The trunk flexion position lets the players carry out soccer-specific movements (e.g., running, passing, or controlling the ball) but these actions may move the field of regard down and limit the visual exploration (Lim et al., 2017; Warman et al., 2019). In addition, soccer is a team sport with continuous running actions, accelerations, decelerations, and changes of directions for each position (Granero-Gil et al., 2020; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d), which induce constant trunk accelerations. Then, the differences on the activity-profile from each position may explain why there were positional differences in G-forces in match play. In consequence, the development of position-specific training drills considering the trunk inclination and G-forces experienced by the players is necessary so as to prepare not only for the physical demands (e.g., training trunk flexion postures with constant G-forces, which may avoid low back pain) (Grosdent et al., 2016) but also for a successful performance in the field of regard (Lim et al., 2017; Warman et al., 2019). However, this consideration does not seem to be so important for the locomotor efficiency ratio since no positional differences were found, which confirms the results reported by a previous investigation (Barrett, Midgley, Reeves, et al., 2016).

Regarding the effect of match half on the trunk kinematics variables, this study showed that professional soccer players reported greater sagittal trunk inclination and G-forces during the first half of the matches while no differences between halves were found for the locomotor efficiency ratio. Previous studies, which have analyzed the influence of match half on the activity-profile of professional soccer players, observed that the physical performance decreased during the second half of the matches (Carling & Dupont, 2011; Castellano et al., 2011; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Mark Russell et al., 2016). For example, the performance in high-intensity actions, which increase trunk inclination angle, is reduced during the second half of the matches (Castellano et al., 2011; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e). This may be one of the reasons why our CD, MF, and WMF adopted significantly more upright postures during the second half. In this regard, the declines in physical performance have been linked to a depletion of muscle glycogen towards the end of the match (Carling & Dupont, 2011; Reilly et al., 2008). These observations have significant practical implications for strength and conditioning coaches since the resistance to fatigue needs to be trained through trunk strength exercises, trunk mobility (e.g., spine sparing exercises) in addition to lumbopelvic control exercises (Grosdent et al., 2016; Oliva-Lozano & Muyor, 2020). However, match half did not significantly affect the locomotor efficiency ratio of the players and these results are in line with the only investigation on this ratio available to date (Barrett, Midgley, Reeves, et al., 2016). This study found that specific phases of the match led to different locomotor efficiency ratios but it did not report differences between halves (Barrett, Midgley, Reeves, et al., 2016). For instance, the ratio was greater during the last 15 minutes of the first half compared to the first 15 minutes of the second half, but this ratio was greater during the last 30 minutes of the match compared to first 15 minutes. In this regard, a previous study also concluded that the skill-related performance measures did not significantly change between halves (Carling & Dupont, 2011). Therefore, future investigations are necessary in order to examine the relationship between locomotor efficiency ratio and the physiological response of professional soccer players.

In addition, this study found that the match day had no effect on the sagittal trunk inclination, G-forces, or locomotor efficiency ratio since there were no significant differences between matches. There results imply that these variables may be closely related to the player's biomechanics and other contextual variables (e.g., match day, opponent team) may have not played a significant role in the sample investigated. For example, the match-to-match variability on total distance covered (~5%) is usually lower than the variability on high-speed running distance (~53%) (Haddad et al., 2018). Unfortunately, these research questions regarding the effects of match day on trunk kinematics have limited answers to date since no study has previously analyzed the influence of match day on the sagittal trunk inclination or G-forces experienced by professional soccer players, and only one study on the locomotor efficiency ratio is available (Barrett, Midgley, Reeves, et al., 2016). In fact, contrary to what was previously shown in our results, a significant variability (~21%) on the locomotor efficiency between matches was observed (Barrett, Midgley, Reeves, et al., 2016). The reason for these contradictory results is not clear, but it is worth mentioning that there was an important difference on the total of matches analyzed since this study included 86 matches (Barrett, Midgley, Reeves, et al., 2016) while ours was limited to 13 league matches.

Unfortunately, limited data is available to date regarding the trunk kinematics of soccer players in the course of a match. The analysis of the trunk inclination, G-forces experienced by the players and locomotor efficiency when running or sprinting should be indispensable for hamstring injury prevention (Schuermans et al., 2017). The reason is that excessive trunk and pelvic motion in addition to the lack of lumbopelvic control during the swing phase of the running action is closely related to the injury risk (Schuermans et al., 2017). Most studies usually analyze the amount of horizontal trunk accelerations per intensity zones based on the activity-demands profile of the sport (e.g., soccer: 0-5 G, 5-6 G, >9 G; basketball: 0-3 G, 3-5 G, 5-8 G, >8 G; rugby: 0-6 G, 6-7 G, 7-8 G, 8-10 G, 10-12 G, >12 G; endurance trail running: 1G ranges from 0 G to 30 G) (Cummins & Orr, 2015; Fernández-Leo et al., 2020; Gómez-Carmona et al., 2018; Rojas-Valverde, Sánchez-Ureña, et al., 2019). However, these studies neither analyzed the total of trunk accelerations nor the average magnitude of these trunk accelerations (i.e., triaxial G-forces), which has been considered as a key external load indicator in professional soccer by a principal component analysis (Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d).

Therefore, the lack of investigations on the trunk kinematics of soccer player limited the discussion of our results. Nevertheless, this study has several limitations, which need to be considered. For example, the sample included in this study was specific to one men's professional soccer team during 13 league matches. In addition, not all the team players could be included because only those who played the total match were considered for the analysis. Also, other playing positions such goalkeepers were not analyzed. Goalkeepers were excluded from the analysis given the differences in the activity-profile. In consequence, further investigations are needed to be done considering these limitations in addition to other physiological variables (e.g., heart rate), which may help to understand the role of fatigue on the sagittal trunk inclination, G-forces and locomotor efficiency experienced by the players.

Furthermore, it is to mention that the data were collected by inertial sensors and GPS technology instead of optical tracking systems. Although the tracking systems used in this study have been considered as valid, reliable and suitable instruments to measure position-related variables (Bastida Castillo et al., 2018; Muñoz-López et al., 2017) and trunk inclination in the sagittal plane (Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b), the gold standard technology for measuring position and orientation of human body segments are optical tracking systems (Fasel et al., 2018; Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b; Poitras et al., 2019). However, the use of optical tracking systems is limited to laboratory settings for technical reasons (Fasel et al., 2018; Oliva-Lozano, Martín-Fuentes, & Muyor, 2020b; Poitras et al., 2019) and thus, tracking systems with inertial sensors and GPS technology have vast implications for human activity monitoring. In consequence, future investigations analyzing the trunk kinematics and postural demands should consider the advantages of using these wearable sensors as well as their validity and reliability for measuring each parameter. For example, these wearables should include methods that compensate the drift error (e.g., multi-sensor fusion from accelerometers, gyroscopes, and magnetometers) in order to provide more accurate data (Fong & Chan, 2010; Guiry et al., 2014; Oliva-Lozano, Martín-Fuentes, & Muyor, 2020a; Qiu et al., 2018). In this regard, an investigation suggested the use of several inertial sensors, which were placed on both shanks, thighs, sacrum, and sternum, as a successful method for reducing the drift error in highly dynamic movements (Fasel et al., 2018). Nevertheless, this last method does not seem to be useful from a practical perspective in professional soccer since wearing different sensors around the body may be uncomfortable and dangerous for the players (Medina et al., 2017).

12.7. Conclusion

The data collected by inertial measurement units and global positioning systems may be used for having a better understanding of the postural demands of professional soccer players. This may be considered as the first study analyzing the trunk kinematics of professional soccer players in official matches. In addition, a novel approach was conducted by analyzing the effect that different contextual variables (e.g., playing position, match half, and match day) had on the postural demands. Although the only investigations that have analyzed the trunk kinematics have been carried out in field hockey players, our study with soccer players tried to improve the applied methodology since these investigations presented two major limitations: the sample of matches (6 matches and 1 match, respectively) (Warman et al., 2018, 2019) and the use of different instruments for data collection within the same investigation (Warman et al., 2019).

The positional differences found on the sagittal trunk inclination and the G-forces experienced by the players imply that the development of position-specific training drills considering the postural demands is necessary so as to prepare the players not only for the physical demands (e.g., training trunk flexion postures with constant G-forces) but also for a successful performance in the field of regard. Also, it is important that strength and conditioning coaches include trunk strength exercises with special focus on flexion positions as well as other compensatory exercises for trunk extension muscles, which balance trunk flexors and trunk extensors, before and after match days. Specifically, it would be important to add perturbations so as to stimulate trunk accelerations (~1-2 G) during trunk strength exercises. In addition, the resistance to fatigue needs to be trained given the differences on the postural demands observed between halves. Finally, it is recommended that the soccer players exercise trunk mobility (e.g., spine sparing exercises) before and after the match with special focus on the posterior chain.

CHAPTER 13

Study XI. Differences in worst-case scenarios calculated by fixed length and rolling average methods in professional soccer match-play

Oliva-Lozano, J. M., Martín-Fuentes, I., Fortes, V., & Muyor, J. M. (2021). Differences in worst-case scenarios calculated by fixed length and rolling average methods in professional soccer match-play. *Biology of Sport*, *38*(3), 325–331. https://doi.org/https://doi.org/10.5114/biolsport.2021.99706

13. DIFFERENCES IN WORST-CASE SCENARIOS CALCULATED BY FIXED LENGTH AND ROLLING AVERAGE METHODS IN PROFESSIONAL SOCCER MATCH-PLAY

13.1. Abstract

The aims of this study were to describe the WCS in professional soccer players calculated by fixed length and rolling average methods with regards to each playing position. This was done firstly, by comparing total distance (TD covered in the WCS; secondly, by comparing high-speed running distance (HSRD); and thirdly, by comparing sprint distance (SPD). The study was conducted over a three-mesocycle competitive period. The WCS of three distance-related variables (TD, HSRD, SPD) in four-time windows (1, 3, 5, 10 minutes) were calculated by playing position (central defender; full-back; midfielder, wide-midfielder, and forward) using fixed length and rolling averages methods. A significant effect of the type of method used to calculate the WCS in TD ($F_{(1, 142)} = 151.49$, $p < 0.001$, $\eta p^2 = 0.52$), HSRD ($F_{(1, 138)} = 336.95$, $p < 0.001$, $\eta p^2 = 0.71$) and SPD ($F_{(1, 138)} = 76.74$, $p < 0.001$, $\eta p^2 = 0.36$) was observed. In addition, there was a significant interaction between type of method and WCS duration in TD ($F_{(1.36, 193.53)} = 41.95$, $p < 0.001$, $\eta p^2 = 0.23$), HSRD ($F_{(2.28, 315.11)} = 21.77$, $p < 0.001$, $\eta p^2 = 0.14$) and SPD ($F_{(2.59, 358.41)} = 6.93$, $p < 0.001$, $\eta p^2 = 0.05$). In conclusion, the use of fixed length methods of different durations significantly underestimated the WCS of TD, HSRD and SPD across the most common playing positions in professional soccer players. Therefore, the application of rolling averages is recommended for an appropriate WCS analysis in professional soccer match-play.

13.2. Keywords

External load, GPS, most demanding passage, football, performance.

13.3. Introduction

New methods have been developed recently aimed at quantifying peak intensity periods, which are also known as the most demanding passages (MDP) (Martín-García, Casamichana, et al., 2018) or worst-case scenarios (WCS) (Cunningham et al., 2018). The WCS are defined as the periods of 1, 3, 5 or 10 minutes of maximum physical output (distance covered at high speed running) throughout a match (Delaney et al., 2018; Reardon et al., 2017). The fixed length method was the first attempt to quantify the WCS (Bradley et al., 2009) and consisted of splitting the total match in fixed periods from the start to the end of the match. For example, periods of 1 minute (0 - 59'', 1 - 1.59'', 2 - 2.59''… until the end of the match); 3 minutes (0 - 2.59'', 3 - 5.59''… until the end of the match); 5 minutes (0 - 4.59'', 5 - 9.59''… until the end of the match) and 10 minutes (0 - 9.59'', 10 - 19.59''… until the end of the match). Nevertheless, the use of the rolling average method is currently considered more accurate for quantifying WCS (Martín-García, Casamichana, et al., 2018) as this method detects the exact period (depending on the time selected for the analysis) in which the player is at peak intensity (Cunningham et al., 2018). Thus, the WCS could be detected, for example, from the period 2'53'' to 3'53'' (1-minute WCS), from 2'53'' to 5'53'' (3-minutes), from 2'53'' to 7'53'' (5-minute WCS) or from 2'53'' to 12'53'' (10-minutes) (Cunningham et al., 2018).

In addition, the performance in the WCS is associated with different contextual variables (e.g., playing position, match location, match outcome, match half or congested calendars) (Casamichana et al., 2019; Castellano et al., 2020; Delaney et al., 2018; Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Oliva-Lozano, Fortes, & Muyor, 2020). For example, the WCS in soccer matches could be specifically analyzed with regards to the playing position (Delaney et al., 2018; Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020e; Oliva-Lozano, Fortes, & Muyor, 2020). It has been recently been observed that midfielders (MF) and wide-midfielders cover greater distance in WCS than other positions (Delaney et al., 2018; Martín-García, Casamichana, et al., 2018), and when longer periods of WCS are analyzed, there are even greater differences between playing positions (Martín-García, Casamichana, et al., 2018). Consequently, these differences are deemed important to optimally prescribe position-specific training load and therefore methodological studies are needed to analyze which analysis technique is more accurate to assess the physical demands of soccer players.

Despite the studies mentioned above, research on WCS has, to date, been limited. Methodological works on the comparison between the use of fixed length and rolling averages methods are scarce in the literature. For example, a recent study found that the use of fixed length methods may underestimate WCS running demands (Fereday et al., 2020). However, variables including very speed running actions such as sprinting distance (i.e., distance covered above 25.2 km/h), which are less frequent (Martín-García, Casamichana, et al., 2018; Oliva-Lozano, Fortes, Krustrup, et al., 2020; Palucci-Vieira et al., 2019), were not analyzed. Consequently, there is a risk of results misinterpretation since the use of fixed length methods may underestimate WCS in low- or medium-speed actions (Cunningham et al., 2018; Fereday et al., 2020) but it may be useful for high-speed actions.

Therefore, the main purpose of this study is to describe the WCS, in professional soccer players, calculated by fixed length and rolling average methods with regards to each playing position. This was done, firstly, by comparing total distance covered in the WCS; secondly, by comparing high-speed running distance covered; and thirdly, by comparing sprint distance covered.

13.4. Methods

Study design

A cohort study was conducted over an in-season three-mesocycle competitive period in LaLiga 123 with a total of twelve official professional soccer matches. The soccer matches were consecutive (one match per week) and played at home or away on Friday, Saturday or Sunday depending on the official calendar. The data was collected through wearable sensors (RealTrack Systems, Almería, Spain) to calculate players' WCS. Four WCS periods were analyzed: 1, 3, 5 and 10 minutes. Every soccer player was categorized according to their playing position: forward (FW), midfielder (MF), wide-midfielder (WMF), full-back (FB) and central defender (CD).

Participants

Nineteen professional soccer players (mean ± SD; age, 26.78 ± 3.77 years old; body mass index, 23.1 ± 0.19) voluntarily participated in the study. The team playing formation was 4-2-3-1. Soccer players who did not complete the full match and goalkeepers were not included in the analysis. The data was derived from daily monitoring over the season and the club provided informed consent to use the dataset for research purposes. The study was also approved by the University of Almeria's Ethics Board.

Procedures

Total distance (TD), high speed running distance (HSRD, above 19.8 km/h) and sprint distance (SPD, above 25.2 km/h) (Martín-García, Casamichana, et al., 2018) were collected using WIMU Pro (RealTrack Systems, Almería, Spain). This is an inertial device with 3D accelerometers, gyroscopes and magnetometers which collects positioning data through a 10Hz Global Positioning System (GPS). These tracking systems are considered as valid (bias in mean speed: 1.2 – 1.3 km/h; bias in distance: 2.3 – 4.3 m) and reliable (intraclass correlation coefficients: above 0.93) instruments for the analysis of time-motion parameters in soccer (Bastida Castillo et al., 2018). The devices were calibrated 30 minutes before the start of each match following the manufacturer's instructions: first, the units were placed on a steady surface; then turned on and finally, waited for 30 seconds before starting the recording of the session. The devices were then placed in a vertical position in the back pocket of a chest vest (Rasán, Valencia, Spain) designed for the players. Each player wore the same device in every match in order to avoid inter-unit error. Once the match had finished, the players returned the devices to the research team. The devices were placed on Smart Station (RealTrack Systems, Almeria, Spain) and the data was transferred to the analysis software.

The data was analyzed using SPro software (RealTrack Systems, Almeria, Spain). This software analyzes GPS Speed raw data and the application of the two methods of analysis: fixed-length and rolling-average. First, fixed length scenarios were obtained by splitting the total match into fixed periods, from the start to the end of the match, of 1, 3, 5 and 10 minutes (Figure 30a). Secondly, the rolling average method was used by means of an algorithm that detected and calculated the WCS of each variable at the four WCS durations (1, 3, 5 and 10 minutes). Given the 10Hz sample frequency of the device (RealTrack Systems, Almería, Spain) and 1-minute WCS for instance (Figure 30b), the rolling average algorithm found the moment (60 seconds = 600 samples) when the player covered the greatest distance. Thus, the fixed length method calculated the WCS in static period samples (1 - 600, 601 - 1200, and so on).

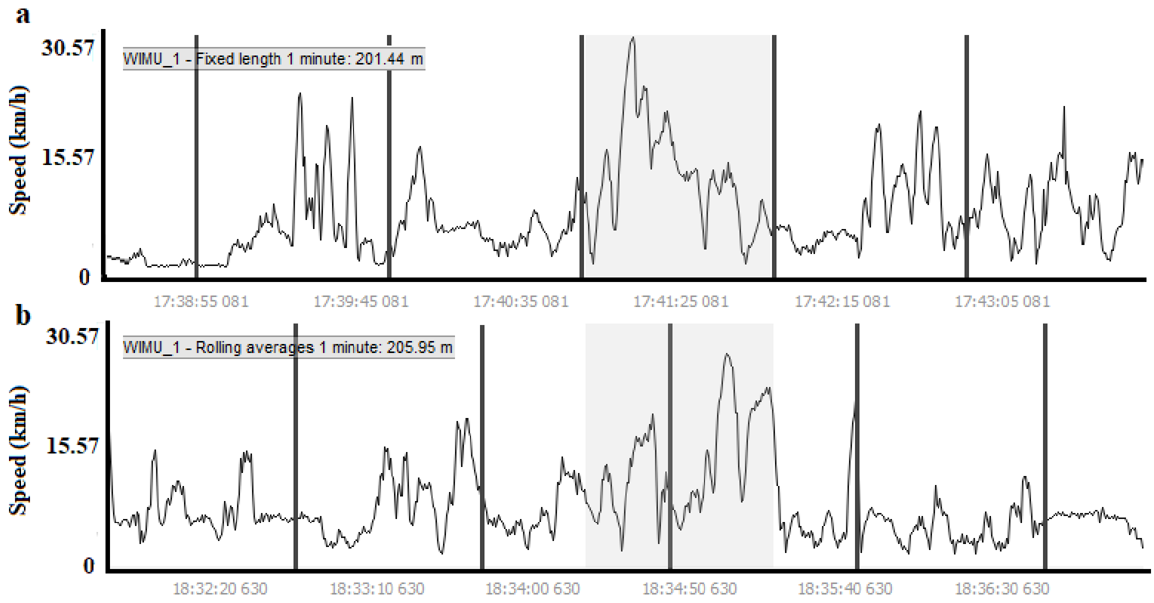

Figure 30. Difference between fixed length (a) and rolling average method (b) for WCS detection

Statistical analysis

Descriptive statistics were calculated for both methods (fixed length and rolling averages) based on playing positions (CD, FB, FW, MF, WMF) and WCS duration (1, 3, 5, 10 minutes). Secondly, the hypothesis of normality in each variable was analyzed using the Shapiro-Wilk test. Thirdly, linear mixed models were performed using a design ANOVA 2 x 5 x 4 (methods*playing positions*WCS duration) to determine the difference between fixed and rolling average methods while accounting for potential effects and interactions with playing position and WCS duration. This analysis compares different means when there are two or more independent variables or factors but, at least, one of the factors should be an intra-subject factor (e.g., method or WCS duration) and between-subjects factor (e.g., playing position). In addition, to assess assumptions of variance, Mauchly's test of sphericity was performed using all the ANOVA results. A Greenhouse–Geisser correction was performed to adjust the degrees of freedom if an assumption was violated, while pairwise comparisons using a Bonferroni adjustment were employed if a significant main effect was observed. Effect sizes were also reported using partial eta-squared (ηp^2). The level of significance was set at $p \leq 0.05$ and the statistical analysis was carried out using IBM SPSS Statistics version 26 (SPSS Inc., Chicago, IL, USA).

13.5. Results

Figure 31 shows TD covered in meters for each WCS duration (1, 3, 5 and 10 minutes), which were calculated by fixed and rolling averages methods. The rolling averages method reported significantly greater TD ($p < 0.05$) than the fixed length method in all positions at each WCS duration. A significant effect of the type of method used to calculate the WCS in TD covered was observed ($F_{(1, 142)} = 151.49$, $p < 0.001$, $\eta p^2 = 0.52$). In addition, there was a significant interaction between type of method and WCS duration ($F_{(1.36, 193.53)} = 41.95$, $p < 0.001$, $\eta p^2 = 0.23$). The interaction was not significant between type of method and playing position ($F_{(5, 142)} = 1.13$, $p = 0.35$, $\eta p^2 = 0.04$) or between method, playing position and WCS duration ($F_{(6.81, 142)} = 1.74$, $p = 0.11$, $\eta p^2 = 0.06$).

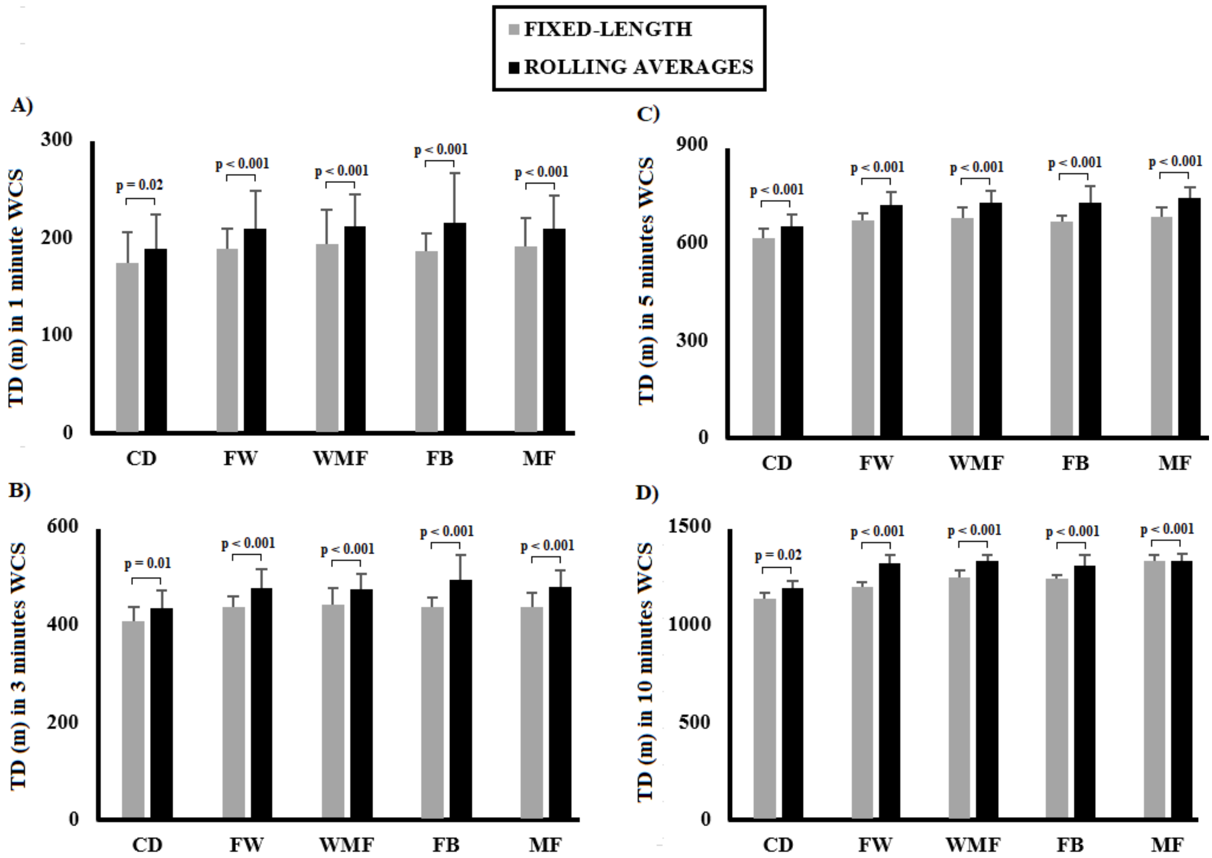

Figure 31. Total distance (TD) covered in every WCS duration calculated for each playing position using fixed length and rolling averages.

HSRD covered in meters for each WCS duration by fixed and rolling averages methods is represented in Figure 32. The rolling averages method reported significantly greater HSRD (*p*

< 0.05) than the fixed length method in all positions at each WCS duration. A significant effect of the type of method used to calculate the WCS in HSRD covered was observed ($F_{(1, 138)}$ = 336.95, p < 0.001, ηp^2 = 0.71). There was a significant interaction between method and playing position ($F_{(5, 138)}$ = 2.63, p = 0.03, ηp^2 = 0.09) and between method and WCS duration ($F_{(2.28, 315.11)}$ = 21.77, p < 0.001, ηp^2 = 0.14). However, the interaction method, playing position and WCS duration was not significant ($F_{(11.41, 138)}$ = 1.16, p = 0.30, ηp^2 = 0.04).

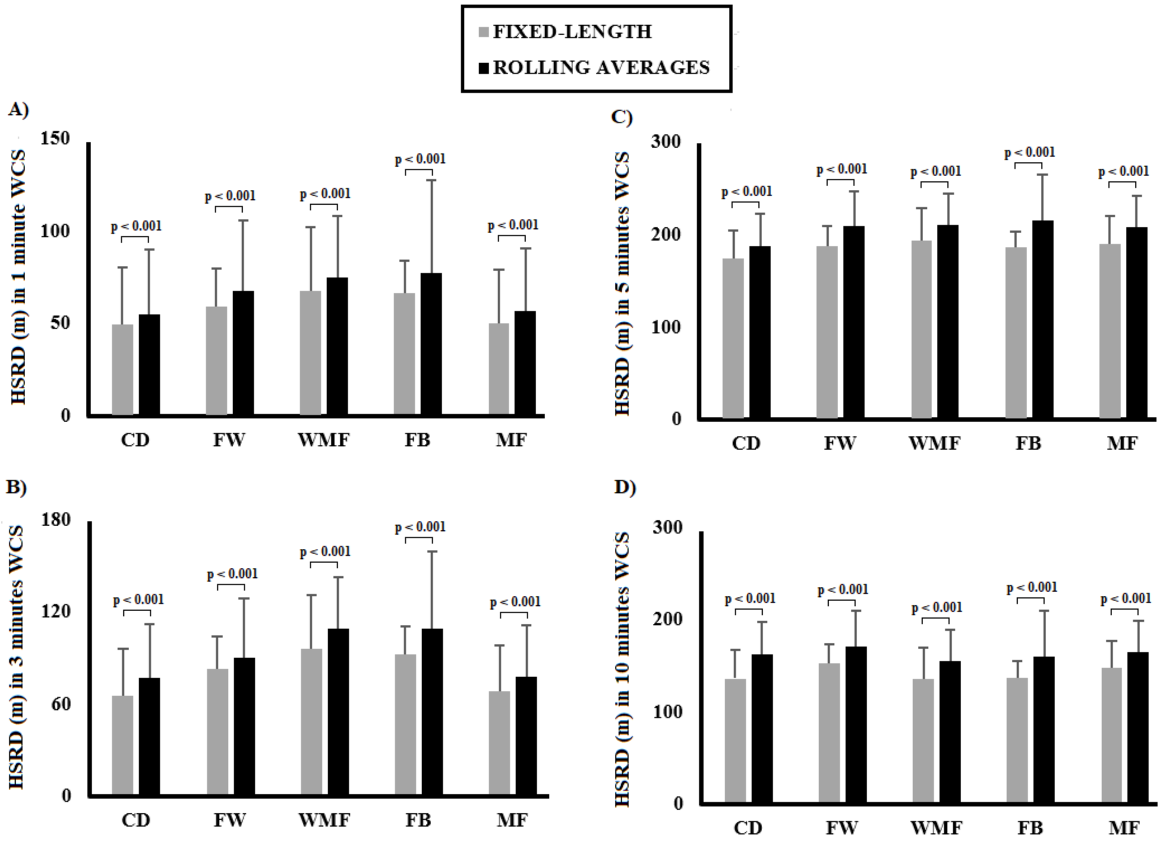

Figure 32. High-speed running distance (HSRD) in every WCS duration calculated for each playing position using fixed length and rolling averages.

Subsequently and with regards to SPD covered (Figure 33), significant differences between fixed length and rolling averages were found for each WCS duration in all playing positions (p < 0.05). A significant effect of the type of method used to calculate the WCS in TD covered was found ($F_{(1, 138)}$ = 76.74, p < 0.001, ηp^2 = 0.36). In addition, there was a significant interaction between type of method and WCS duration ($F_{(2.59, 358.41)}$ = 6.93, p < 0.001, ηp^2 = 0.05). The interaction was not significant between type of method and playing position ($F_{(5, 138)}$ = 0.54, p

= 0.75, ηp^2 = 0.02) or between method, playing position and WCS duration ($F_{(12.99, 138)}$ = 0.91, p = 0.54, ηp^2 = 0.03).

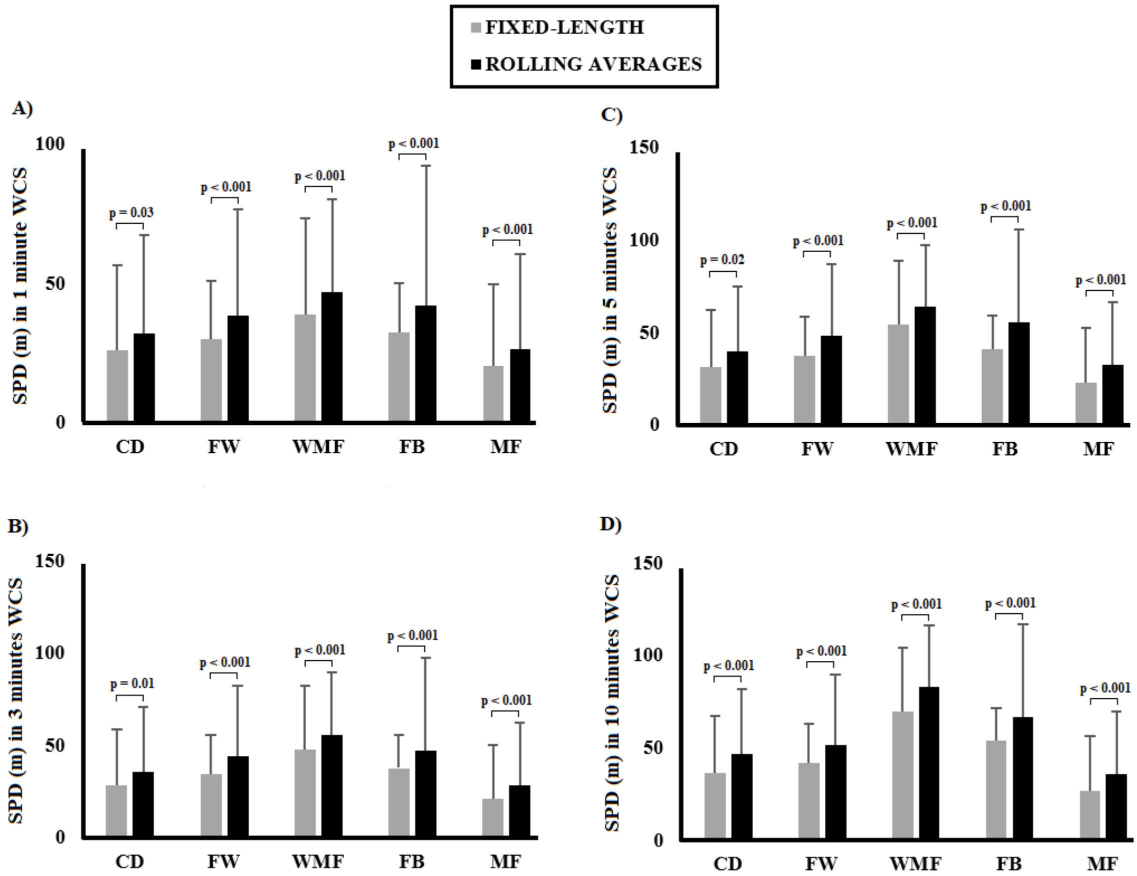

Figure 33. Sprint distance (SPD) covered in every WCS duration calculated for each playing position using fixed length and rolling averages.

13.6. Discussion

This study compared the WCS calculated by fixed length and rolling averages methods taking into consideration soccer playing positions and four WCS durations (1, 3, 5 and 10 minutes) in professional matches. From a practical perspective, it was necessary to investigate the interchangeability of both methods for the analysis of WCS in TD, HSRD and SPD, a methodology which had never been conducted in the scientific literature in relation to soccer. The main finding was that the use of fixed length methods of different durations significantly underestimated the WCS of TD, HSRD and SPD in all playing positions. In addition, a significant interaction between WCS duration and the method used to calculate the WCS was observed in all the external load variables.

Rolling averages calculated significantly greater TD (p < 0.05) than fixed length epochs in all positions at each WCS duration. Previous studies, which compared both methods in soccer players, also concluded that fixed method reported significantly lower values compared to rolling averages in TD (10.1% difference) for 1 minute (Fereday et al., 2020), 3 minutes (8.2% difference) (Fereday et al., 2020), 5 minutes (7.5% difference and 25.2%, respectively) (Fereday et al., 2020; M. C. Varley et al., 2012), and 10 minutes (6.7% difference). This comparison has also been applied to rugby players and fixed length method underestimated the rolling averages WCS of TD for 1 minute (11.8% difference), 3 minutes (12.2% difference) and 5 minutes (11.4% difference) (Cunningham et al., 2018). One of the main findings of this study was that WCS duration had a significant interaction with the method used to calculate the WCS ($F_{(1.36, 193.53)} = 41.95$, $p < 0.001$, $\eta p^2 = 0.23$). Contrary to the findings of Ferraday et al. (Fereday et al., 2020), which reported that the longer the WCS the lower the differences between methods, this study observed that the longer the WCS the greater the differences between fixed and length method in all playing positions. Since the same interaction was found but with different conclusions, future studies could investigate the association WCS duration and type of method used to calculate the WCS and therefore, replicate the results in a larger sample size.

In addition, MF, WMF and FB positions experienced higher peak demands in TD covered in soccer matches than positions such as FW and CD. This is consistent with previous research on the WCS of soccer matches which showed that there were positional differences in TD covered in 1-minute WCS (MF: ~204m; WMF: ~201m; FB: ~194m; CD: ~181m; FW: ~181m), 3-minute WCS (MF: ~483m; WMF: ~471m; FB: ~453m; CD: ~429m; FW: ~414m), 5-minute WCS (MF: ~750m; WMF: ~730m; FB: ~695m; CD: ~665m; FW: ~640m) and 10-minute WCS (MF: ~1400m; WMF: ~1350m; FB: ~1280m; ~CD: 1270m; FW: ~1170m) (Martín-García, Casamichana, et al., 2018). However, the results from our study showed that the interaction was not significant between the method used to calculate the WCS and playing position. Since the same results were obtained in a previous investigation (Fereday et al., 2020), this suggests that soccer playing position does not have any significant influence on the method applied to calculate the WCS. Therefore, rolling averages are considered as the most appropriate method to quantify TD covered in WCS (Delaney et al., 2018; Fereday et al., 2020; Martin-Garcia et al., 2019).

Regarding HSRD, a significant effect of the method was observed ($F_{(1, 138)} = 336.95$, $p < 0.001$, $\eta p^2 = 0.71$). Rolling averages method reported significantly greater HSRD covered ($p < 0.05$) than the fixed length method in all positions at each WCS duration. Few studies have previously compared HSRD using both methods in team sport matches (Cunningham et al., 2018; Fereday et al., 2020) but these authors found similar results to the current study. For example, HSRD was underestimated in WCS of 1 minute (10.6% and 11.7% difference, respectively) (Cunningham et al., 2018; Fereday et al., 2020), 3 minutes (19.5% and 21.1% difference, respectively) (Cunningham et al., 2018; Fereday et al., 2020), 5 minutes (21.3% and 22% difference, respectively) (Cunningham et al., 2018; Fereday et al., 2020), and 10 minutes (14.2% difference). Although there was a significant interaction between method and playing position, the effect size was low ($F_{(5, 138)} = 2.63$, $p = 0.03$, $\eta p^2 = 0.09$). This implies that playing position doesn't have a meaningful impact on the differences between methods even though the effect of position on HSRD is higher than on TD. Perhaps, this could be explained the influence of high-speed variables on decreasing distance covered (Martín-García, Casamichana, et al., 2018). However, the interaction between method and WCS duration was significant ($F_{(2.28, 315.11)} = 21.77$, $p < 0.001$, $\eta p^2 = 0.14$). The differences between methods were greater in longer WCS ($p < 0.001$), specially from 1 to 10 minutes. Consequently, the use of rolling averages for HSRD WCS detection is recommended and supported not only by previous research (Cunningham et al., 2018; Delaney et al., 2018; Fereday et al., 2020; Lacome et al., 2018; Martín-García, Casamichana, et al., 2018) but also by this study, which showed how HSRD was always underestimated using fixed length method across all positions in every WCS duration.

Additionally, when SPD was analyzed, rolling averages once again attained greater values than fixed length method with statistically significant differences for each WCS duration and playing position. This is the first study to compare both methods of WCS in SPD covered and it is relevant to highlight that the only significant interaction observed was between WCS duration and method ($F_{(2.59, 358.41)} = 6.93$, $p < 0.001$, $\eta p^2 = 0.05$). Given the nature of sprinting actions, in which the player needs to overcome 25.2 km/h, SPD might be time-dependent (Delaney et al., 2018; Lacome et al., 2018; Martín-García, Casamichana, et al., 2018), which could explain why the effect of WCS duration on the differences between methods is lower in SPD compared to TD or HSRD. In addition, SPD might be position-dependent (Martín-García, Casamichana, et al., 2018). However, the results from our study showed that the interaction was not significant between the method used to calculate the WCS and playing position ($F_{(5, 138)} = 0.54$, $p = 0.75$, $\eta p^2 = 0.02$), which implies that playing position does not have any significant effect on the method applied to calculate the WCS. Therefore, it could be concluded that SPD covered in WCS was directly dependent on the method used, suggesting rolling averages as the most appropriate method to quantify SPD.

This research has several limitations since it only analyzes WCS of professional soccer players in four WCS durations (1, 3, 5 and 10 minutes) which were based on three variables (TD, HSRD and SPD). As this is the first research on the comparison between fixed length and rolling averages method, future studies are needed to provide more details about this analysis. Future research could focus on the analysis of shorter or longer WCS durations, analyze a different population (e.g., youth players) or include other variables such as accelerations/decelerations (Aamot et al., 2016) and total of high intensity actions (Aquino, Munhoz-Martins, et al., 2017).

13.7. Conclusion

This study showed that fixed length methods underestimated the TD, HSRD and SPD covered in 1-minute, 3-minutes, 5-minutes, and 10-minutes WCS across the most common playing positions in professional soccer players. Therefore, the use of rolling-averages is recommended. Gaining knowledge on how technology is used to quantify WCS is important for applied practitioners who daily attempt to optimize performance through position-specific load management. For example, the values reported by rolling averages for TD, HSRD or SPD could serve as a reference when prescribing a 5-minute training drill trying to meet match WCS demands. However, the values reported by fixed-length method would underestimate WCS across all playing positions. Thus, the results of this study also help to understand competitive match-play demands and plan strategies to prepare the players for official soccer matches.

CHAPTER 14

Study XII. Understanding the FIFA Quality performance reports for electronic performance and tracking systems: from science to practice

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14. UNDERSTANDING THE FIFA QUALITY PERFORMANCE REPORTS FOR ELECTRONIC PERFORMANCE AND TRACKING SYSTEMS: FROM SCIENCE TO PRACTICE

14.1. Abstract

The world's soccer-governing body, FIFA, developed the FIFA Quality Programme to set internationally recognized industry standards for electronic performance and tracking systems (EPTS). The positioning and velocity data from different EPTS, discretized into velocity bands, were validated against criteria measures. Discussions have been ongoing between practitioners regarding the FIFA quality performance reports, particularly when the findings are used to compare accuracy between systems. However, there are important methodological issues that should be addressed when interpreting these findings. The aim of this article is to provide practitioners with guidance on interpreting the results of FIFA's EPTS quality performance reports. We demonstrate that several methodological factors should be considered. For example, EPTS reports evaluate individual systems against criteria measures but systems are often not evaluated concurrently (e.g., on the same day using the same participants). Furthermore, technical considerations such as the total number of cameras used for optical (OPT) systems, the total number of antennas used by local positioning systems (LPS), the total number of satellites available for global navigation satellite systems (GNSS) and the velocity bands should be considered before interpreting the post-test results reported for each EPTS. Specifically, comparisons between GNSS, LPS and/or OPT systems are inadvisable unless they are used within the same observation.

14.2. Keywords

Accuracy, Validity, Soccer.

14.3. Introduction

The sport industry has developed a wide variety of EPTS, including optical tracking systems (OPT), local positioning systems (LPS) and global navigation satellite systems (GNSS) (Linke et al., 2018). Sports organizations require EPTS to meet their needs and fall within their budget, but also crucially that the data generated are of acceptable quality (i.e., valid and reliable) (Linke et al., 2018; Malone et al., 2017). An instrument's validity indicates if it measures what it is intended to measure (Currell & Jeukendrup, 2008) while its reliability refers to the measurement consistency (Weir, 2005).

Recently, FIFA has developed the FIFA Quality Programme to set internationally-recognized EPTS industry standards (FIFA, 2017). In this regard, FIFA invited all interested EPTS providers to take part in a new testing and certification event - the FIFA Quality Programme. Developed in collaboration with researchers, the program serves to establish the concurrent validity of EPTS positioning and velocity data (discretized into velocity bands) by comparing them to criteria measures (FIFA, 2017). These include the gold standard system for motion capture (Vicon Motion Systems Ltd, Oxford, United Kingdom), which is set in a 30x30m area, and the Vision Kit system (Victoria University, Melbourne, Australia), used to track players over the full area of the pitch (FIFA, 2019). The data collection protocols were conducted in soccer stadia and each protocol was characterized by circuits with self-paced walking, self-paced jogging, maximal accelerations and changes of direction as well as small-sided games, series of maximal sprints and jogging along the internal lines of the pitch to ensure the entire pitch is covered (FIFA, 2019).

The data collection was conducted in collaboration with the manufacturers, who submitted their data once the session ended. Although the manufacturers could submit their data at different sample rates, they were assessed at 10 Hz. Additionally, the motion capture data were provided at a 100 Hz sample rate while the computer vision data were provided at 25 Hz (FIFA, 2019). Since different sample rates were used, the data from the reference systems were imported and synchronized with the manufacturers' data. Specifically, these data were analyzed following the protocol described in the "Handbook of test methods for EPTS devices" (FIFA, 2019). Finally, the FIFA quality performance reports for EPTS were listed online using a color-coded scale, ranking the results for both the positioning and velocity data in different velocity bands (FIFA, 2020). Box plot values were used to determine thresholds which informed such grading based on current industry standards (Well Above: Q1 - 1.5 * IQR to 25^{th} percentile; Above: 25^{th} percentile to median; Standard: median to 75^{th}; Below: 75^{th} percentile to Q3 + 1.5 * IQR; Well-Below: everything greater than the Below level) (FIFA, 2019).

Currently, researchers, sport scientists, fitness coaches and other professionals share information and openly debate the FIFA quality performance reports (through social networks etc.). Unfortunately, many professionals do not interpret them according to how the data are collected: for example, comparing EPTS systems or ranking individual products against one another (Carolan, 2019; Dahl, 2020; Sporttechie, 2019). Furthermore, EPTS manufacturers, who continually look for competitive advantages, promote their products as “the best GPS on the market” (Catapult Sports, 2019). Although the data collection procedures standardized the practical measures (i.e., EPTS) and the criteria measures, there are important methodological considerations related to the validation conditions when comparing EPTS that were evaluated on different days at different stadia. Therefore, the aim of this article is to provide practitioners with guidance in understanding the EPTS results from FIFA quality performance reports.

14.4. Methods

This commentary article reviews the FIFA quality performance reports for EPTS, which are published online (FIFA, 2020). The last review was conducted on 3rd August 2020 to obtain the most up-to-date version of the reports. All the reports provided by FIFA on OPT, GNSS, and LPS system performance were examined.

Two researchers read each report, extracting the following data: name of the product tested and its manufacturer, testing day, testing venue, time required by the manufacturer after the test to submit the data collected on its product, characteristics of the sample participating in the test, drills performed by the participants, velocity bands assessed, total of satellites for GNSS, total of LPS antennas, and total of cameras for OPT systems.

14.5. Results

A total of 11 EPTS performance reports were found (FIFA, 2020). These included 5 GNSS (Table 13), 2 LPS (Table 14), and 4 OPT systems (Table 15).

GNSS

Table 13 details the GNSS testing conditions. Although the data from all the GNSS were submitted following a similar deadline, two different testing venues were used (Camp Nou and Miniestadi). The GNSS were tested on three different dates (21st November 2018, 22nd November 2018 and 10th October 2019) with different satellite availability being observed for Apex on 21st November 2018 (STATSports, Newry, Northern Ireland). Regarding the participants' age, this was not specified for OhCoach Cell B (Fitogether Inc., Seoul, South Korea) or Vector (Catapult Sports, Melbourne, Australia). Different drills were included in addition to the 3v3 game, some of which were tested in 2018 but not included in the 2019 tests, for example, the sprinting drill. Finally, only two GNSS (OhCoach Cell B and Vector) reported results for all velocity bands. One report from the GNSS group (STATSports, Newry, Northern Ireland) showed no results for several high-velocity zones (20-25 km/h and above 25 km/h).

Table 13. FIFA Quality Programme testing conditions for Global Navigation Satellite Systems (GNSS)

Product	OhCoach Cell B	S5	Vector	Apex	WIMU Pro
Manufacturer	Fitogether Inc[1]	Catapult[2]	Catapult[2]	STATSports[3]	RealTrack Systems[4]
Testing day	10th October 2019	21st November 2018	10th October 2019	21st November 2018	22nd November 2018
Testing venue	Camp Nou (Barcelona)	Miniestadi (Barcelona)	Camp Nou (Barcelona)	Miniestadi (Barcelona)	Miniestadi (Barcelona)
Total satellites	13 - 16	13 - 16	13 - 16	12 - 14	13 - 16
Submission time	1 hour	1 hour	1 hour	1 hour	1 hour
Participants	Unspecified	Under 13	Unspecified	Under 13	Under 13
Drills	Circuit, 2v2 game, 5v5 game, sprints, FPC	Circuit, 2v2 game, 3v3 game, 5v5 game, FPC	Circuit, 2v2 game, 5v5 game, sprints, FPC	Circuit, 2v2 game, 3v3 game, 5v5 game, FPC	Circuit, 2v2 game, 3v3 game, 5v5 game, FPC
Velocity bands assessed	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, >25 km/h, *	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, *	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, >25 km/h, *	0-7 km/h, 7-15 km/h, 15-20 km/h, *	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, *

Note: FPC, full pitch coverage; *, only velocity data were analyzed; [1]Fitogether Inc., Seoul, South Korea; [2]Catapult Sports, Melbourne, Australia; [3]STATSports, Newry, Northern Ireland; [4]RealTrack Systems, Almería, Spain; Data retrieved: 3rd August 2020 (FIFA, 2020)

LPS

Table 14 details the LPS testing conditions. These LPS were tested on different dates (22nd November 2018 and 10th October 2019) and venues (Miniestadi and Camp Nou). Regarding the participants' age, under-13 players were selected for WIMU Pro (RealTrack Systems, Almeria, Spain) while the age was unspecified for Vector. Moreover, different drills were observed; for instance, the 3v3 game was tested in the first test but not included in the second. Instead, the 2019 test included a new sprinting drill. Finally, no results for actions above 25 km/h were available for WIMU Pro.

Table 14. FIFA Quality Programme testing conditions for Local Positioning Systems (LPS)

Product	Vector	WIMU Pro
Manufacturer	Catapult[1]	RealTrack Systems[2]
Testing day	10th October 2019	22nd November 2018
Testing venue	Camp Nou (Barcelona)	Miniestadi (Barcelona)
Total antennas	24	8
Submission time	1 hour	1 hour
Participants	Unspecified	Under 13
Drills	Circuit, 2v2 game, 5v5 game, sprints, FPC	Circuit, 2v2 game, 3v3 game, 5v5 game, FPC
Velocity bands assessed	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, >25 km/h	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h,

Note: FPC, full pitch coverage; [1]Catapult Sports, Melbourne, Australia; [2]RealTrack Systems, Almeria, Spain; Data retrieved: 3rd August 2020 (FIFA, 2020)

OPT

Table 15 details the testing conditions for the OPT systems (FIFA, 2020). These OPT were tested at different venues (Camp Nou and Miniestadi) and dates (22nd November 2018, 10th and 11th October 2019). The sample for TRACAB Gen5 (ChyronHego AB2, Stockholm, Sweden) was collected from under-13 players while the reports did not specify the age of the participants for Coach160 (TRACK160 Ltd., Tel Aviv, Israel), InStat Fitness (Instat, Dublin, Ireland) or Ball & Player Tracking (Hawk-eye, Basingstoke, England). Furthermore, different drills were observed - the 3v3 game, tested in 2018, was not included in the 2019 tests. In addition, TRACAB Gen5 did not report data for the full pitch coverage drill, nor did they provide results for velocities above 25 km/h. Finally, the data submission deadlines were significantly different (1 hour and 24 hours post testing).

Table 15. FIFA Quality Programme testing conditions for Optical Tracking Systems (OPT)

Product	InStat Fitness	Coach160	Ball & Player Tracking	TRACAB Gen5
Manufacturer	InStat[1]	TRACK160 Ltd.[2]	Hawk-Eye.[3]	ChyronHego AB[4]
Testing day	10th October 2019	11th October 2019	11th October 2019	22nd November 2018
Testing venue	Camp Nou (Barcelona)	Camp Nou (Barcelona)	Camp Nou (Barcelona)	Miniestadi (Barcelona)
Total cameras	3	3	12	16
Submission time	24 hours	24 hours	1 hour	1 hour
Participants	Unspecified	Unspecified	Unspecified	Under 13
Drills	Circuit, 2v2 game, 5v5 game, sprints, FPC	Circuit, 2v2 game, 5v5 game, sprints, FPC	Circuit, 2v2 game, 5v5 game, sprints, FPC	Circuit, 2v2 game, 3v3 game, 5v5 game
Velocity bands assessed	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, >25 km/h	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, >25 km/h	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h, >25 km/h	0-7 km/h, 7-15 km/h, 15-20 km/h, 20-25 km/h

Note: FPC, full pitch coverage; [1]InStat, Dublin, Ireland; [2]TRACK160 Ltd., Tel Aviv, Israel; [3]Hawk-eye, Basingstoke, England; [4]ChyronHego AB, Stockholm, Sweden; Data retrieved: 3rd August 2020

14.6. Discussion

The FIFA quality performance reports quantify the accuracy of the EPTS positioning and velocity data in different velocity bands. However, there are methodological issues that may significantly affect the results' interpretation. Although these issues are limited to the information available in the existing FIFA quality performance reports (FIFA, 2020), a total of six important methodological issues can be identified to help practitioners interpret EPTS reports.

Testing day

Given the number of EPTS available, it would impossible to test all of them on the same days or exactly replicate the test conditions. For example, if an EPTS is tested on a different day from another EPTS, the calibration procedures should be carried out on days other than the test days. Although motion capture systems have demonstrated high levels of accuracy, any minor modifications to the calibration procedure may affect the results (Windolf et al., 2008). A previous study, analyzing the influence of different calibration procedures on the data accuracy of the Vicon-460 motion capture system reported greater accuracy when the wand motion was performed by a robot rather than manually by a human in a tiny capture space (Windolf et al., 2008). Other studies suggested that lighting and weather conditions should be considered when standardizing the experiment since these factors might also affect data accuracy (Gray et al., 2010; Terrier & Schutz, 2005; van der Kruk & Reijne, 2018; Windolf et al., 2008). For instance, optical-passive motion capture systems, which use retro-reflective markers, depend on lighting conditions since they work by reflecting light back to the sensor (van der Kruk & Reijne, 2018). Consequently, this does not necessarily reduce the validity of the within-trial comparisons (i.e., single EPTS vs criteria measures, which is the aim of the FIFA quality performance reports) but it does influence the ability to compare findings between EPTS systems if the calibration procedure is carried out on separate days and other testing conditions change (as occurred during these tests). Nonetheless, the calibration process was carried out before the start of the testing process to ensure that the errors fell within suitable values. The "Handbook of test methods for EPTS devices" (FIFA, 2019) states that the error values should be less than 1 mm for the Vicon motion capture system while the test area dimensions should be as accurate as possible to calibrate the computer vision software.

Testing venue

Although there are very good reasons for testing EPTS in different venues, since these systems are used in many stadium-types globally, EPTS may be affected by the testing venue since the stadium structures vary. For example, the positioning of OPT system cameras changes from one stadium to another because the best place to locate them varies in each; this requires manufacturers to establish individual software processing parameters for each data collection (Barros et al., 2007). The literature scarcely considers this since manufacturers' procedures are subject to intellectual property protection and there are details they do not disclose to users (Malone et al., 2017). Likewise, the positioning of LPS antennas varies, and different metal structures may interfere with the accuracy of the data collected (Alarifi et al., 2016; H. Liu et al., 2007). Regarding GNSS, the main concern is the stadia roofs because GNSS satellites transmit two low-power radio signals that travel by line of sight (Terrier & Schutz, 2005). The signals can pass through clouds but not through most solid objects (Terrier & Schutz, 2005). Consequently, stadia with high walls and curved roofs may have an impact on the data quality (Cummins et al., 2013).

Therefore, comparing EPTS that have been tested in different stadia is not recommended. Furthermore, the testing area on the field should be considered since it may have a significant effect on the data quality. For example, it is not advisable to compare two GNSS if one was tested on a 30m^2 center area of the pitch while the other was tested on a 30m^2 corner area or closer to the stadium roof (e.g., Miniestadi or Camp Nou) given the above-mentioned reasons (Cummins et al., 2013; Terrier & Schutz, 2005). Previous research showed that factors such as satellite availability (Cummins et al., 2013; Malone et al., 2017; Witte & Wilson, 2004) or playing area (e.g., due to the proximity of nearby buildings such as the stadia roof) (Larsson, 2003; Taberner et al., 2020; Williams & Morgan, 2009) should be considered when interpreting data obtained by GNSS.

Regarding the total number of available cameras, antennas for local positioning systems or satellites, this is also a methodological issue related to the testing venue. For example, the stadium size may lead to difficulties collecting data on the opposite side of the field from the cameras (Barros et al., 2007). Hence, more cameras should be placed around the stadium to improve accuracy (Barros et al., 2007; Manafifard et al., 2017). In addition, the number of available satellites that interact with the EPTS receivers influences the data accuracy (Cummins et al., 2013; Malone et al., 2017; Witte & Wilson, 2004). For instance, the velocity error may increase when less satellites are available (Witte & Wilson, 2004). Similarly, the number of antennas used with local positioning systems may vary depending on the testing area (Bastida-Castillo et al., 2019; Bastida Castillo et al., 2018; Frencken et al., 2010; Ogris et al., 2012).

Perhaps the variation in the number of cameras used in different OPT systems, or the number of antennas used in different LPS, is closely related to the stadium structure itself and the manufacturer's ability to adapt to such conditions. What is certain is that GNSS technology is fundamentally dependent on environmental conditions. This does not preclude the possibility of GNSS validity testing taking place, but comparing different EPTS is not recommended if this methodological issue may influence data accuracy. Although the reports indicate the minimum number of satellites required for system accuracy, this only allows one to conclude that an EPTS is valid, it is not advisable to make comparisons between EPTS.

Data submission deadline

This part of the testing process informs on how quickly data can be delivered. There are two main reasons why this methodological consideration is important. Firstly, if the FIFA quality performance report shows that the data were submitted to the research team at different time intervals, it suggests that there may be significant differences in the data processing. Secondly, and with this in mind, the submission deadlines can highlight how quickly the performance reports will be available; this can be an important factor since coaching staff usually require them at the end of each session (or within a couple of hours). Consequently, it would not be practical to compare the results from an EPTS that submitted its data one hour post testing to an EPTS that submitted them 24-hours post testing.

Drills, velocity bands, and sample characteristics

Although the data were not collected under real match conditions (e.g., 11 vs 11), all the EPTS need to be tested for the same drills and velocity bands as set in the protocol. However, certain EPTS presented no results for several high-velocity zones (20-25 km/h or above 25 km/h) and not all the EPTS were tested for the same drills. This methodological issue is important since the magnitude of error increases at greater speeds (Bastida Castillo et al., 2018; Linke et al., 2018; Pons et al., 2019) and different demands may be observed based on the testing drill (Clemente, Sarmento, et al., 2019). If a report provides the EPTS accuracy for each velocity band, one also needs to know how many actions were tested and/or the percentage of time spent in each band. The effect of different drills being completed by players of different standards means variability is possible between testing conditions for the number of actions/speed of samples recorded at each speed threshold.

Consequently, the characteristics of the sample included in a study are another key aspect since factors such as height, age, and fitness may influence the data collected. On the one hand, there are EPTS (e.g., OPT systems) in which the occlusion phenomenon is a primary concern even though multiple cameras are used (Manafifard et al., 2017). This occurs when players hide each other from view, either partially or completely, and it may be challenging to track soccer players because sometimes not even the human observer can see the occluded player (Manafifard et al., 2017). Therefore, the player’s height may influence the camera positioning and the resulting data accuracy (Manafifard et al., 2017). If the data is collected from under-15 players, their height and fitness are likely to vary from professional soccer players; for example, the sprint and acceleration profiles are different (Loturco et al., 2018; Mendez-Villanueva et al., 2011). Professional soccer players reach higher sprinting speeds and their acceleration capacity is greater than younger players (e.g., under-15s) (Loturco et al., 2018). However, these types of actions usually increase the magnitude of EPTS error (Bastida Castillo et al., 2018; Linke et al., 2018; Pons et al., 2019). This implies that if the test is conducted on a young under-15 player sample, the accuracy of the EPTS data reported is specific to that sample. Therefore, the results from each EPTS carried out in the FIFA tests are only suitable for comparing the reference systems; comparisons between EPTS should not be made.

14.7. Conclusion

The FIFA quality performance reports serve as a method for quantifying the accuracy of EPTS positioning and velocity data in different velocity bands. While these reports can certainly be commended for their intentions, there are several methodological issues regarding the testing conditions that need to be considered before interpreting the results from each EPTS. Specifically, comparisons between GNSS, LPS and/or OPT systems are not advisable. Consequently, practitioners should consider the main aim of this FIFA testing process and place greater importance on comparing the different EPTS to the gold standard rather than directly comparing between the results obtained from each EPTS.

CHAPTER 15

Study XIII. Monitoring professional soccer players physical performance using real-time data generated by electronic performance and tracking systems

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15. MONITORING PROFESSIONAL SOCCER PLAYERS PHYSICAL PERFORMANCE USING REAL-TIME DATA GENERATED BY ELECTRONIC PERFORMANCE AND TRACKING SYSTEMS

15.1. Abstract

The aims of this technical report were to analyze the validity of real-time data collected by electronic performance and tracking systems (EPTS) and investigate the effect of varying real-time receiver's position on the real-time data collected. Physical performance data were collected from professional soccer players using EPTS. In addition, three real-time receivers, which were placed in different positions (i.e., central area of the stadium stands and right and left technical areas), were used to collect real-time data. The real-time data collected by each receiver were visualized on SVivo (RealTrack Systems, Almeria, Spain) and compared to the data downloaded directly from the device on SPro (RealTrack Systems, Almeria, Spain). The results showed no statistically significant differences between the data collected by the real-time receivers compared to post-session data in any variable ($p > 0.05$), except for total distance (TD) and high-speed running distance (HSRD) covered, which showed significant differences but trivial effect size ($p < 0.05$; $d = 0.01$). The coefficient of determination (R^2) and intraclass correlation coefficient (ICC) were greater than 0.97 and 0.99, respectively. Regarding the analysis of varying the receiver's position on the real-time data collected, the results showed that there was no significant effect of the receiver's position on any variable ($p > 0.05$). Therefore, valid physical performance data may be obtained by real-time tracking systems such as SVivo, regardless of the position of the real-time receivers and distance to the players. Specifically, high-intensity running actions, distances covered at low and high speed as well as accelerometer-derived variables such as player load may be accurately tracked by this real-time tracking software.

15.2. Keywords

Accuracy, validation, training, tracking, performance.

15.3. Introduction

The data collected by EPTS are usually analyzed at the end of each session (Oliva-Lozano, Fortes, & Muyor, 2020; Rojas-Valverde, Gómez-Carmona, et al., 2019). However, some EPTS provide these physical performance parameters in real time, which may be very useful for practitioners since some decisions may be made during the session (Barrett, 2017; Rojas-Valverde, Gómez-Carmona, et al., 2019). For example, coaches can compare the live data to the training objectives and may adjust the session volume or intensity accordingly (Weaving et al., 2017). In consequence, these data may assist coaching and medical staff to maximize fitness and minimize the risk of injury or overtraining (Cummins et al., 2013; Oliva-Lozano, Rago, Fortes, et al., 2021).

Nevertheless, EPTS manufacturers use different protocols to obtain real-time data and post-session data (Weaving et al., 2017). For example, real-time data arrives at the end-user through a specific receiver (e.g., ANT+ technology, which is based on a wireless protocol for sending information from one device to another) while post-session data are directly downloaded from the EPTS (Barrett, 2017; Weaving et al., 2017). This implies that the real-time data depends on the quality of connection between the EPTS and the real-time receiver. In this regard, previous investigations suggested that caution should be taken when interpreting real-time data given the mean typical measurement errors observed in real-time compared to post-session reports (Barrett, 2017). For instance, the error for high-speed variables such as sprinting distance was greater compared to total distance (Barrett, 2017).

In addition, there is little information regarding the effect of varying the position of the real-time receivers on the accuracy of the real-time data collected. The protocol for real-time receivers positioning varies across all the studies that have been published to date (Barrett, 2017; Johnston et al., 2020; Weaving et al., 2017). One study followed the manufacturers' recommendations and the receiver was positioned 5 meters away from the in-goal line of a rugby pitch (Weaving et al., 2017). However, the receiver was positioned 2 meters behind the half-way line in another study with rugby players (Johnston et al., 2020). In addition, a previous study on professional soccer only specified that the receiver was placed close to the half-way line (Barrett, 2017). This implies that none of the investigations considered the influence of varying the receiver's location, which may be important to analyze given the differences in the radius of distance between the receiver and the EPTS or possible occlusion that may occur between players during the game.

However, this is important from a practical perspective. If the receiver's location or playing areas have a significant impact on the data reported by the real-time software, the sport scientist or fitness coach may make wrong decisions because of inaccurate data. Therefore, the aims of this technical report were to analyze the validity of real-time data collected by EPTS and investigate the effect of varying real-time receiver's position on the real-time data collected.

15.4. Methods

Study design

An observational research design was conducted to collect data from professional soccer players, who voluntarily participated in the testing session. Tracking systems were used to collect performance-related variables. In addition, real-time data were collected during the session by three receivers, which were placed in different locations. This study was conducted ethically based on the Declaration of Helsinki and it was approved by the Institutional Ethics Committee.

Participants

A total of 17 professional soccer players (age: 25.25 ± 6.71 years old; height: 1.81 ± 0.07 m; weight; 72.75 ± 7.72 kg) took part in the study. This sample was selected in order to ensure that size and intensity of the movements in the testing tasks were representative of high-level players. In this regard, only players, who were available to compete in the following match, were included. Thus, players who reported any injury before the start of the session were not included. The club and players were informed of the aims, procedures, risks, and benefits before data collection. Then, informed consent was given by the club and players to conduct this research.

Procedures

The testing session took place in a local soccer stadium with official pitch dimensions. The real-time receivers were positioned in three different areas of the soccer stadium (Figure 34). The receiver 1 (R1) was positioned in the central area of the stadium stands (from a greater height) and the receivers 2 (R2) and 3 (R3) were positioned in the technical areas.

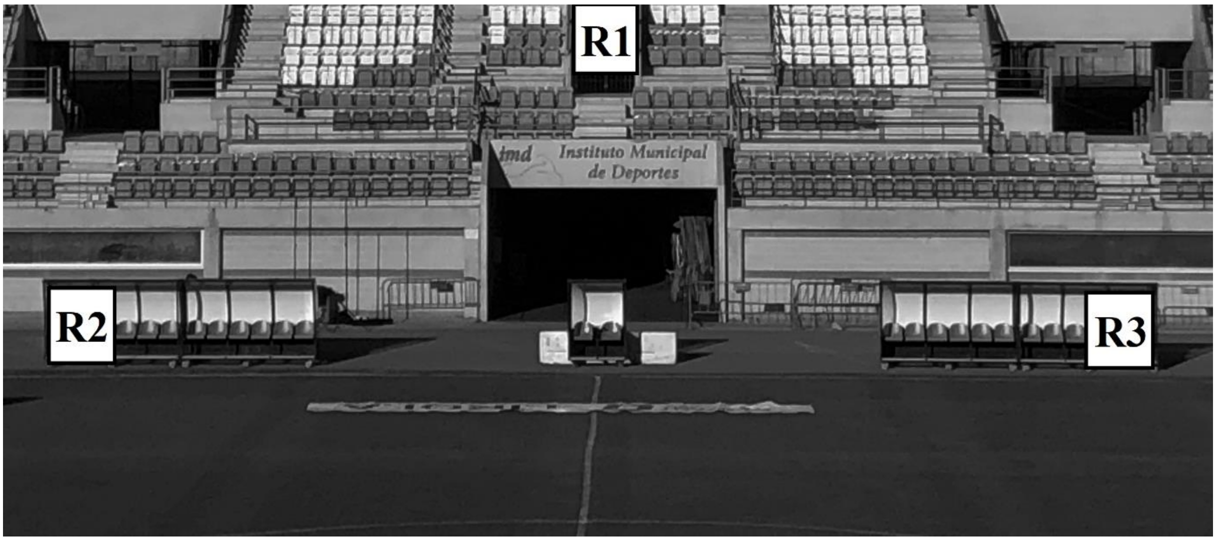

Figure 34. Real-time receivers' location in the soccer stadium. R1: receiver positioned in the central area of the stadium stands; R2: receiver positioned in the right technical area; R3: receiver positioned in the left technical area.

WIMU Pro units (RealTrack Systems, Almeria, Spain), which were placed on the player's chest vest, were used to collect the physical performance data. These EPTS have been certified by the FIFA Quality Programme (FIFA, 2020) and according to previous investigations also considered as valid and reliable instruments for the collection of time-motion variables in soccer (Bastida Castillo et al., 2018). The EPTS were calibrated 20 minutes before the start of the sessions following these steps (Oliva-Lozano, Fortes, Krustrup, et al., 2020): 1) the tracking systems were placed in the Smart Station (RealTrack Systems, Almería, Spain); 2) this station was placed on a flat surface without nearby magnetic devices; 3) the devices were turned on and sixty seconds later, the recording button was pressed; 4) the devices were placed on the chest vests.

The real-time receivers were ANT+ USB sticks (Garmin Ltd., Olathe, Kansas, United States), which were placed on the different areas of the soccer stadium (bench on the right technical area, bench on the left technical area, and central area of the stadium stands) and connected to three different ASUS X541U laptops (ASUSTeK Computer, Inc., Taipei, Taiwan). The real-time data collected by each receiver were visualized on SVivo (RealTrack Systems, Almeria, Spain) and post-session data on SPro (RealTrack Systems, Almeria, Spain), which showed the data downloaded directly from the device. Both physical performance reports were downloaded in order to compare the differences between real-time and post-session data from a training session consisting of two main parts. Firstly, small-sided games and transitional drills and secondly, 11 v 11 match. Specifically, the following external load variables, which are commonly used in applied practice and research related to physical performance monitoring in soccer, were selected: total distance covered (TD), high-speed running distance (HSRD, above 21 km/h), high-speed running actions (HSRA, above 21 km/h), sprinting distance (SPD, above 24 km/h), sprinting actions (SPA, above 24 km/h), total of high intensity accelerations (ACC_{HIGH}, above 3 m/s^2), total of high-intensity decelerations (DEC_{HIGH}, below -3 m/s^2) and player load (PL, which is measured in arbitrary units and combines the accelerations in anterior-posterior, medial-lateral, and vertical axis) (Gómez-Carmona et al., 2020; Oliva-Lozano, Rojas-Valverde, Gómez-Carmona, et al., 2020d; Oliva-Lozano, Fortes, Krustrup, et al., 2020). PL was calculated using the formula from Figure 35.

$$\mathrm{PL} = \sum_{n=0}^{m} \mathrm{PL}_n \text{ x } 0.01 \qquad \Bigg| \qquad \mathrm{PL}_n = \sqrt{\frac{(\mathrm{X}_n - \mathrm{X}_{n-1})^2 + (\mathrm{Y}_\mathrm{n} - \mathrm{Y}_{n-1})^2 + (\mathrm{Z}_\mathrm{n} - \mathrm{Z}_{n-1})^2}{100}}$$

Figure 35. Player Load formula (Gómez-Carmona et al., 2020)

Statistical analysis

The descriptive statistics from each performance-related variable were reported based on the real-time data collected from each receiver on SVivo and post-session data from SPro. The Shapiro-Wilk test was used to test the normality of the data. Then, the sphericity was obtained through Mauchly's test. A linear model with analysis of variance for repeated measures was performed. The external load variables were set as dependent variables while the data collection method (i.e., real-time data collected from SVivo or post-session data from SPro) was considered as the independent variable. Specifically, the comparisons between real-time and post-session data were obtained through Bonferroni post hoc. The effect size for the multiple comparisons were calculated using Cohen's *d* and categorized as trivial (0-0.19), small (0.20-0.49), moderate (0.50-0.79), and large (≥ 0.80) (Cohen, 1988). A 95% confidence interval was reported to display the range of values that the reader may be 95% certain contains the true mean of the sample population. The statistical analysis was run on SPSS Statistics (IBM Corp., Armonk, NY, USA) and the level of significance set at $p \leq 0.05$.

15.5. Results

Table 16 shows the validity of the data collected by real-time receivers compared to the data directly downloaded from the device. There were no significant differences between the data collected by the real-time receivers compared to post-session data in any variable ($p > 0.05$), except for TD and HSRD covered, which showed significant differences but trivial effect size ($p < 0.05$; $d = 0.01$). In addition, the coefficient of determination ($R^2 > 0.97$) and the intraclass correlation coefficient (ICC > 0.99) were very close to 1.

Table 16. Validity of data collected by real-time receivers compared to post-session data from SPRO software

Variables	Receiver	SPRO	*p*	*d*	SEM	R^2	ICC (95% CI)
TD (m)	R1: 6344.2 ± 1666.1	6362.1 ± 1661.2	**0.001**	0.01	3.43	1.00	1.000 (0.998-1.000)
	R2: 6345.7 ± 1666.2	6362.1 ± 1661.2	**0.001**	0.01	3.41	1.00	1.000 (0.999-1.000)
	R3: 6341.6 ± 1665.1	6362.1 ± 1661.2	**0.001**	0.01	3.41	1.00	1.000 (0.996-1.000)
HSRD (m)	R1: 124.76 ± 91.46	125.28 ± 91.44	**0.001**	0.01	0.07	1.00	1.000 (0.999-1.000)
	R2: 124.76 ± 91.46	125.28 ± 91.44	**0.001**	0.01	0.07	1.00	1.000 (0.999-1.000)
	R3: 124.76 ± 91.46	125.28 ± 91.44	**0.001**	0.01	0.07	1.00	1.000 (0.999-1.000)
HSRA (count)	R1: 10.24 ± 5.67	10.24 ± 5.67	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
	R2: 10.24 ± 5.67	10.24 ± 5.67	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
	R3: 10.24 ± 5.67	10.24 ± 5.67	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
SPD (m)	R1: 40.71 ± 54.33	40.80 ± 54.61	1.00	0.00	0.37	0.99	1.000 (0.999-1.000)
	R2: 40.71 ± 54.33	40.80 ± 54.61	1.00	0.00	0.37	0.99	1.000 (0.999-1.000)
	R3: 40.71 ± 54.33	40.80 ± 54.61	1.00	0.00	0.37	0.99	1.000 (0.999-1.000)
SPA (count)	R1: 2.88 ± 3.20	2.82 ± 3.21	1.00	0.02	0.06	0.99	0.997 (0.992-0.999)
	R2: 2.88 ± 3.20	2.82 ± 3.21	1.00	0.02	0.06	0.99	0.997 (0.992-0.999)
	R3: 2.88 ± 3.20	2.82 ± 3.21	1.00	0.02	0.06	0.99	0.997 (0.996-0.999)
ACC_{HIGH} (count)	R1: 40.82 ± 11.23	40.82 ± 11.23	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
	R2: 40.82 ± 11.23	40.82 ± 11.23	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
	R3: 40.82 ± 11.23	40.82 ± 11.23	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
DEC_{HIGH} (count)	R1: 52.35 ± 18.97	52.35 ± 18.97	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
	R2: 52.35 ± 18.97	52.35 ± 18.97	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
	R3: 52.35 ± 18.97	52.35 ± 18.97	1.00	0.00	0.00	1.00	1.000 (1.000-1.000)
PL (a.u.)	R1: 80.09 ± 22.96	80.17 ± 22.92	0.26	0.00	0.04	1.00	1.000 (1.000-1.000)
	R2: 80.09 ± 22.96	80.17 ± 22.92	0.47	0.00	0.04	1.00	1.000 (1.000-1.000)
	R3: 80.05 ± 22.96	80.17 ± 22.92	0.06	0.01	0.04	1.00	1.000 (1.000-1.000)

Note: SEM = standard error of measurement; ICC = intraclass correlation coefficient; CI = confidence interval; R1 = receiver positioned in the central area of the stadium stands; R2 = receiver positioned in the right technical area; R3 = receiver positioned in the left technical area; Values in bold indicate significant difference ($p < 0.05$).

Regarding the analysis of varying the receiver's position on the real-time data collected, the results show that there was no significant effect of the receiver's position on the TD ($F_{(1, 17)}$ = 3.22; p = 0.09; ηp^2 = 0.17), PL ($F_{(2, 32)}$ = 1.21; p = 0.31; ηp^2 = 0.07), ACC_{HIGH}, DEC_{HIGH}, HSRA, HSRD, SPA, or SPD ($F_{(2, 32)}$ =0.00; p = 1.00; ηp^2 = 0.00).

15.6. Discussion

The purpose of this study was to analyze the validity of real-time data collected by EPTS and investigate the effect of varying the receivers' positions on the real-time data collected. Given the high accuracy of the real-time data in comparison to post-session data, the main findings were that valid physical performance data may be obtained by real-time tracking systems such as SVivo, regardless of the three positions of the real-time receivers investigated and distance to the players. In addition, these are novel findings considering that no previous study analyzed the influence of varying receiver position on the real-time data collected and no validation studies for SVivo software, which is commonly used for physical performance analysis, were available to date.

The results showed that real-time data visualized on SVivo software may be used for monitoring professional soccer player's physical performance. This is explained by the very low systematic bias and SEM between instruments as well as the R^2 and ICC very close to 1 in all the variables during a testing session which include a wide range of low and high intensity actions. This is consistent with two previous studies which observed that real-time data was strongly correlated with the data downloaded directly from the device (Barrett, 2017; Johnston et al., 2020). However, other investigations found that the difference between instruments might increase when running at high-intensity (e.g., running above ~18 km/h or ~25 km/h) (Aughey & Falloon, 2010; Weaving et al., 2017). Considering that soccer players continually perform high-intensity actions (Oliva-Lozano, Fortes, Krustrup, et al., 2020), our study showed significant differences for TD and HSRD. However, these differences were rated as trivial based on the effect size, so practitioners may be confident when interpreting these variables. In addition, a previous study concluded that caution should be taken with accelerometer-derived variables such as PL, which are registered at different sampling frequencies than GPS-related variables (e.g., accelerometers: 100 Hz vs GPS: 10 Hz) (Weaving et al., 2017). Regarding the data collected using the SVivo software for our study, the type of variable (i.e., GPS-derived variables such as HSRA or accelerometer-derived variables such as PL) was not of main concern.

Another novel finding of the study was the analysis of the receiver's position, which had no influence on the real-time data. This may have significant practical implications because the performance analysts may sit in the bench of the right or left technical areas during matches, while they may stay in the stadium stands (i.e., from a greater height and distance to the players) during training sessions. Real-time data arrives at the end-user through a specific receiver (e.g., ANT+ technology) and possible occlusion that may occur between players during the game as well as the differences in the radius of distance between the receiver and the EPTS might influence the results. Previous studies positioned the receivers close to the players (e.g., 5 meters away from the goal line or 2 meters behind the half-way line of rugby pitches) (Johnston et al., 2020; Weaving et al., 2017) and this is the reason why this study included a real-time receiver (i.e., R1) which was placed in the stadium stands at a greater distance from the players. However, future studies should analyze the influence of varying the receiver position on the real-time data for other tracking systems which are commonly used in the context of physical performance analysis.

In addition, it is important to acknowledge some limitations of this study. For example, no internal load (e.g., mean heart rate) or tactical parameters (e.g., team length and width) were included in the analysis (Folgado, Lemmink, et al., 2014; B. Gonçalves et al., 2017). Also, position-related metrics (e.g., TD, HSRD, HSRA, SPD, SPA, ACC_{HIGH}, or DEC_{HIGH}) were only collected by GPS technology while ultra-wideband data may be used as well (Pino-Ortega et al., 2021). In this regard, future studies may also analyze the validity of real-time data provided by other tracking instruments such as optical tracking systems (Pons et al., 2019). Moreover, the data were only compared for totals across the entire session, so no raw data were obtained (Linke et al., 2018). In addition, the real-time receivers were placed in three different positions, where the performance analyst usually stays in training and match days. However, there may be other positions, which may be of interest for the collection of real-time data (e.g., suites at the top of the stadium stands for broadcasters), as well as other contextual factors (e.g., characteristics of the stadium), which need to be considered.

15.7. Conclusion

Practitioners can be confident that the real-time data collected by this tracking software are valid for load monitoring purposes. Specifically, high-intensity running actions (e.g., HSRA, SPA, ACC_{HIGH}, and DEC_{HIGH}), distances covered at low and high speed (e.g., TD, HSRD, SPD) as well as accelerometer-derived variables (e.g., PL) may be accurately tracked. In addition, these real-time receivers may be placed in the bench of the right or left technical areas while they may stay in the stadium stands behind the technical areas. Furthermore, it is important to note that using ANT+ USB sticks as real-time receivers is recommended given their portability (size: 1.9 cm x 1.1 cm x 0.4 cm; weight: ~5 g).

THESIS CONCLUSION

This thesis analyzed the physical performance of professional soccer players with an approach based on load monitoring through EPTS. The first aim of the thesis was to analyze the key load indicators of professional soccer players in match and training sessions. In this regard, the results suggest that strength and conditioning coaches may use the performance indicators obtained by the PCA for load monitoring purposes. It is recommended to use the PCA in the context of team sports in order to reduce the large number of variables, which are daily managed by strength and conditioning coaches. The PCA may help coaches visualize and interpret large training and match load data. Also, the PCA may help coaches select key load indicators in the context of each team (e.g., team level, team formation, style of play, etc.), regardless of the tracking system used for data collection.

The second aim of the study was to analyze the load variability of professional soccer players in training and match. This thesis explained why the analysis of load variability of each training and match day within the microcycle is also recommended. For instance, coaches should be cautious in post-match training sessions (e.g., +1MD) given the high load variability. Competitive fixtures present as the most demanding sessions within a professional soccer microcycle. The results showed that individual changes in representative GPS-derived measures of match physical performance (TD, TAcc and V_{MAX}) of ±~10–15% can be considered practically significant. That is, beyond the normal match-to-match variability and by a magnitude greater than the smallest worthwhile change. This was with the exception of HSRD, where thresholds were considerably higher ($\gtrsim$ 60%). However, physical performance may also depend on match-related contextual variables since these had an impact on the subsequent weekly training load.

When it comes to the analysis of physical performance considering high-intensity actions and most demanding passages of play in professional soccer players, the findings provide meaningful information for practitioners. Positional differences exist across playing positions in both the sprint and acceleration profiles, which should be considered by strength and conditioning coaches when designing effective match-based drills in training sessions. Despite strength and conditioning coaches still focusing on training sprint actions starting at zero speed, most of these actions are performed at 5-6 km/h in match-play. In addition, different Vo were observed between high-intensity and low-intensity accelerations as well as high-intensity and low-intensity decelerations.

In addition, this thesis showed the type of passage (i.e., first, second or third MDP of play) had a significant effect on all the variables included in the study (DIS, HSRD, SPD, ACC_{HIGH}, DEC_{HIGH}). Significant differences in the physical demands existed between the first, second, and third MDP of play in all playing positions and passage durations. However, there were some cases (e.g., DIS and ACC_{HIGH}) in which no significant differences were found between the first, second, and third MDP of play.

Furthermore, this thesis investigated contextual variables associated with high-intensity actions and most demanding passages of play in professional soccer players. The first 15-minute period of the matches (0'-15') elicited the MDP of play for DIS, SPD, HMLD, ACC_{HIGH} and DEC_{HIGH}. Given the observed decline in physical performance during the MDP of play as the matches progressed, strength and conditioning coaches should design specific training drills (e.g., from 1-minute to 10-minute passages considering area per player) in order to prepare the players for match's high intensity periods. In addition, another study of this thesis showed that the first period of each match half (i.e., period 1 and period 4) elicited the greatest amount of maximum intensity sprints in competitive match play, regardless of playing position.

Nevertheless, the playing position had a significant effect on the role of the maximum intensity sprint and the field area in which the sprint occurred. When it comes to the effect of different contextual variables on the sprint-related performance variables, no significant effect from any contextual variable on ACC_{MAX}, DEC_{MAX} or Vo was observed. However, the contextual variables had a significant effect on SPD (from ball possession, sprint trajectory, and role of the sprint action) and V_{MAX} (from ball possession and playing position). In addition, although non-linear sprints are the most frequent maximum speed actions and special focus should be put on sprints with different trajectories, linear sprint training is also positive since it may lead to improvements in non-linear sprints too (Fílter et al., 2020). Overall, the training drills should be based on the demands of match-play. For instance, players need to be prepared for sprints longer than 30 m, achieving speeds above 30 km/h as well as high intensity accelerations and decelerations (accelerations above 3 m/s^2 and decelerations below -4 m/s^2. Furthermore, the sprints need to be trained with starting speeds about 7-10 km/h.

Moreover, this thesis highlighted the importance of a 3-dimensional analysis of the locomotor load experienced by the players. For example, PL_{TOTAL} and the triaxial data provided by performance tracking systems (i.e., PL_V, PL_{AP}, PL_{ML}) may be used for load monitoring purposes in training sessions and matches. Given the differences observed between each axis of movement, training strategies need to be adopted in order to tolerate the load experienced by professional soccer players. However, given the large contribution of PL_V to PL_{TOTAL}, special focus should be placed on the vertical component. In addition, given the relationship between distance covered and PL_{TOTAL}, and that PL_{TOTAL} is a triaxial accelerometry-based metric which combines the accelerations in anterior-posterior, medial-lateral, and vertical movements, strength and conditioning coaches are encouraged to use this parameter as a measure of total body load.

In addition, our studies showed how the data collected by EPTS may be used for the analysis of the postural demands of professional soccer players. For example, the volume of trunk flexion observed implies that soccer players may unconsciously move the field of regard down and position-specific training drills at different speeds are necessary in order to properly prepare the players for the perception-action demands (i.e., visual exploration and decision making) of the match. This may be considered as the first investigation analyzing the trunk kinematics of professional soccer players in official matches. In addition, a novel approach was conducted by analyzing the effect that different contextual variables (e.g., playing position, match half, and match day) had on the postural demands.

Finally, this thesis explained why some methodological issues related to load monitoring using EPTS are important. For instance, the application of rolling averages is recommended for an appropriate analysis of the MDP of play. In addition, practitioners are encouraged to test the accuracy of the real-time data collected by their tracking software since this may help coaches make decisions during the course of a match or training session. Moreover, when reading the FIFA quality performance reports, practitioners need to understand the methodological issues regarding the testing conditions before interpreting the results from each EPTS.

LIMITATIONS AND FUTURE INVESTIGATIONS

All studies, which were included in the thesis, highlighted the main limitations and suggestions for future investigations in the discussion section. However, it is important to mention that the analysis of physical performance in professional soccer is limited to the context itself. In other words, the physical performance may vary based on multiple contextual variables (e.g., physical fitness and wellbeing of the player, team level, style of play, team formation, characteristics of the training session, etc.) and, unfortunately, not all the variables can be under control.

This thesis is just an approach to the analysis of physical performance using EPTS. Different research questions have been investigated and given the complexity of this team sport, future investigations are necessary to have a better understanding of physical performance in professional soccer. For example, this thesis was mainly focused on external load variables while the analysis of internal load is a research topic that may have key practical implications for sports performance and medical practitioners. Nonetheless, one of the main conclusions after completing the thesis is that future studies should keep a contextualized perspective when trying to analyze physical performance.

REFERENCES

Aamot, I.-L., Karlsen, T., Dalen, H., & Støylen, A. (2016). Long-term exercise adherence after high-intensity interval training in cardiac rehabilitation: a randomized study. *Physiotherapy Research International*, *21*(1), 54–64. https://doi.org/10.1002/pri.1619

Abbott, W., Brickley, G., Smeeton, N. J., & Mills, S. (2018). Individualizing acceleration in English Premier League academy soccer players. *Journal of Strength and Conditioning Research*, *32*(12), 3503–3510. https://doi.org/10.1519/JSC.0000000000002875

Ade, J., Fitzpatrick, J., & Bradley, P. S. (2016). High-intensity efforts in elite soccer matches and associated movement patterns, technical skills and tactical actions. Information for position-specific training drills. *Journal of Sports Sciences*, *34*(24), 2205–2214. https://doi.org/10.1080/02640414.2016.1217343

Akenhead, R., Harley, J. A., & Tweddle, S. P. (2016). Examining the external training load of an English Premier League football team with special reference to acceleration. *Journal of Strength and Conditioning Research*, *30*(9), 2424–2432. https://doi.org/10.1519/JSC.0000000000001343

Akenhead, R., Hayes, P. R., Thompson, K. G., & French, D. (2013). Diminutions of acceleration and deceleration output during professional football match play. *Journal of Science and Medicine in Sport*, *16*(6), 556–561. https://doi.org/10.1016/j.jsams.2012.12.005

Alarifi, A., Al-Salman, A., Alsaleh, M., Alnafessah, A., Al-Hadhrami, S., Al-Ammar, M., & Al-Khalifa, H. (2016). Ultra wideband indoor positioning technologies: analysis and recent advances. *Sensors*, *16*(5), 1–36. https://doi.org/10.3390/s16050707

Anderson, L., Orme, P., Di Michele, R., Close, G. L., Morgans, R., Drust, B., & Morton, J. P. (2016). Quantification of training load during one-, two- and three-game week schedules in professional soccer players from the English Premier League: implications for carbohydrate periodisation. *Journal of Sports Sciences*, *34*(13), 1250–1259. https://doi.org/10.1080/02640414.2015.1106574

Andrzejewski, M., Chmura, J., & Pluta, B. (2014). Analysis of motor and technical activities of professional soccer players of the UEFA Europa League. *International Journal of Performance Analysis in Sport*, *14*(2), 504–523. https://doi.org/10.1080/24748668.2014.11868739

Andrzejewski, M., Chmura, J., Pluta, B., & Konarski, J. M. (2015). Sprinting activities and distance covered by top level Europa League soccer players. *International Journal of Sports Science & Coaching*, *10*(1), 39–50. https://doi.org/10.1260/1747-9541.10.1.39

Aquino, R., Munhoz-Martins, G. H., Palucci-Vieira, L. H., & Menezes, R. P. (2017). Influence of match location, quality of opponents, and match status on movement patterns in Brazilian professional football players. *Journal of Strength and Conditioning Research*, *31*(8), 2155–2161. https://doi.org/10.1519/JSC.0000000000001674

Aquino, R., Vieira, L. H. P., Carling, C., Martins, G. H. M., Alves, I. S., & Puggina, E. F. (2017). Effects of competitive standard, team formation and playing position on match running performance of Brazilian professional soccer players. *International Journal of Performance Analysis in Sport*, *17*(5), 695–705. https://doi.org/10.1080/24748668.2017.1384976

Asian-Clemente, J., Rabano-Muñoz, A., Muñoz, B., Franco, J., & Suarez-Arrones, L. (2021). Can small-side games provide adequate high-speed training in professional soccer? *International Journal of Sports Medicine*, *42*(6), 523–528. https://doi.org/10.1055/a-1293-8471

Aughey, R. J., & Falloon, C. (2010). Real-time versus post-game GPS data in team sports. *Journal of Science and Medicine in Sport*, *13*(3), 348–349. https://doi.org/10.1016/j.jsams.2009.01.006

Azcárate, U., Yanci, J., & Los Arcos, A. (2018). Influence of match playing time and the length of the between-match microcycle in Spanish professional soccer players' perceived training load. *Science and Medicine in Football*, *2*(1), 23–28. https://doi.org/10.1080/24733938.2017.1386322

Bandyopadhyay, K. (2017). *Legacies of great men in world soccer*. Routledge.

Bangsbo, J., Mohr, M., & Krustrup, P. (2006). Physical and metabolic demands of training and match-play in the elite football player. *Journal of Sports Sciences*, *24*(7), 665–674. https://doi.org/10.1080/02640410500482529

Barrett, S. (2017). Monitoring elite soccer players' external loads using real-time data. *International Journal of Sports Physiology and Performance*, *12*(10), 1285–1287. https://doi.org/10.1123/ijspp.2016-0516

Barrett, S., Midgley, A., Reeves, M., Joel, T., Franklin, E., Heyworth, R., Garrett, A., & Lovell, R. (2016). The within-match patterns of locomotor efficiency during professional soccer match play: implications for injury risk? *Journal of Science and Medicine in Sport*, *19*(10), 810–815. https://doi.org/10.1016/j.jsams.2015.12.514

Barrett, S., Midgley, A. W., Towlson, C., Garrett, A., Portas, M., & Lovell, R. (2016). Within-match PlayerLoad™ patterns during a simulated soccer match: potential implications for unit positioning and fatigue management. *International Journal of Sports Physiology and Performance*, *11*(1), 135–140. https://doi.org/10.1123/ijspp.2014-0582

Barros, R. M. L., Misuta, M. S., Menezes, R. P., Figueroa, P. J., Moura, F. A., Cunha, S. A., Anido, R., & Leite, N. J. (2007). Analysis of the distances covered by first division Brazilian soccer players obtained with an automatic tracking method. *Journal of Sports Science and Medicine*, *6*(2), 233–242.

Bastida-Castillo, A., Gómez-Carmona, C. D., De la Cruz-Sánchez, E., Reche-Royo, X., Ibáñez, S., & Pino Ortega, J. (2019). Accuracy and inter-unit reliability of ultra-wide-band tracking system in indoor exercise. *Applied Sciences*, *9*(5), 1–11. https://doi.org/10.3390/app9050939

Bastida Castillo, A., Gómez-Carmona, C. D., De la cruz sánchez, E., & Pino Ortega, J. (2018). Accuracy, intra- and inter-unit reliability, and comparison between GPS and UWB-based position-tracking systems used for time–motion analyses in soccer. *European Journal of Sport Science*, *18*(4), 450–457. https://doi.org/10.1080/17461391.2018.1427796

Besier, T. F., Lloyd, D. G., Cochrane, J. L., & Ackland, T. R. (2001). External loading of the knee joint during running and cutting maneuvers. *Medicine and Science in Sports and Exercise, 33*(7), 1168–1175. https://doi.org/10.1097/00005768-200107000-00014

Bloomfield, J., Polman, R., & O'Donoghue, P. (2007a). Deceleration movements performed during FA Premier League soccer matches. *Journal of Sports Science & Medicine*, *6*(10), 6–11.

Bloomfield, J., Polman, R., & O'Donoghue, P. (2007b). Physical demands of different positions in FA Premier League soccer. *Journal of Sports Science & Medicine*, *6*(1), 63–70. https://pubmed.ncbi.nlm.nih.gov/24149226

Boyd, L. J., Ball, K., & Aughey, R. J. (2011). *The Reliability of MinimaxX Accelerometers for Measuring Physical Activity in Australian Football*. *6*(3), 311–321. https://doi.org/https://doi.org/10.1123/ijspp.6.3.311

Bradley, P. S., Carling, C., Archer, D., Roberts, J., Dodds, A., Di Mascio, M., Paul, D., Gomez Diaz, A., Peart, D., & Krustrup, P. (2011). The effect of playing formation on high-intensity running and technical profiles in English FA Premier League soccer matches. *Journal of Sports Sciences*, *29*(8), 821–830. https://doi.org/10.1080/02640414.2011.561868

Bradley, P. S., Carling, C., Gomez Diaz, A., Hood, P., Barnes, C., Ade, J., Boddy, M., Krustrup, P., & Mohr, M. (2013). Match performance and physical capacity of players in the top three competitive standards of English professional soccer. *Human Movement Science*, *32*(4), 808–821. https://doi.org/10.1016/j.humov.2013.06.002

Bradley, P. S., & Noakes, T. D. (2013). Match running performance fluctuations in elite soccer: Indicative of fatigue, pacing or situational influences? *Journal of Sports Sciences*, *31*(15), 1627–1638. https://doi.org/10.1080/02640414.2013.796062

Bradley, P. S., Sheldon, W., Wooster, B., Olsen, P., Boanas, P., & Krustrup, P. (2009). High-intensity running in English FA Premier League soccer matches. *Journal of Sports Sciences*, *27*(2), 159–168. https://doi.org/10.1080/02640410802512775

Brito, J., Hertzog, M., & Nassis, G. P. (2016). Do match-related contextual variables influence training load in highly trained soccer players? *Journal of Strength and Conditioning Research*, *30*(2), 393–399. https://doi.org/10.1519/JSC.0000000000001113

Brito Souza, D., López-Del Campo, R., Blanco-Pita, H., Resta, R., & Del Coso, J. (2020).

Association of match running performance with and without ball possession to football performance. *International Journal of Performance Analysis in Sport*, 1–12. https://doi.org/10.1080/24748668.2020.1762279

Buchheit, M., Simpson, B., & Mendez-Villanueva, A. (2012). Repeated high-speed activities during youth soccer games in relation to changes in maximal sprinting and aerobic speeds. *International Journal of Sports Medicine*, *34*(1), 40–48. https://doi.org/10.1055/s-0032-1316363

Buchheit, Martin, Samozino, P., Glynn, J. A., Michael, B. S., Al Haddad, H., Mendez-Villanueva, A., & Morin, J. B. (2014). Mechanical determinants of acceleration and maximal sprinting speed in highly trained young soccer players. *Journal of Sports Sciences*, *32*(20), 1906–1913. https://doi.org/10.1080/02640414.2014.965191

Buchheit, Martin, & Simpson, B. M. (2017). Player-tracking technology: half-full or half-empty glass? *International Journal of Sports Physiology and Performance*, *12*(2), 35–41. https://doi.org/10.1123/ijspp.2016-0499

Burland, J. P., Outerleys, J. B., Lattermann, C., & Davis, I. S. (2021). Reliability of wearable sensors to assess impact metrics during sport-specific tasks. *Journal of Sports Sciences, 39*(4), 406–411. https://doi.org/10.1080/02640414.2020.1823131

Cardinale, M., & Varley, M. C. (2017). Wearable training-monitoring technology: applications, challenges, and opportunities. *International Journal of Sports Physiology and Performance*, *12*(2), 55–62. https://doi.org/10.1123/ijspp.2016-0423

Carling, C. (2010). Analysis of physical activity profiles when running with the ball in a professional soccer team. *Journal of Sports Sciences*, *28*(3), 319–326. https://doi.org/10.1080/02640410903473851

Carling, C., Bradley, P., McCall, A., & Dupont, G. (2016). Match-to-match variability in high-speed running activity in a professional soccer team. *Journal of Sports Sciences*, *34*(24), 2215–2223. https://doi.org/10.1080/02640414.2016.1176228

Carling, C., & Dupont, G. (2011). Are declines in physical performance associated with a reduction in skill-related performance during professional soccer match-play? *Journal of*

Sports Sciences, *29*(1), 37–41. https://doi.org/10.1080/02640414.2010.521945

Carling, C., Gall, F. L., & Reilly, T. P. (2010). Effects of physical efforts on injury in elite soccer. *International Journal of Sports Medicine*, *31*(3), 180–185. https://doi.org/10.1055/s-0029-1241212

Carolan, D. (2019). *Interesting to see the results of the @FIFA assessments of EPTS (Tracking) systems. @ChyronHego TRACAB, @catapultsports (LPS) systems proving most accurate; @statsports for GPS...* Twitter. https://twitter.com/davecarolan/status/1205775857031294978?s=20

Casamichana, D., & Castellano, J. (2015). The relationship between intensity indicators in small-sided soccer games. *Journal of Human Kinetics*, *46*(1), 119–128. https://doi.org/10.1515/hukin-2015-0040

Casamichana, D., Castellano, J., Calleja-Gonzalez, J., San Román, J., & Castagna, C. (2013). Relationship between indicators of training load in soccer players. *Journal of Strength and Conditioning Research*, *27*(2), 369–374. https://doi.org/10.1519/JSC.0b013e3182548af1

Casamichana, D., Castellano, J., Diaz, A. G., Gabbett, T. J., & Martin-Garcia, A. (2019). The most demanding passages of play in football competition: A comparison between halves. *Biology of Sport*, *36*(3), 233–240. https://doi.org/10.5114/biolsport.2019.86005

Castellano, J., Blanco-Villaseñor, A., & Álvarez, D. (2011). Contextual variables and time-motion analysis in soccer. *International Journal of Sports Medicine*, *32*(6), 415–421. https://doi.org/10.1055/s-0031-1271771

Castellano, J., & Casamichana, D. (2013). Differences in the number of accelerations between small-sided games and friendly matches in soccer. *Journal of Sports Science & Medicine*, *12*(1), 209.

Castellano, J., Martin-Garcia, A., & Casamichana, D. (2020). Most running demand passages of match play in youth soccer congestion period. *Biology of Sport*, *37*(4), 367–373. https://doi.org/https://doi.org/10.5114/biolsport.2020.96853

Catapult Sports. (2019). *Catapult's Clearsky receives FIFA quality certification with best-*

performing wearable technology. https://www.catapultsports.com/blog/catapults-clearsky-receives-fifa-quality-certification-with-best-performing-wearable-technology

Chambers, R., Gabbett, T. J., Cole, M. H., & Beard, A. (2015). The use of wearable microsensors to quantify sport-specific movements. *Sports Medicine*, *45*(7), 1065–1081. https://doi.org/10.1007/s40279-015-0332-9

Chmura, P., Konefał, M., Chmura, J., Kowalczuk, E., Zając, T., Rokita, A., & Andrzejewski, M. (2018). Match outcome and running performance in different intensity ranges among elite soccer players. *Biology of Sport*, *35*(2), 197–203. https://doi.org/10.5114/biolsport.2018.74196

Clemente, F. M., Martins, F. M. L., Wong, P. Del, Kalamaras, D., & Mendes, R. S. (2015). Midfielder as the prominent participant in the building attack: A network analysis of national teams in FIFA World Cup 2014. *International Journal of Performance Analysis in Sport*, *15*(2), 704–722. https://doi.org/10.1080/24748668.2015.11868825

Clemente, F. M., Owen, A., Serra-Olivares, J., Nikolaidis, P. T., van der Linden, C. M. I., & Mendes, B. (2019). Characterization of the weekly external load profile of professional soccer teams from Portugal and the Netherlands. *Journal of Human Kinetics*, *66*(1), 155–164. https://doi.org/10.2478/hukin-2018-0054

Clemente, F. M., Rabbani, A., Conte, D., Castillo, D., Afonso, J., Truman Clark, C. C., Nikolaidis, P. T., Rosemann, T., & Knechtle, B. (2019). Training/match external load ratios in professional soccer players: A full-season study. *International Journal of Environmental Research and Public Health*, *16*(17), 1–11. https://doi.org/10.3390/ijerph16173057

Clemente, F. M., Sarmento, H., Rabbani, A., Van Der Linden, C. M. I. (Niels), Kargarfard, M., & Costa, I. T. (2019). Variations of external load variables between medium- and large-sided soccer games in professional players. *Research in Sports Medicine*, *27*(1), 50–59. https://doi.org/10.1080/15438627.2018.1511560

Cnaan, A., Laird, N. M., & Slasor, P. (1997). Using the general linear mixed model to analyse unbalanced repeated measures and longitudinal data. *Statistics in Medicine*, *16*(20), 2349–2380. https://doi.org/10.1002/(SICI)1097-0258(19971030)16:20<2349::AID-

SIM667>3.0.CO;2-E

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). L. Erlbaum Associates. https://www.worldcat.org/title/statistical-power-analysis-for-the-behavioral-sciences/oclc/17877467

Cook, J. A., Julious, S. A., Sones, W., Hampson, L. V, Hewitt, C., Berlin, J. A., Ashby, D., Emsley, R., Fergusson, D. A., Walters, S. J., Wilson, E. C. F., MacLennan, G., Stallard, N., Rothwell, J. C., Bland, M., Brown, L., Ramsay, C. R., Cook, A., Armstrong, D., … Vale, L. D. (2018). DELTA 2 guidance on choosing the target difference and undertaking and reporting the sample size calculation for a randomised controlled trial. *BMJ*, *363*, 1–7. https://doi.org/10.1136/bmj.k3750

Cummins, C., & Orr, R. (2015). Analysis of physical collisions in elite national rugby league match play. *International Journal of Sports Physiology and Performance*, *10*(6), 732–739. https://doi.org/10.1123/ijspp.2014-0541

Cummins, C., Orr, R., O'Connor, H., & West, C. (2013). Global Positioning Systems and microtechnology sensors in team sports: a systematic review. *Sports Medicine*, *43*(10), 1025–1042. https://doi.org/10.1007/s40279-013-0069-2

Cunningham, D. J., Shearer, D. A., Carter, N., Drawer, S., Pollard, B., Bennett, M., Eager, R., Cook, C. J., Farrell, J., Russell, M., & Kilduff, L. P. (2018). Assessing worst case scenarios in movement demands derived from global positioning systems during international rugby union matches: Rolling averages versus fixed length epochs. *PLOS ONE*, *13*(4), 1–14. https://doi.org/10.1371/journal.pone.0195197

Currell, K., & Jeukendrup, A. E. (2008). Validity, reliability and sensitivity of measures of sporting performance. *Sports Medicine*, *38*(4), 297–316. https://doi.org/10.2165/00007256-200838040-00003

Curtis, R. M., Huggins, R. A., Benjamin, C. L., Sekiguchi, Y., Adams, W. M., Arent, S. M., Jain, R., Miller, S. J., Walker, A. J., & Casa, D. J. (2019). Contextual factors influencing external and internal training loads in collegiate men's soccer. *Journal of Strength and Conditioning Research*, 1. https://doi.org/10.1519/JSC.0000000000003361 da Mota, G. R., Thiengo, C. R., Gimenes, S. V., & Bradley, P. S. (2016). The effects of ball possession status on physical and technical indicators during the 2014 FIFA World Cup Finals. *Journal of Sports Sciences*, *34*(6), 493–500. https://doi.org/10.1080/02640414.2015.1114660

Dahl, S. (2020). *It's not the most accurate. More results will be published*. Twitter. https://twitter.com/Flunx/status/1221040647198605317?s=20

Dalen, T., Aune, T. K., Hjelde, G. H., Ettema, G., Sandbakk, Ø., & McGhie, D. (2020). Player load in male elite soccer: Comparisons of patterns between matches and positions. *PLOS ONE*, *15*(9), 1–13. https://doi.org/10.1371/journal.pone.0239162

Dalen, T., Jørgen, I., Gertjan, E., Geir Havard, H., & Ulrik, W. (2016). Player load, acceleration, and deceleration during forty-five competitive matches of elite soccer. *Journal of Strength and Conditioning Research*, *30*(2), 351–359. https://doi.org/10.1519/JSC.0000000000001063

De Hoyo, M., Cohen, D. D., Sañudo, B., Carrasco, L., Álvarez-Mesa, A., del Ojo, J. J., Domínguez-Cobo, S., Mañas, V., & Otero-Esquina, C. (2016). Influence of football match time–motion parameters on recovery time course of muscle damage and jump ability. *Journal of Sports Sciences*, *34*(14), 1363–1370. https://doi.org/10.1080/02640414.2016.1150603

De Hoyo, M., Sañudo, B., Suárez-Arrones, L., Carrasco, L., Joel, T., Domínguez-Cobo, S., & Núñez, F. J. (2018). Analysis of the acceleration profile according to initial speed and positional role in elite professional male soccer players. *The Journal of Sports Medicine and Physical Fitness*, *58*(12), 22. https://doi.org/10.23736/S0022-4707.17.08003-3

Delaney, J. A., Thornton, H. R., Rowell, A. E., Dascombe, B. J., Aughey, R. J., & Duthie, G. M. (2018). Modelling the decrement in running intensity within professional soccer players. *Science and Medicine in Football*, *2*(2), 86–92. https://doi.org/10.1080/24733938.2017.1383623

Dellal, A., Chamari, K., Wong, D. P., Ahmaidi, S., Keller, D., Barros, R., Bisciotti, G. N., & Carling, C. (2011). Comparison of physical and technical performance in European soccer match-play: FA Premier League and La Liga. *European Journal of Sport Science*, *11*(1), 51–59. https://doi.org/10.1080/17461391.2010.481334

Di Salvo, V., Baron, R., Tschan, H., Calderon Montero, F. J., Bachl, N., & Pigozzi, F. (2007). Performance characteristics according to playing position in elite soccer. *International Journal of Sports Medicine*, *28*(3), 222–227. https://doi.org/10.1055/s-2006-924294

Doncaster, G., Page, R., White, P., Svenson, R., & Twist, C. (2020). Analysis of physical demands during youth soccer match-play: considerations of sampling method and epoch length. *Research Quarterly for Exercise and Sport*, *91*(2), 326–334. https://doi.org/10.1080/02701367.2019.1669766

Drust, B., Cable, N. T., & Reilly, T. (2000). Investigation of the effects of the pre-cooling on the physiological responses to soccer-specific intermittent exercise. *European Journal of Applied Physiology and Occupational Physiology*, *81*(1–2), 11–17. https://doi.org/10.1007/PL00013782

Dubois, R., Bru, N., Paillard, T., Le Cunuder, A., Lyons, M., Maurelli, O., Philippe, K., & Prioux, J. (2020). Rugby game performances and weekly workload: Using of data mining process to enter in the complexity. *PLOS ONE*, *15*(1), 1–21. https://doi.org/10.1371/journal.pone.0228107

Edwards, W. B. (2018). Modeling overuse injuries in sport as a mechanical fatigue phenomenon. *Exercise and Sport Sciences Reviews*, *46*(4), 224–231. https://doi.org/10.1249/JES.0000000000000163

Fasel, B., Sporri, J., Chardonnens, J., Kroll, J., Muller, E., & Aminian, K. (2018). Joint inertial sensor orientation drift reduction for highly dynamic movements. *IEEE Journal of Biomedical and Health Informatics*, *22*(1), 77–86. https://doi.org/10.1109/JBHI.2017.2659758

Faude, O., Koch, T., & Meyer, T. (2012). Straight sprinting is the most frequent action in goal situations in professional football. *Journal of Sports Sciences*, *30*(7), 625–631. https://doi.org/10.1080/02640414.2012.665940

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior*

Research Methods, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Fereday, K., Hills, S. P., Russell, M., Smith, J., Cunningham, D. J., Shearer, D., McNarry, M., & Kilduff, L. P. (2020). A comparison of rolling averages versus discrete time epochs for assessing the worst-case scenario locomotor demands of professional soccer match-play. *Journal of Science and Medicine in Sport*, *23*(8), 764–769. https://doi.org/10.1016/j.jsams.2020.01.002

Fernández-Leo, A., Gómez-Carmona, C. D., García-Rubio, J., & Ibáñez, S. J. (2020). Influence of contextual variables on physical and technical performance in male amateur basketball: a case study. *International Journal of Environmental Research and Public Health*, *17*(4), 1–16. https://doi.org/10.3390/ijerph17041193

Fernandez-Navarro, J., Fradua, L., Zubillaga, A., & McRobert, A. P. (2018). Influence of contextual variables on styles of play in soccer. *International Journal of Performance Analysis in Sport*, *18*(3), 423–436. https://doi.org/10.1080/24748668.2018.1479925

Fessi, M. S., Zarrouk, N., Di Salvo, V., Filetti, C., Barker, A. R., & Moalla, W. (2016). Effects of tapering on physical match activities in professional soccer players. *Journal of Sports Sciences*, *34*(24), 2189–2194. https://doi.org/10.1080/02640414.2016.1171891

FIFA. (2017). *FIFA Quality Programme for EPTS*. https://football-technology.fifa.com/en/media-tiles/fifa-quality-programme-for-epts/

FIFA. (2019). *Handbook of test methods for EPTS*.

FIFA. (2020). *FIFA Quality performance reports for EPTS*. https://football-technology.fifa.com/en/media-tiles/fifa-quality-performance-reports-for-epts/

Filter, A., Olivares-Jabalera, J., Santalla, A., Morente-Sánchez, J., Robles-Rodríguez, J., Requena, B., & Loturco, I. (2020). Curve sprinting in soccer: kinematic and neuromuscular analysis. *International Journal of Sports Medicine*, 744–750. https://doi.org/10.1055/a-1144-3175

Fílter, A., Olivares, J., Santalla, A., Nakamura, F. Y., Loturco, I., & Requena, B. (2020). New curve sprint test for soccer players: reliability and relationship with linear sprint. *Journal* *of Sports Sciences*, *38*(11–12), 1320–1325. https://doi.org/10.1080/02640414.2019.1677391

Folgado, H., Duarte, R., Fernandes, O., & Sampaio, J. (2014). Competing with lower level opponents decreases intra-team movement synchronization and time-motion demands during pre-season soccer matches. *PLoS ONE*, *9*(5), 1–9. https://doi.org/10.1371/journal.pone.0097145

Folgado, H., Lemmink, K. A. P. M., Frencken, W., & Sampaio, J. (2014). Length, width and centroid distance as measures of teams tactical performance in youth football. *European Journal of Sport Science*, *14*(1), 487–492. https://doi.org/10.1080/17461391.2012.730060

Fong, D., & Chan, Y.-Y. (2010). The Use of Wearable Inertial Motion Sensors in Human Lower Limb Biomechanics Studies: A Systematic Review. *Sensors*, *10*(12), 11556–11565. https://doi.org/10.3390/s101211556

Fradua, L., Zubillaga, A., Caro, O., Iván Fernández-García, A., Ruiz-Ruiz, C., & Tenga, A. (2013). Designing small-sided games for training tactical aspects in soccer: extrapolating pitch sizes from full-size professional matches. *Journal of Sports Sciences*, *31*(6), 573–581. https://doi.org/10.1080/02640414.2012.746722

Fransson, D., Krustrup, P., & Mohr, M. (2017). Running intensity fluctuations indicate temporary performance decrement in top-class football. *Science and Medicine in Football*, *1*(1), 10–17. https://doi.org/10.1080/02640414.2016.1254808

Frencken, W. G. P., Lemmink, K. A. P. M., & Delleman, N. J. (2010). Soccer-specific accuracy and validity of the local position measurement LPM system. *Journal of Science and Medicine in Sport*, *13*(6), 641–645. https://doi.org/10.1016/j.jsams.2010.04.003

Gabbett, T. J. (2016). The training—injury prevention paradox: should athletes be training smarter and harder? *British Journal of Sports Medicine*, *50*(5), 273–280. https://doi.org/10.1136/bjsports-2015-095788

Gastin, P. B., Hunkin, S. L., Fahrner, B., & Robertson, S. (2019). Deceleration, acceleration, and impacts are strong contributors to muscle damage in professional australian football. *Journal of Strength and Conditioning Research*, *Epub: Ahea*, 10.

https://doi.org/10.1519/JSC.0000000000003023

Gaudino, P., Alberti, G., & Iaia, F. M. (2014). Estimated metabolic and mechanical demands during different small-sided games in elite soccer players. *Human Movement Science, 36*, 123–133. https://doi.org/10.1016/j.humov.2014.05.006

Gaudino, P., Iaia, F. M., Strudwick, A. J., Hawkins, R. D., Alberti, G., Atkinson, G., & Gregson, W. (2015). Factors influencing perception of effort (session rating of perceived exertion) during elite soccer training. *International Journal of Sports Physiology and Performance*, *10*(7), 860–864. https://doi.org/10.1123/ijspp.2014-0518

Gómez-Carmona, C. D., Bastida-Castillo, A., García-Rubio, J., Ibáñez, S. J., & Pino-Ortega, J. (2019). Static and dynamic reliability of WIMU PRO™ accelerometers according to anatomical placement. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, *233*(2), 238–248. https://doi.org/10.1177/1754337118816922

Gómez-Carmona, C. D., Bastida-Castillo, A., González-Custodio, A., Olcina, G., & Pino-Ortega, J. (2019). Using an inertial device (WIMU PRO) to quantify neuromuscular load in running. *Journal of Strength and Conditioning Research*, 1–9. https://doi.org/10.1519/JSC.0000000000003106

Gómez-Carmona, C. D., Bastida-Castillo, A., Ibáñez, S. J., & Pino-Ortega, J. (2020). Accelerometry as a method for external workload monitoring in invasion team sports. A systematic review. *PLOS ONE*, *15*(8), 1–25. https://doi.org/10.1371/journal.pone.0236643

Gómez-Carmona, C. D., Gamonales, J., Pino-Ortega, J., & Ibáñez, S. (2018). Comparative analysis of load profile between small-sided games and official matches in youth soccer players. *Sports*, *6*(4), 173. https://doi.org/10.3390/sports6040173

Gómez-Carmona, C. D., Pino-Ortega, J., Sánchez-Ureña, B., Ibáñez, S. J., & Rojas-Valverde, D. (2019). Accelerometry-based external load indicators in sport: too many options, same practical outcome? *International Journal of Environmental Research and Public Health*, *16*(24), 1–13. https://doi.org/10.3390/ijerph16245101

Gonçalves, B., Esteves, P., Folgado, H., Ric, A., Torrents, C., & Sampaio, J. (2017). Effects of pitch area-restrictions on tactical behavior, physical, and physiological performances in soccer large-sided games. *Journal of Strength and Conditioning Research*, *31*(9), 2398–2408. https://doi.org/10.1519/JSC.0000000000001700

Gonçalves, L., Kalva-Filho, C. A., Nakamura, F. Y., Rago, V., Afonso, J., Bedo, B. L. de S., & Aquino, R. (2020). Effects of match-related contextual factors on weekly load responses in professional Brazilian soccer players. *International Journal of Environmental Research and Public Health*, *17*(14), 5163. https://doi.org/10.3390/ijerph17145163

Granero-Gil, P., Gómez-Carmona, C. D., Bastida-Castillo, A., Rojas-Valverde, D., de la Cruz, E., & Pino-Ortega, J. (2020). Influence of playing position and laterality in centripetal force and changes of direction in elite soccer players. *PLOS ONE*, *15*(4), 1–13. https://doi.org/10.1371/journal.pone.0232123

Gray, A. J., Jenkins, D., Andrews, M. H., Taaffe, D. R., & Glover, M. L. (2010). Validity and reliability of GPS for measuring distance travelled in field-based team sports. *Journal of Sports Sciences*, *28*(12), 1319–1325. https://doi.org/10.1080/02640414.2010.504783

Gregson, W., Drust, B., Atkinson, G., & Salvo, V. (2010). Match-to-match variability of high-speed activities in Premier League soccer. *International Journal of Sports Medicine, 31*(04), 237–242. https://doi.org/10.1055/s-0030-1247546

Grosdent, S., Demoulin, C., Rodriguez de La Cruz, C., Giop, R., Tomasella, M., Crielaard, J.-M., & Vanderthommen, M. (2016). Lumbopelvic motor control and low back pain in elite soccer players: a cross-sectional study. *Journal of Sports Sciences, 34*(11), 1021–1029. https://doi.org/10.1080/02640414.2015.1085077

Grünbichler, J., Federolf, P., & Gatterer, H. (2019). Workload efficiency as a new tool to describe external and internal competitive match load of a professional soccer team: A descriptive study on the relationship between pre-game training loads and relative match load. *European Journal of Sport Science*, 1–8. https://doi.org/10.1080/17461391.2019.1697374

Guiry, J., van de Ven, P., & Nelson, J. (2014). Multi-Sensor Fusion for Enhanced Contextual Awareness of Everyday Activities with Ubiquitous Devices. *Sensors*, *14*(3), 5687–5701.

https://doi.org/10.3390/s140305687

Haddad, H. Al, Méndez-Villanueva, A., Torreño, N., Munguia-Izquierdo, D., & Suárez-Arrones, L. (2018). Variability of GPS-derived running performance during official matches in elite professional soccer players. *Journal of Sports Medicine and Physical Fitness*, *58*(10), 1439–1445. https://doi.org/10.23736/S0022-4707.17.07500-4

Hader, K., Mendez-Villanueva, A., Palazzi, D., Ahmaidi, S., & Buchheit, M. (2016). Metabolic power requirement of change of direction speed in young soccer players: not all is what it seems. *PLOS ONE*, *11*(3), 1–21. https://doi.org/10.1371/journal.pone.0149839

Hader, K., Rumpf, M. C., Hertzog, M., Kilduff, L. P., Girard, O., & Silva, J. R. (2019). Monitoring the athlete match response: can external load variables predict post-match acute and residual fatigue in soccer? A systematic review with meta-analysis. *Sports Medicine - Open*, *5*(1), 1–19. https://doi.org/10.1186/s40798-019-0219-7

Harper, D. J., Carling, C., & Kiely, J. (2019). High-intensity acceleration and deceleration demands in elite team sports competitive match play: a systematic review and meta-analysis of observational studies. *Sports Medicine*, *49*(12), 1923–1947. https://doi.org/10.1007/s40279-019-01170-1

Harper, D. J., & Kiely, J. (2018). Damaging nature of decelerations: Do we adequately prepare players? *BMJ Open Sport & Exercise Medicine*, *4*(1), 1–3. https://doi.org/10.1136/bmjsem-2018-000379

Harriss, D., & Atkinson, G. (2015). Ethical standards in sport and exercise science research: 2016 update. *International Journal of Sports Medicine*, *36*(14), 1121–1124. https://doi.org/10.1055/s-0035-1565186

Haugen, T. A., Tønnessen, E., Hisdal, J., & Seiler, S. (2014). The role and development of sprinting speed in soccer. *International Journal of Sports Physiology and Performance*, *9*(3), 432–441. https://doi.org/10.1123/ijspp.2013-0121

Haugen, T. A., Tønnessen, E., & Seiler, S. (2013). Anaerobic performance testing of professional soccer players 1995–2010. *International Journal of Sports Physiology and Performance*, *8*(2), 148–156. https://doi.org/10.1123/ijspp.8.2.148

Hides, J. A., Oostenbroek, T., Franettovich Smith, M. M., & Mendis, M. D. (2016). The effect of low back pain on trunk muscle size/function and hip strength in elite football (soccer) players. *Journal of Sports Sciences*, *34*(24), 2303–2311. https://doi.org/10.1080/02640414.2016.1221526

Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Medicine & Science in Sports & Exercise*, *41*(1), 3–12. https://doi.org/10.1249/MSS.0b013e31818cb278

Hulin, B. T., Gabbett, T. J., Johnston, R. D., & Jenkins, D. G. (2018). PlayerLoad variables: sensitive to changes in direction and not related to collision workloads in rugby league match play. *International Journal of Sports Physiology and Performance*, *13*(9), 1136–1142. https://doi.org/10.1123/ijspp.2017-0557

Hunter, F., Bray, J., Towlson, C., Smith, M., Barrett, S., Madden, J., Abt, G., & Lovell, R. (2015). Individualisation of time-motion analysis: A method comparison and case report series. *International Journal of Sports Medicine*, *36*(1), 41–48. https://doi.org/10.1055/s-0034-1384547

Impellizzeri, F. M., Marcora, S. M., & Coutts, A. J. (2019). Internal and external training load: 15 years on. *International Journal of Sports Physiology and Performance*, *14*(2), 270–273. https://doi.org/10.1123/ijspp.2018-0935

Ingebrigtsen, J., Dalen, T., Hjelde, G. H., Drust, B., & Wisløff, U. (2015). Acceleration and sprint profiles of a professional elite football team in match play. *European Journal of Sport Science*, *15*(2), 101–110. https://doi.org/10.1080/17461391.2014.933879

Jaspers, A., Brink, M. S., Probst, S. G. M., Frencken, W. G. P., & Helsen, W. F. (2017). Relationships between training load indicators and training outcomes in professional soccer. *Sports Medicine*, *47*(3), 533–544. https://doi.org/10.1007/s40279-016-0591-0

Jeffreys, I. (2008). Movement training for field sports: Soccer. *Strength and Conditioning Journal*, *30*(4), 19–27. https://doi.org/10.1519/SSC.0b013e31818021c1

Johnston, R. D., Gabbett, T. J., Seibold, A. J., & Jenkins, D. G. (2014). Influence of physical contact on neuromuscular fatigue and markers of muscle damage following small-sided games. *Journal of Science and Medicine in Sport*, *17*(5), 535–540. https://doi.org/10.1016/j.jsams.2013.07.018

Johnston, R. D., Hewitt, A., & Duthie, G. (2020). Validity of real-time ultra-wideband global navigation satellite system data generated by a wearable microtechnology unit. *Journal of Strength and Conditioning Research, 34*(7), 2071–2075. https://doi.org/10.1519/JSC.0000000000003059

Kelly, D. M., Strudwick, A. J., Atkinson, G., Drust, B., & Gregson, W. (2020). Quantification of training and match-load distribution across a season in elite English Premier League soccer players. *Science and Medicine in Football, 4*(1), 59–67. https://doi.org/10.1080/24733938.2019.1651934

Koehler, K. J., & Larntz, K. (1980). An empirical investigation of goodness-of-fit statistics for sparse multinomials. *Journal of the American Statistical Association*, *75*(370), 336. https://doi.org/10.2307/2287455

Konefał, M., Chmura, P., Andrzejewski, M., Pukszta, D., & Chmura, J. (2015). Analysis of match performance of full-backs from selected European soccer leagues. *Central European Journal of Sport Sciences and Medicine, 11*(3), 45–53. https://doi.org/10.18276/cej.2015.3-05

Konefał, M., Chmura, P., Zając, T., Chmura, J., Kowalczuk, E., & Andrzejewski, M. (2019). A new approach to the analysis of pitch-positions in professional soccer. *Journal of Human Kinetics, 66*(1), 143–153. https://doi.org/10.2478/hukin-2018-0067

Kos, M., & Kramberger, I. (2017). A Wearable device and system for Movement and biometric data acquisition for sports applications. *IEEE Access, 5*, 6411–6420. https://doi.org/10.1109/ACCESS.2017.2675538

Krustrup, P., Mohr, M., Steensberg, A., Bencke, J., Kjaer, M., & Bangsbo, J. (2006). Muscle and blood metabolites during a soccer game: implications for sprint performance. *Medicine and Science in Sports and Exercise, 38*(6), 1165–1174. https://doi.org/10.1249/01.mss.0000222845.89262.cd

Lacome, M., Simpson, B. M., Cholley, Y., Lambert, P., & Buchheit, M. (2018). Small-sided games in elite soccer: does one size fit all? *International Journal of Sports Physiology and Performance*, *13*(5), 568–576. https://doi.org/10.1123/ijspp.2017-0214

Lago-Peñas, C., & Lago-Ballesteros, J. (2011). Game location and team quality effects on performance profiles in professional soccer. *Journal of Sports Science & Medicine*, *10*(3), 465–471.

Larsson, P. (2003). Global positioning system and sport-specific testing. *Sports Medicine*, *33*(15), 1093–1101. https://doi.org/10.2165/00007256-200333150-00002

Lim, J., Palmer, C. J., Busa, M. A., Amado, A., Rosado, L. D., Ducharme, S. W., Simon, D., & Van Emmerik, R. E. A. (2017). Additional helmet and pack loading reduce situational awareness during the establishment of marksmanship posture. *Ergonomics*, *60*(6), 824–836. https://doi.org/10.1080/00140139.2016.1222001

Lindsay, T. R., Yaggie, J. A., & McGregor, S. J. (2014). Contributions of lower extremity kinematics to trunk accelerations during moderate treadmill running. *Journal of NeuroEngineering and Rehabilitation*, *11*(1), 162. https://doi.org/10.1186/1743-0003-11-162

Linke, D., Link, D., & Lames, M. (2018). Validation of electronic performance and tracking systems EPTS under field conditions. *PLOS ONE*, *13*(7), 1–19. https://doi.org/10.1371/journal.pone.0199519

Little, T., & Williams, A. G. (2005). Specificity of acceleration, maximum speed, and agility in professional soccer players. *The Journal of Strength and Conditioning Research*, *19*(1), 76–78. https://doi.org/10.1519/14253.1

Liu, H., Darabi, H., Banerjee, P., & Liu, J. (2007). Survey of wireless indoor positioning techniques and systems. *IEEE Transactions on Systems, Man and Cybernetics*, *37*(6), 1067–1080. https://doi.org/10.1109/TSMCC.2007.905750

Liu, L., Qiu, S., Wang, Z., Li, J., & Wang, J. (2020). Canoeing motion tracking and analysis via multi-sensors fusion. *Sensors*, *20*(7), 1–17. https://doi.org/10.3390/s20072110

Loturco, I., Bishop, C., Freitas, T. T., Pereira, L. A., & Jeffreys, I. (2020). Vertical force production in soccer: mechanical aspects and applied training strategies. *Strength & Conditioning Journal*, *42*(2), 6–15. https://doi.org/10.1519/SSC.0000000000000513

Loturco, I., Jeffreys, I., Kobal, R., Cal Abad, C. C., Ramirez-Campillo, R., Zanetti, V., Pereira, L. A., & Nakamura, F. Y. (2018). Acceleration and speed performance of Brazilian elite soccer players of different age-categories. *Journal of Human Kinetics*, *64*(1), 205–218. https://doi.org/10.1515/hukin-2017-0195

Loturco, I., Pereira, L. A., Kobal, R., Zanetti, V., Gil, S., Kitamura, K., Abad, C. C. C., & Nakamura, F. Y. (2015). Half-squat or jump squat training under optimum power load conditions to counteract power and speed decrements in Brazilian elite soccer players during the preseason. *Journal of Sports Sciences*, *33*(12), 1283–1292. https://doi.org/10.1080/02640414.2015.1022574

Malone, J. J., Di Michele, R., Morgans, R., Burgess, D., Morton, J. P., & Drust, B. (2015). Seasonal training-load quantification in elite English Premier League soccer players. *International Journal of Sports Physiology and Performance*, *10*(4), 489–497. https://doi.org/10.1123/ijspp.2014-0352

Malone, J. J., Lovell, R., Varley, M. C., & Coutts, A. J. (2017). Unpacking the black box: applications and considerations for using GPS devices in sport. *International Journal of Sports Physiology and Performance*, *12*(2), 18–26. https://doi.org/10.1123/ijspp.2016-0236

Manafifard, M., Ebadi, H., & Abrishami Moghaddam, H. (2017). A survey on player tracking in soccer videos. *Computer Vision and Image Understanding*, *159*, 19–46. https://doi.org/10.1016/j.cviu.2017.02.002

Marta, G., Simona, F., Andrea, C., Dario, B., Stefano, S., Federico, V., Marco, B., Francesco, B., Stefano, M., & Alessandra, P. (2020). Wearable biofeedback suit to promote and monitor aquatic exercises: a feasibility study. *IEEE Transactions on Instrumentation and Measurement*, *69*(4), 1219–1231. https://doi.org/10.1109/TIM.2019.2911756

Martin-Garcia, A. A. A., Castellano, J., Diaz, A. G., Cos, F., & Casamichana, D. (2019). Positional demands for various-sided games with goalkeepers according to the most demanding passages of match play in football. *Biology of Sport*, *36*(2), 171–180.

https://doi.org/10.5114/biolsport.2019.83507

Martín-García, A., Casamichana, D., Gómez Díaz, A., Cos, F., & Gabbett, T. J. (2018). Positional differences in the most demanding passages of play in football competition. *Journal of Sports Science and Medicine*, *17*(4), 563–570.

Martín-García, A., Gómez Díaz, A., Bradley, P. S., Morera, F., & Casamichana, D. (2018). Quantification of a professional football team's external load using a microcycle structure. *Journal of Strength and Conditioning Research*, *32*(12), 3511–3518. https://doi.org/10.1519/JSC.0000000000002816

McLaren, S. J., Weston, M., Smith, A., Cramb, R., & Portas, M. D. (2016). Variability of physical performance and player match loads in professional rugby union. *Journal of Science and Medicine in Sport*, *19*(6), 493–497. https://doi.org/10.1016/j.jsams.2015.05.010

Medina, D., Pons, E., Gomez, A., Guitart, M., Martin, A., Vazquez-Guerrero, J., Camenforte, I., Carles, B., & Font, R. (2017). Are there potential safety problems concerning the use of Electronic Performance-Tracking Systems? The experience of a multisport elite club. *International Journal of Sports Physiology and Performance*, *12*(8), 1115–1118. https://doi.org/10.1123/ijspp.2016-0368

Mendez-Villanueva, A., Buchheit, M., Kuitunen, S., Douglas, A., Peltola, E., & Bourdon, P. (2011). Age-related differences in acceleration, maximum running speed, and repeated-sprint performance in young soccer players. *Journal of Sports Sciences*, *29*(5), 477–484. https://doi.org/10.1080/02640414.2010.536248

Merks, B. M. T., Frencken, W. G. P., Den Otter, A. R., & Brink, M. S. (2021). Quantifying change of direction load using positional data from small-sided games in soccer. *Science and Medicine in Football*, 1–7. https://doi.org/10.1080/24733938.2021.1912382

Miñano-Espin, J., Casáis, L., Lago-Peñas, C., & Gómez-Ruano, M. Á. (2017). High speed running and sprinting profiles of elite soccer players. *Journal of Human Kinetics*, *58*(1), 169–176. https://doi.org/10.1515/hukin-2017-0086

Moalla, W., Fessi, M. S., Farhat, F., Nouira, S., Wong, D. P., & Dupont, G. (2016). Relationship between daily training load and psychometric status of professional soccer players. *Research in Sports Medicine*, *24*(4), 387–394. https://doi.org/10.1080/15438627.2016.1239579

Mohr, M., Krustrup, P., & Bangsbo, J. (2003). Match performance of high-standard soccer players with special reference to development of fatigue. *Journal of Sports Sciences*, *21*(7), 519–528. https://doi.org/10.1080/0264041031000071182

Morgans, R., Orme, P., Anderson, L., & Drust, B. (2014). Principles and practices of training for soccer. *Journal of Sport and Health Science*, *3*(4), 251–257. https://doi.org/10.1016/j.jshs.2014.07.002

Morin, J.-B., & Sève, P. (2011). Sprint running performance: comparison between treadmill and field conditions. *European Journal of Applied Physiology*, *111*(8), 1695–1703. https://doi.org/10.1007/s00421-010-1804-0

Müller, R., Ertelt, T., & Blickhan, R. (2015). Low back pain affects trunk as well as lower limb movements during walking and running. *Journal of Biomechanics*, *48*(6), 1009–1014. https://doi.org/10.1016/j.jbiomech.2015.01.042

Muñoz-López, A., Granero-Gil, P., Pino-Ortega, J., & De Hoyo, M. (2017). The validity and reliability of a 5-hz GPS device for quantifying athletes' sprints and movement demands specific to team sports. *Journal of Human Sport and Exercise*, *12*(1), 156–166. https://doi.org/10.14198/jhse.2017.121.13

Murphy, K. R., & Myors, B. (1999). Testing the hypothesis that treatments have negligible effects: Minimum-effect tests in the general linear model. *Journal of Applied Psychology*, *84*(2), 234–248. https://doi.org/10.1037/0021-9010.84.2.234

Nédélec, M., Halson, S., Abaidia, A.-E., Ahmaidi, S., & Dupont, G. (2015). Stress, sleep and recovery in elite soccer: a critical review of the literature. *Sports Medicine*, *45*(10), 1387–1400. https://doi.org/10.1007/s40279-015-0358-z

Nédélec, M., McCall, A., Carling, C., Legall, F., Berthoin, S., & Dupont, G. (2012). Recovery in soccer. *Sports Medicine*, *42*(12), 997–1015. https://doi.org/10.2165/11635270-000000000-00000

Ogris, G., Leser, R., Horsak, B., Kornfeind, P., Heller, M., & Baca, A. (2012). Accuracy of the LPM tracking system considering dynamic position changes. *Journal of Sports Sciences*, *30*(14), 1503–1511. https://doi.org/10.1080/02640414.2012.712712

Oliva-Lozano, J. M., Barbier, X., Fortes, V., & Muyor, J. M. (2021). Key load indicators and load variability in professional soccer players: a full season study. *Research in Sports Medicine*, 1–13. https://doi.org/10.1080/15438627.2021.1954517

Oliva-Lozano, J. M., Conte, D., Fortes, V., & Muyor, J. M. (2021). Exploring the use of player load in elite soccer players. *Sports Health: A Multidisciplinary Approach*.

Oliva-Lozano, J. M., Fortes, V., Krustrup, P., & Muyor, J. M. (2020). Acceleration and sprint profiles of professional male football players in relation to playing position. *PLOS ONE*, *15*(8), 1–12. https://doi.org/10.1371/journal.pone.0236959

Oliva-Lozano, J. M., Fortes, V., & Muyor, J. M. (2020). The first, second, and third most demanding passages of play in professional soccer: a longitudinal study. *Biology of Sport*, *38*(2), 165–174. https://doi.org/10.5114/biolsport.2020.97674

Oliva-Lozano, J. M., Fortes, V., & Muyor, J. M. (2021). When and how do elite soccer players sprint in match play? A longitudinal study in a professional soccer league. *Research in Sports Medicine (Print)*, 1–12. https://doi.org/10.1080/15438627.2021.1929224

Oliva-Lozano, J. M., Gómez-Carmona, C. D., Fortes, V., & Pino-Ortega, J. (2022). Effect of training day, match, and length of the microcycle on workload periodization in professional soccer players: a full-season study. *Biology of Sport*, *39*(2), 397–406.

Oliva-Lozano, J. M., Gómez-Carmona, C. D., Pino-Ortega, J., Moreno-Pérez, V., & Rodríguez-Pérez, M. A. (2020a). Match and training high intensity activity-demands profile during a competitive mesocycle in youth elite soccer players. *Journal of Human Kinetics*, *75*, 131–141. https://doi.org/10.2478/hukin-2020-0050

Oliva-Lozano, J. M., Gómez-Carmona, C. D., Rojas-Valverde, D., Fortes, V., & Pino-Ortega, J. (2021). Effect of training day, match, and length of the microcycle on the worst-case scenarios in professional soccer players. *Research in Sports Medicine*, 1–14. https://doi.org/10.1080/15438627.2021.1895786

Oliva-Lozano, J. M., Maraver, E. F., Fortes, V., & Muyor, J. M. (2020b). Effect of playing position, match half, and match day on the trunk inclination, g-forces, and locomotor efficiency experienced by elite soccer players in match play. *Sensors*, *20*, 1–12. https://doi.org/10.3390/s20205814

Oliva-Lozano, J. M., Maraver, E. F., Fortes, V., & Muyor, J. M. (2020). Kinematic analysis of the postural demands in professional soccer match play using inertial measurement units. *Sensors*, *20*(21), 1–11. https://doi.org/10.3390/s20215971

Oliva-Lozano, J. M., Martín-Fuentes, I., Fortes, V., & Muyor, J. M. (2021). Differences in worst-case scenarios calculated by fixed length and rolling average methods in professional soccer match-play. *Biology of Sport*, *38*(3), 325–331. https://doi.org/https://doi.org/10.5114/biolsport.2021.99706

Oliva-Lozano, J. M., Martín-Fuentes, I., Granero-Gil, P., & Muyor, J. M. (2021). Monitoring elite soccer players physical performance using real-time data generated by electronic performance and tracking systems. *Journal of Strength and Conditioning Research*, 1–5. https://doi.org/10.1519/JSC.0000000000004082

Oliva-Lozano, J. M., Martín-Fuentes, I., & Muyor, J. M. (2020a). Validity and reliability of an inertial device for measuring dynamic weight-bearing ankle dorsiflexion. *Sensors*, *20*(2), 1–10. https://doi.org/10.3390/s20020399

Oliva-Lozano, J. M., Martín-Fuentes, I., & Muyor, J. M. (2020b). Validity and reliability of a new inertial device for monitoring range of motion at the pelvis during sexual intercourse. *International Journal of Environmental Research and Public Health*, *17*(8), 1–11. https://doi.org/10.3390/ijerph17082884

Oliva-Lozano, J. M., Martínez-Puertas, H., Fortes, V., & Muyor, J. M. (2021). When do soccer players experience the most demanding passages of match play? A longitudinal study in a professional team. *Research in Sports Medicine*, 1–11. https://doi.org/10.1080/15438627.2021.1943390

Oliva-Lozano, J. M., & Muyor, J. M. (2020). Core muscle activity during physical fitness exercises: a systematic review. *International Journal of Environmental Research and Public Health*, *17*(12), 1–38. https://doi.org/10.3390/ijerph17124306

Oliva-Lozano, J. M., & Muyor, J. M. (2021). Understanding the FIFA quality performance reports for electronic performance and tracking systems: from science to practice. *Science and Medicine in Football*, 1–6. https://doi.org/10.1080/24733938.2021.1984557

Oliva-Lozano, J. M., Muyor, J. M., Fortes, V., & McLaren, S. J. (2021). Decomposing the variability of match physical performance in professional soccer: Implications for monitoring individuals. *European Journal of Sport Science*, *21*(11), 1588–1596. https://doi.org/10.1080/17461391.2020.1842513

Oliva-Lozano, J. M., & Rago, V. (2020). *El Sport Scientist y la monitorización de la carga con EPTS en deportes de equipo*. Editorial Universidad de Almería.

Oliva-Lozano, J. M., Rago, V., Fortes, V., & Muyor, J. M. (2021). Impact of match-related contextual variables on weekly training load in a professional soccer team: a full season study. *Biology of Sport*, *39*(1), 125–134. https://doi.org/10.5114/biolsport.2021.102927

Oliva-Lozano, J. M., Rojas-Valverde, D., Gómez-Carmona, C. D., Fortes, V., & Pino-Ortega, J. (2020d). Impact of contextual variables on the representative external load profile of Spanish professional soccer match-play: a full season study. *European Journal of Sport Science, 21*(4), 497–506. https://doi.org/10.1080/17461391.2020.1751305

Oliva-Lozano, J. M., Rojas-Valverde, D., Gómez-Carmona, C. D., Fortes, V., & Pino, J. (2020e). Worst case scenario match analysis and contextual variables in professional soccer players: a longitudinal study. *Biology of Sport*, *37*(4), 429–436. https://doi.org/10.5114/biolsport.2020.97067

Osgnach, C., Poser, S., Bernardini, R., Rinaldo, R., & Di Prampero, P. E. (2010). Energy cost and metabolic power in elite soccer. *Medicine & Science in Sports & Exercise*, *42*(1), 170–178. https://doi.org/10.1249/MSS.0b013e3181ae5cfd

Owen, A. L., Lago-Peñas, C., Gómez, M.-Á., Mendes, B., & Dellal, A. (2017). Analysis of a training mesocycle and positional quantification in elite European soccer players. *International Journal of Sports Science & Coaching*, *12*(5), 665–676. https://doi.org/10.1177/1747954117727851

Page, R. M., Marrin, K., Brogden, C. M., & Greig, M. (2015). Biomechanical and physiological response to a contemporary soccer match-play simulation. *Journal of Strength and Conditioning Research*, *29*(10), 2860–2866. https://doi.org/10.1519/JSC.0000000000000949

Palucci-Vieira, L. H., Aquino, R., Lago-Peñas, C., Munhoz-Martins, G. H., Puggina, E. F., Barbieri, F. A., Palucci Vieira, L. H., Aquino, R., Lago-Peñas, C., Munhoz Martins, G. H., Puggina, E. F., & Barbieri, F. A. (2018). Running performance in Brazilian professional football players during a congested match schedule. *Journal of Strength and Conditioning Research*, *32*(2), 313–325. https://doi.org/10.1519/JSC.0000000000002342

Palucci-Vieira, L. H., Aquino, R., Moura, F. A., Barros, R., Arpini, V. M., Oliveira, L. P., Bedo, B. L. ., & Santiago, P. R. . (2019). Team dynamics, running, and skill-related performances of Brazilian U11 to professional soccer players during official matches. *Journal of Strength and Conditioning Research,* *33*(8), 2202–2216. https://doi.org/10.1519/JSC.0000000000002577

Parmar, N., James, N., Hearne, G., & Jones, B. (2018). Using principal component analysis to develop performance indicators in professional rugby league. *International Journal of Performance Analysis in Sport*, *18*(6), 938–949. https://doi.org/10.1080/24748668.2018.1528525

Pino-Ortega, J., Oliva-Lozano, J. M., Gantois, P., Nakamura, F. Y., & Rico-González, M. (2021). Comparison of the validity and reliability of local positioning systems against other tracking technologies in team sport: A systematic review. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, 175433712098823. https://doi.org/10.1177/1754337120988236

Piras, A., Raffi, M., Atmatzidis, C., Merni, F., & Di Michele, R. (2017). The energy cost of running with the ball in soccer. *International Journal of Sports Medicine, 38*(12), 877–822. https://doi.org/10.1055/s-0043-118340

Poitras, I., Dupuis, F., Bielmann, M., Campeau-Lecours, A., Mercier, C., Bouyer, L., & Roy, J.-S. (2019). Validity and reliability of wearable sensors for joint angle estimation: a systematic review. *Sensors*, *19*(7), 1–17. https://doi.org/10.3390/s19071555

Pons, E., García-Calvo, T., Resta, R., Blanco, H., López del Campo, R., Díaz García, J., &

Pulido, J. J. (2019). A comparison of a GPS device and a multi-camera video technology during official soccer matches: Agreement between systems. *PLOS ONE*, *14*(8), 1–12. https://doi.org/10.1371/journal.pone.0220729

Qiu, S., Wang, Z., Zhao, H., Qin, K., Li, Z., & Hu, H. (2018). Inertial/magnetic sensors based pedestrian dead reckoning by means of multi-sensor fusion. *Information Fusion*, *39*, 108–119. https://doi.org/10.1016/j.inffus.2017.04.006

Rago, V., Brito, J., Figueiredo, P., Costa, J., Barreira, D., Krustrup, P., & Rebelo, A. (2020). Methods to collect and interpret external training load using microtechnology incorporating GPS in professional football: a systematic review. *Research in Sports Medicine*, *28*(3), 437–458. https://doi.org/10.1080/15438627.2019.1686703

Rago, V., Brito, J., Figueiredo, P., Krustrup, P., & Rebelo, A. (2020). Application of individualized speed zones to quantify external training load in professional soccer. *Journal of Human Kinetics*, *72*(1), 279–289. https://doi.org/10.2478/hukin-2019-0113

Rago, V., Rebelo, A., Krustrup, P., & Mohr, M. (2019). Contextual variables and training load throughout a competitive period in a top-level male soccer team. *Journal of Strength and Conditioning Research*, 1–7. https://doi.org/10.1519/jsc.0000000000003258

Rago, V., Silva, J., Mohr, M., Randers, M., Barreira, D., Krustrup, P., & Rebelo, A. (2018). Influence of opponent standard on activity profile and fatigue development during preseasonal friendly soccer matches: a team study. *Research in Sports Medicine*, *26*(4), 413–424. https://doi.org/10.1080/15438627.2018.1492400

Rago, V., Silva, J. R., Mohr, M., Barreira, D., Krustrup, P., & Rebelo, A. N. (2019). Variability of activity profile during medium-sided games in professional soccer. *The Journal of Sports Medicine and Physical Fitness*, *59*(4). https://doi.org/10.23736/S0022-4707.18.08376-7

Rampinini, E., Coutts, A., Castagna, C., Sassi, R., & Impellizzeri, F. (2007). Variation in Top Level Soccer Match Performance. *International Journal of Sports Medicine*, *28*(12), 1018–1024. https://doi.org/10.1055/s-2007-965158

Rampinini, E., Impellizzeri, F., Castagna, C., Coutts, A. J., & Wisløff, U. (2009). Technical performance during soccer matches of the Italian Serie A league: effect of fatigue and competitive level. *Journal of Science and Medicine in Sport*, *12*(1), 227–233. https://doi.org/10.1016/j.jsams.2007.10.002

Reardon, C., Tobin, D. P., Tierney, P., & Delahunt, E. (2017). The worst case scenario: Locomotor and collision demands of the longest periods of gameplay in professional rugby union. *PLOS ONE*, *12*(5), e0177072. https://doi.org/10.1371/journal.pone.0177072

Reche-Soto, P., Cardona-Nieto, D., Diaz-Suarez, A., Bastida-Castillo, A., Gomez-Carmona, C. D., Garcia-Rubio, J., & Pino-Ortega, J. (2019). Player Load and metabolic power dynamics as load quantifiers in soccer. *Journal of Human Kinetics*, *69*(1), 259–269. https://doi.org/10.2478/hukin-2018-0072

Reilly, T., Drust, B., & Clarke, N. (2008). Muscle fatigue during football match-play. *Sports Medicine*, *38*(5), 357–367. https://doi.org/10.2165/00007256-200838050-00001

Riboli, A., Esposito, F., & Coratella, G. (2021). The distribution of match activities relative to the maximal intensities in elite soccer players: implications for practice. *Research in Sports Medicine*, 1–12. https://doi.org/10.1080/15438627.2021.1895788

Riboli, A., Semeria, M., Coratella, G., & Esposito, F. (2021). Effect of formation, ball in play and ball possession on peak demands in elite soccer. *Biology of Sport*, *38*(2), 195–205. https://doi.org/10.5114/biolsport.2020.98450

Rico-González, M., Los Arcos, A., Rojas-Valverde, D., Clemente, F. M., & Pino-Ortega, J. (2020). A survey to assess the quality of the data obtained by radio-frequency technologies and microelectromechanical systems to measure external workload and collective behavior variables in team sports. *Sensors*, *20*(8), 1–16. https://doi.org/10.3390/s20082271

Rojas-Valverde, D., Gómez-Carmona, C. D., Gutiérrez-Vargas, R., & Pino-Ortega, J. (2019). From big data mining to technical sport reports: the case of inertial measurement units. *BMJ Open Sport & Exercise Medicine*, *5*(1), 1–3. https://doi.org/10.1136/bmjsem-2019-000565

Rojas-Valverde, D., Pino-Ortega, J., Gómez-Carmona, C. D., & Rico-González, M. (2020). A systematic review of methods and criteria standard proposal for the use of principal component analysis in team's sports science. *International Journal of Environmental Research and Public Health*, *17*(23), 8712. https://doi.org/10.3390/ijerph17238712

Rojas-Valverde, D., Sánchez-Ureña, B., Pino-Ortega, J., Gómez-Carmona, C. D., Gutiérrez-Vargas, R., Timón, R., & Olcina, G. (2019). External workload indicators of muscle and kidney mechanical injury in endurance trail running. *International Journal of Environmental Research and Public Health*, *16*(20), 1–13. https://doi.org/10.3390/ijerph16203909

Rosnow, R. L., Rosenthal, R., & Rubin, D. B. (2000). Contrasts and correlations in effect-size estimation. *Psychological Science*, *11*(6), 446–453. https://doi.org/10.1111/1467-9280.00287

Russell, M., Sparkes, W., Northeast, J., Cook, C. J., Bracken, R. M., & Kilduff, L. P. (2016). Relationships between match activities and peak power output and Creatine Kinase responses to professional reserve team soccer match-play. *Human Movement Science*, *45*, 96–101. https://doi.org/10.1016/j.humov.2015.11.011

Russell, Mark, Sparkes, W., Northeast, J., Cook, C. J., Love, T. D., Bracken, R. M., & Kilduff, L. P. (2016). Changes in acceleration and deceleration capacity throughout professional soccer match-play. *Journal of Strength and Conditioning Research*, *30*(10), 2839–2844. https://doi.org/10.1519/JSC.0000000000000805

Saunders, S. W., Schache, A., Rath, D., & Hodges, P. W. (2005). Changes in three dimensional lumbo-pelvic kinematics and trunk muscle activity with speed and mode of locomotion. *Clinical Biomechanics*, *20*(8), 784–793. https://doi.org/10.1016/j.clinbiomech.2005.04.004

Schuermans, J., Van Tiggelen, D., Palmans, T., Danneels, L., & Witvrouw, E. (2017). Deviating running kinematics and hamstring injury susceptibility in male soccer players: Cause or consequence? *Gait and Posture*, *57*, 270–277. https://doi.org/10.1016/j.gaitpost.2017.06.268

Simoni, L., Pancani, S., Vannetti, F., Macchi, C., & Pasquini, G. (2020). Relationship between lower limb kinematics and upper trunk acceleration in recreational runners. *Journal of*

Healthcare Engineering, *20*, 1–7. https://doi.org/10.1155/2020/8973010

Sonderegger, K., Tschopp, M., & Taube, W. (2016). The challenge of evaluating the intensity of short actions in soccer: a new methodological approach using percentage acceleration. *PLOS ONE*, *11*(11), 1–10. https://doi.org/10.1371/journal.pone.0166534

Souglis, A., Bogdanis, G. C., Chryssanthopoulos, C., Apostolidis, N., & Geladas, N. D. (2018). Time course of oxidative stress, inflammation, and muscle damage markers for 5 days after a soccer match: effects of sex and playing position. *Journal of Strength and Conditioning Research*, *32*(7), 2045–2054. https://doi.org/10.1519/JSC.0000000000002436

Souza, R. B. (2016). An evidence-based videotaped running biomechanics analysis. *Physical Medicine and Rehabilitation Clinics of North America*, *27*(1), 217–236. https://doi.org/10.1016/j.pmr.2015.08.006

Sporttechie. (2019). *FIFA Names Catapult's ClearSky Motion Tracking System the Best Wearable Tech in World Soccer*. https://www.sporttechie.com/catapult-clearsky-motion-tracking-system-fifa/

Stevens, T. G. A., de Ruiter, C. J., Twisk, J. W. R., Savelsbergh, G. J. P., & Beek, P. J. (2017). Quantification of in-season training load relative to match load in professional Dutch Eredivisie football players. *Science and Medicine in Football*, *1*(2), 117–125. https://doi.org/10.1080/24733938.2017.1282163

Suárez, L., Torreno, N., Requena, B., De Villarreal, E. S., Casamichana, D., Barbero-Álvarez, J. C., & Munguia-Izquierdo, D. (2014). Match-play activity profile in professional soccer players during official games and the relationship between external and internal load. *J. Sports Med. Phys. Fitness*, *55*, 1417–1422.

Sweeting, A. J., Cormack, S. J., Morgan, S., & Aughey, R. J. (2017). When is a sprint a sprint? A review of the analysis of team-sport athlete activity profile. *Frontiers in Physiology*, *20*(8), 1–12. https://doi.org/10.3389/fphys.2017.00432

Taberner, M., O'Keefe, J., Flower, D., Phillips, J., Close, G., Cohen, D. D., Richter, C., & Carling, C. (2020). Interchangeability of position tracking technologies; can we merge the data? *Science and Medicine in Football*, *4*(1), 76–81. https://doi.org/10.1080/24733938.2019.1634279

Teng, H. L., & Powers, C. M. (2014a). Influence of trunk posture on lower extremity energetics during running. *Medicine and Science in Sports and Exercise*, *47*(3), 625–630. https://doi.org/10.1249/MSS.0000000000000436

Teng, H. L., & Powers, C. M. (2014b). Sagittal plane trunk posture influences patellofemoral joint stress during running. *Journal of Orthopaedic and Sports Physical Therapy*, *44*(10), 785–792. https://doi.org/10.2519/jospt.2014.5249

Terrier, P., & Schutz, Y. (2005). How useful is satellite positioning system (GPS) to track gait parameters? A review. *Journal of Neuroengineering and Rehabilitation*, *28*(2), 1–11. https://doi.org/10.1186/1743-0003-2-28

Tierney, P. J., Young, A., Clarke, N. D., & Duncan, M. J. (2016). Match play demands of 11 versus 11 professional football using Global Positioning System tracking: variations across common playing formations. *Human Movement Science*, *49*, 1–8. https://doi.org/10.1016/j.humov.2016.05.007

Torreño, N., Munguía-Izquierdo, D., Coutts, A., de Villarreal, E. S., Asian-Clemente, J., & Suarez-Arrones, L. (2016). Relationship between external and internal loads of professional soccer players during full matches in official games using Global Positioning Systems and heart-rate technology. *International Journal of Sports Physiology and Performance*, *11*(7), 940–946. https://doi.org/10.1123/ijspp.2015-0252

Trewin, J., Meylan, C., Varley, M. C., & Cronin, J. (2018). The match-to-match variation of match-running in elite female soccer. *Journal of Science and Medicine in Sport*, *21*(2), 196–201. https://doi.org/10.1016/j.jsams.2017.05.009

Turner, A. N., & Stewart, P. F. (2014). Strength and conditioning for soccer players. *Strength and Conditioning Journal*, *36*(4), 1–13. https://doi.org/10.1519/SSC.0000000000000054

Vaeyens, R., Lenoir, M., Williams, A. M., Mazyn, L., & Philippaerts, R. M. (2007). The effects of task constraints on visual search behavior and decision-making skill in youth soccer players. *Journal of Sport and Exercise Psychology*, *29*(2), 147–169.

https://doi.org/10.1123/jsep.29.2.147

van der Kruk, E., & Reijne, M. M. (2018). Accuracy of human motion capture systems for sport applications; state-of-the-art review. *European Journal of Sport Science*, *18*(6), 806–819. https://doi.org/10.1080/17461391.2018.1463397

Vanrenterghem, J., Nedergaard, N. J., Robinson, M. A., & Drust, B. (2017). Training load monitoring in team sports: a novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Medicine*, *47*(11), 2135–2142. https://doi.org/10.1007/s40279-017-0714-2

Vänttinen, T., Blomqvist, M., & Häkkinen, K. (2010). Development of body composition, hormone profile, physical fitness, general perceptual motor skills, soccer skills and on-the-ball performance in soccer-specific laboratory test among adolescent soccer players. *Journal of Sports Science & Medicine*, *9*(4), 547–556. https://doi.org/24149780

Varley, M., & Aughey, R. (2012). Acceleration profiles in elite Australian soccer. *International Journal of Sports Medicine*, *34*(1), 34–39. https://doi.org/10.1055/s-0032-1316315

Varley, M. C., Elias, G. P., & Aughey, R. J. (2012). Current match-analysis techniques ' underestimation of intense periods of high-velocity Running. *International Journal of Sports Physiology and Performance*, *7*, 183–185.

Vigh-Larsen, J. F., Dalgas, U., & Andersen, T. B. (2018). Position-specific acceleration and deceleration profiles in elite youth and senior soccer players. *Journal of Strength and Conditioning Research*, *32*(4), 1114–1122. https://doi.org/10.1519/JSC.0000000000001918

Ward, P., & Williams, A. M. (2003). Perceptual and cognitive skill development in soccer: the multidimensional nature of expert performance. *Journal of Sport and Exercise Psychology*, *25*(1), 93–111. https://doi.org/10.1123/jsep.25.1.93

Warman, G. E., Chalkley, D., Cole, M. H., & Pepping, G.-J. (2018). Utilising GPS data to quantify torso range of motion in field hockey athletes. *Proceedings*, *2*(6), 1–6. https://doi.org/10.3390/proceedings2060294

Warman, G. E., Cole, M. H., Johnston, R. D., Chalkley, D., & Pepping, G.-J. (2019). Using microtechnology to quantify torso angle during match-play in field hockey. *Journal of Strength and Conditioning Research*, *33*(10), 2648–2654. https://doi.org/10.1519/JSC.0000000000003238

Weaving, D., Dalton, N. E., Black, C., Darrall-Jones, J., Phibbs, P. J., Gray, M., Jones, B., & Roe, G. A. B. (2018). The same story or a unique novel? Within-participant principal-component analysis of measures of training load in professional Rugby Union skills training. *International Journal of Sports Physiology and Performance*, *13*(9), 1175–1181. https://doi.org/10.1123/ijspp.2017-0565

Weaving, D., Whitehead, S., Till, K., & Jones, B. (2017). Validity of real-time data generated by a wearable microtechnology device. *Journal of Strength and Conditioning Research*, *31*(10), 2876–2879. https://doi.org/10.1519/JSC.0000000000002127

Weir, J. P. (2005). Quantifying Test-Retest Reliability Using the Intraclass Correlation Coefficient and the SEM. *The Journal of Strength and Conditioning Research*, *19*(1), 231–240. https://doi.org/10.1519/15184.1

West, S. W., Clubb, J., Torres-Ronda, L., Howells, D., Leng, E., Vescovi, J. D., Carmody, S., Posthumus, M., Dalen-Lorentsen, T., & Windt, J. (2021). More than a metric: how training load is used in elite sport for athlete management. *International Journal of Sports Medicine*, *42*(4), 300–306. https://doi.org/10.1055/a-1268-8791

Weston, M., Siegler, J., Bahnert, A., McBrien, J., & Lovell, R. (2015). The application of differential ratings of perceived exertion to Australian Football League matches. *Journal of Science and Medicine in Sport*, *18*(6), 704–708. https://doi.org/10.1016/j.jsams.2014.09.001

White, A., Hills, S. P., Cooke, C. B., Batten, T., Kilduff, L. P., Cook, C. J., Roberts, C., & Russell, M. (2018). Match-play and performancetest responses of soccer goalkeepers: a review of current literature. *Sports Medicine*, *48*(11), 2497–2516. https://doi.org/10.1007/s40279-018-0977-2

Williams, M., & Morgan, S. (2009). Horizontal positioning error derived from stationary GPS units: A function of time and proximity to building infrastructure. *International Journal* *of Performance Analysis in Sport*, *9*(2), 275–280. https://doi.org/10.1080/24748668.2009.11868483

Windolf, M., Götzen, N., & Morlock, M. (2008). Systematic accuracy and precision analysis of video motion capturing systems-exemplified on the Vicon-460 system. *Journal of Biomechanics*, *41*(12), 2776–2780. https://doi.org/10.1016/j.jbiomech.2008.06.024

Witte, T. H., & Wilson, A. M. (2004). Accuracy of non-differential GPS for the determination of speed over ground. *Journal of Biomechanics*, *37*(12), 1891–1898. https://doi.org/10.1016/j.jbiomech.2004.02.031

Yi, Q., Gómez, M. A., Wang, L., Huang, G., Zhang, H., & Liu, H. (2019). Technical and physical match performance of teams in the 2018 FIFA World Cup: effects of two different playing styles. *Journal of Sports Sciences*, *37*(22), 2569–2577. https://doi.org/10.1080/02640414.2019.1648120

Young, W., Benton, D., & Pryor, J. (2001). Resistance training for short sprints and maximum-speed sprints. *Strength and Conditioning Journal*, *23*(2), 1–7. https://doi.org/10.1519/00126548-200104000-00001

Zhou, C., Hopkins, W. G., Mao, W., Calvo, A. L., & Liu, H. (2019). Match performance of soccer teams in the Chinese Super League—Effects of situational and environmental factors. *International Journal of Environmental Research and Public Health*, *16*(21), 1–13. https://doi.org/10.3390/ijerph16214238

ANNEX 1. LINK TO PUBLISHED ARTICLES

Article	Website	QR Code
Oliva-Lozano, J. M., Barbier, X., Fortes, V., & Muyor, J. M. (2021). Key load indicators and load variability in professional soccer players: a full season study. *Research in Sports Medicine*, 1–13.	https://www.tandfonline.com/doi/abs/10.1080/15438627.2021.1954517?journalCode=gspm20	
Oliva-Lozano, J. M., Muyor, J. M., Fortes, V., & McLaren, S. J. (2021). Decomposing the variability of match physical performance in professional soccer: Implications for monitoring individuals. *European Journal of Sport Science*, *21*(11), 1588–1596.	https://www.tandfonline.com/doi/abs/10.1080/17461391.2020.1842513?journalCode=tejs20	
Oliva-Lozano, J. M., Rago, V., Fortes, V., & Muyor, J. M. (2021). Impact of match-related contextual variables on weekly training load in a professional soccer team: a full season study. *Biology of Sport*, *39*(1), 125–134	https://www.termedia.pl/Impact-of-match-related-contextual-variables-on-weekly-training-load-in-a-professional-soccer-team-a-full-season-study,78,43100,0,1.html	
Oliva-Lozano, J. M., Fortes, V., Krustrup, P., & Muyor, J. M. (2020). Acceleration and sprint profiles of professional male football players in relation to playing position. *PLOS ONE*, *15*(8), 1–12	https://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0236959&type=printable	
Oliva-Lozano, J. M., Fortes, V., & Muyor, J. M. (2020). The first, second, and third most demanding passages of play in professional soccer: a longitudinal study. *Biology of Sport*, *38*(2), 165–174.	https://www.termedia.pl/The-first-second-and-third-most-demanding-passages-of-play-in-professional-soccer-a-longitudinal-study,78,41433,0,1.html	
Oliva-Lozano, J. M., Martínez-Puertas, H., Fortes, V., & Muyor, J. M. (2021). When do soccer players experience the most demanding passages of match play? A longitudinal study in a professional team. *Research in Sports Medicine*, 1-11.	https://www.tandfonline.com/doi/abs/10.1080/15438627.2021.1943390?journalCode=gspm20#:~:text=The%20first%20period%20reported%20the,%25%3B%20DECHIGH%3A%2034.6%25	
Oliva-Lozano, J. M., Fortes, V., & Muyor, J. M. (2021). When and how do elite soccer players sprint in match play? A longitudinal study in a professional soccer league. *Research in Sports Medicine*, 1–12.	https://www.tandfonline.com/doi/abs/10.1080/15438627.2021.1929224	

Oliva-Lozano, J. M., Conte, D., Fortes, V., & Muyor, J. M. (2022). Exploring the use of player load in elite soccer players. *Sports Health*, 1-6.	https://journals.sagepub.com/doi/10.1177/19417381211065768?url_ver=Z39.88-2003&rfr_id=ori:rid:crossref.org&rfr_dat=cr_pub%20%200pubmed	
Oliva-Lozano, J. M., Maraver, E. F., Fortes, V., & Muyor, J. M. (2020). Kinematic analysis of the postural demands in professional soccer match play using inertial measurement units. *Sensors*, *20*(21), 1-11.	https://www.mdpi.com/1424-8220/20/21/5971	
Oliva-Lozano, J. M., Maraver, E. F., Fortes, V., & Muyor, J. M. (2020). Effect of playing position, match half, and match day on the trunk inclination, g-forces, and locomotor efficiency experienced by elite soccer players in match play. *Sensors*, 20, 1–12.	https://www.mdpi.com/1424-8220/20/20/5814	
Oliva-Lozano, J. M., Martín-Fuentes, I., Fortes, V., & Muyor, J. M. (2021). Differences in worst-case scenarios calculated by fixed length and rolling average methods in professional soccer match-play. *Biology of Sport*, *38*(3), 325–331.	https://www.termedia.pl/Differences-in-worst-case-scenarios-calculated-by-fixed-length-and-rolling-average-methods-in-professional-soccer-match-play,78,42004,0,1.html	
Oliva-Lozano, J. M., & Muyor, J. M. (2021). Understanding the FIFA quality performance reports for electronic performance and tracking systems: from science to practice. *Science and Medicine in Football*, 1-6.	https://www.tandfonline.com/doi/abs/10.1080/24733938.2021.1984557	
Oliva-Lozano, J. M., Martín-Fuentes, I., Granero-Gil, P., & Muyor, J. M. (2021). Monitoring elite soccer players physical performance using real-time data generated by electronic performance and tracking systems. *Journal of Strength and Conditioning Research*, 1-5.	https://journals.lww.com/nsca-jscr/Abstract/9000/Monitoring_Elite_Soccer_Players_Physical.93953.aspx	