


Football movement profile analysis and creatine kinase relationships in youth national team players

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ABSTRACT

Objective: Creatine kinase (CK) is widely used as a monitoring tool to make inferences on fatigue and readiness in elite soccer. Previous studies have examined the relationship between CK and GPS parameters, however these metrics may not accurately describe the players' load during soccer-specific movements. Football Movement Profile (FMP) monitoring is a viable option for such purposes, providing solely inertial sensor-based data and categorizing movements according to intensity (very low, low, medium, high) and movement type (running-linear locomotive, dynamic – change of direction or speed). *Methods:* We investigated the relationship between the FMP distribution of youth (U16–U21) national team soccer players and the absolute day-to-day change in CK. We applied Spearman's correlations, principal component analysis and K-means clustering to classify players' CK

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responses according to their specific FMP. *Results:* Moderate to large negative associations were found between very low intensity FMP parameters and CK change ($r = -0.43 \pm 0.12$) while large positive associations were identified between CK change and other FMP metrics ($r = 0.62 \pm 0.12$). Best fitting clustering methods were used to group players depending on their CK sensitivity to FMP values. Principal component analysis explained 83.0% of the variation with a Silhouette score of 0.61 for the 4 clusters. *Conclusions:* Our results suggest that soccer players can be clustered based on the relationship between FMP measures and the CK change. These findings can help to plan soccer training or recovery sessions according to the desired load on skeletal muscle, as FMP monitoring might bridge the limitations of GPS telemetry.

KEYWORDS

soccer, elite, GPS, load, monitoring, FMP

INTRODUCTION

The physical demands of soccer have increased considerably in recent years, with players required to perform more high-intensity efforts and sprints, and explosive actions during Premier League matches [1]. Global Positioning System (GPS) technology is widely used for recording and analysing match and training load of players [2].

Despite the general popularity of GPS, it also has its limitations. Closed stadiums, indoor training sessions, sampling frequency, and other external factors can affect the usability and accuracy of traditional GPS parameters, such as high-intensity actions, sprint running distance and total distance covered [3, 4]. Since most modern monitoring units are also equipped with microsensors (accelerometer, gyroscope, magnetometer), they are able to provide Inertial Measurement Unit (IMU) data and certain external load parameters without the use of GPS function. Overcoming the limitations of GPS systems to precisely monitor soccer-specific movements, athlete monitoring company Catapult Sports has developed the Football Movement Profile (FMP) algorithm, which relies solely on IMU data. FMP assigns all soccer movements into categories based on their intensity (very low, low, medium, high) and movement type (running – linear locomotive; dynamic – change of direction or speed) [5].

Creatine Kinase (CK) is commonly used as a blood marker to monitor the muscle damage and impact of soccer matches and training load on players [6]. Serum CK level is elevated after extensive mechanical load, indicating damage in the skeletal muscle [7]. Previous studies have demonstrated that CK is highest 24–48 h after matches and returns to baseline after 72 h or even later in special circumstances, such as congested schedules [8, 9]. The CK response to external load also shows large inter-individual variation [10]. Several authors have investigated the relationship between external load (recorded via GPS) and subsequent CK response in soccer [11–17]. Total number of accelerations and decelerations, as well as sprint distance is positively associated with elevated CK activity after soccer matches [11, 18]. In the most recent studies, relationships between high-intensity ($>5.5 \text{ m s}^{-1}$) running distance and CK activity have also been found [12, 13]. However, many studies investigated the GPS volume parameters [12–14, 17, 18], with few investigating intensity parameters [11, 15]. In the



aforementioned studies, significant correlations between high intensity GPS parameters (distance/min, high intensity distance/min, number of sprints/min) and CK response were reported, but only in the 24 h post-match [11, 15]. In our recent work with youth players, we also found differences among playing positions and activity type (training, compensation, match) for the external load parameters influencing CK change [16]. As technological developments provide opportunities to more accurately monitor and quantify soccer-specific movements, understanding the relationship between soccer-specific load and the internal load response (measured as CK increase in blood) represents an important pursuit for practitioners working with football players.

Therefore, the first aim of this study was to examine the relationship between Football Movement Profile parameters and CK change in the subsequent day in youth national team soccer players. Secondly, we aimed to find a best fit clustering method in order to group players based on their CK sensitivity to specific FMP parameters recorded during matches and training sessions. Based on the published studies and our previous results we hypothesized that day-to-day CK change will be influenced mainly by medium and high intensity FMP parameters. Furthermore, we hypothesized that players' CK change would demonstrate individual dependent responsivity. Our results may assist practitioners to better plan and evaluate their training load according to the expected individual CK response.

MATERIALS AND METHODS

Experimental approach to the problem

National team settings represent a special congested schedule for players, having to compete in intense international matches, occasionally every 2–3 days. In such a demanding environment load (internal and external), fatigue and 'readiness' monitoring is paramount. For this reason, training and match monitoring and CK measurements are an important part of the daily routine in national team training camps.

In this longitudinal retrospective study, we monitored the match and training physical data of youth national team players. External load and blood marker analysis was part of the standardized daily national team routine. Although CK response to many external load parameters has been measured, in our study we investigated the relationship between day-to-day CK change and the different FMP parameters.

Subjects

Training and match data of 31 elite youth (U-16–U-21) national team soccer players (age 18.3 ± 1.1 years; weight 72.6 ± 5.4 kg; height 181.1 ± 6.7 cm) were collected between July 2019 and March 2021. The large variance of participating players' age was due to the intention of creating a larger data set with more individual datapoints. Players' data were only included in the analysis if they had at least 20 data pairs (FMP and CK). The football specific position distribution was as follows: 3 goalkeepers, 4 central defenders, 7 full backs, 9 central midfielders, 4 wide midfielders, 4 strikers. All participants were elite soccer players having at least five years of football experience and performed 5–7 training sessions and 1–3 matches per week during the sampling periods. The study was approved by the ethical



review board of the University of Physical Education (Budapest) and conformed to the Code of Ethics of the World Medical Association (Declaration of Helsinki) (TE-KEB/No9S/2020). Players and their parents/guardians provided written consent for the use of physical and medical data.

Procedures

Football movement profile (FMP) monitoring. The physical activity of players was recorded during training sessions and international matches (friendly and competitive) with 10 Hz GPS units (Catapult Sports, Melbourne, Australia; S7–field players; G7–goalkeepers), worn in a custom-made vest between the shoulder blades. Each player wore the same unit during the study period, to avoid inter-unit differences. Devices were equipped with 100 Hz micro-sensors (accelerometer, gyroscope, magnetometer) providing non-GPS derived data for the Inertial Movement Analysis (IMA). IMA analysis includes data from accelerations, decelerations, jumps and changes of directions; good reliability and validity has been shown for this analysis [19]. The Football Movement Profile (FMP) was recently developed by Catapult Sports, for the purpose of quantifying the intensity of soccer-specific activities [5]. The FMP algorithm is based on the IMA measurements excluding GPS data and assigns all soccer movements into one of six movement categories, defined by a combination of intensity (very low, low, medium, high) and movement type (running-linear locomotive, dynamic–change of direction or speed):

- *Very Low Duration %* (Standing like movements)
- *Low Duration %* (Walking like movements)
- *Running Medium Duration %* (Steady state linear and curved jogging and running movements at medium intensity)
- *Running High Duration %* (Steady state linear and curved running movements at high intensity)
- *Dynamic Medium Duration %* (Medium-intensity multi-directional movements, linear acceleration and deceleration movements)
- *Dynamic High Duration %* (High-intensity multidirectional movements, linear acceleration and deceleration movements)

The relative FMP distribution of the entire session can also be described by taking the absolute variables and expressing them relative to the duration in each activity zone. The intensity thresholds of the FMP algorithm are based on Player LoadTM values, a parameter derived from accelerometer data, which has previously been shown to be a valid and reliable metric [20]. Differentiation between running and dynamic movements is based on variance in data in the medio-lateral and posterior-anterior planes. We used the following parameters: 1. Duration % of activity in each FMP zone; 2. Duration (minutes) of activity in each FMP zone; 3. Aggregated parameters (Running medium + high duration %; Dynamic medium + high duration %; Running + Dynamic duration %; Running + dynamic high duration %).

Creatine kinase (CK). Capillary blood samples were taken from fingertips after overnight fasting, every morning as part of the normal protocol at a standardized time in order to measure



CK levels (CK-MM isoenzyme). Blood samples were collected and analysed using a Reflotron Plus Clinical Chemistry Analyzer (Roche, Mannheim, Germany) according to the manufacturer's instructions. The validity of this method has been determined in previous studies, with very large correlations reported between capillary and venous samples ($P < 0.01$, $r = 0.99$ and $r \geq 0.99$ respectively) [14]. CK response was defined as a day-to-day change in absolute values ($\Delta\text{CK}_{\text{ABS}} = \text{abs} [\text{CK}_{\text{day1}} - \text{CK}_{\text{day2}}]$) and as a percentage ($\Delta\text{CK}\% = \text{CK}_{\text{day1}}/\text{CK}_{\text{day2}}$). Our preliminary analysis found superior correlation coefficients for $\Delta\text{CK}_{\text{ABS}}$, and we subsequently excluded the $\Delta\text{CK}\%$ values from our statistical procedures.

Statistical analysis

The main goal of the statistical procedures was to separate the players into groups based on the relationship between their daily FMP parameters and CK levels. Spearman's correlation test was used to describe the relationship, after which Principal Component Analysis (PCA) and K-Means clustering were applied to find the most suitable cluster format to group the players.

The filtered dataset was tested for normality and as our data was not normally distributed, multiple Spearman's correlation tests were performed. For each player's $\Delta\text{CK}_{\text{ABS}}$, values were paired with every FMP parameter's value and a correlation test was performed. The p -values from these tests were adjusted using the Benjamini-Hochberg procedure [21]. In the further steps only the significant correlation coefficients ($P \leq 0.05$) were kept, and the non-significant ones were excluded from the clustering process. Therefore, the zero cluster includes players with no significant correlation between $\Delta\text{CK}_{\text{ABS}}$ and FMP parameters. Players with one or more significant correlations of the examined parameters were clustered based on their correlation coefficient. We interpreted the coefficient values as trivial (0.0–0.1), small (0.1–0.3), moderate (0.3–0.5), large (0.5–0.7), very large (0.7–0.9), and nearly perfect (0.9–1.0) [22].

PCA was applied to the data for the purpose of creating two principal components from the primary correlation results [23]. Thereafter, the first and second principal components were used for clustering with the K-Means algorithm [24]. Multiple sets of clusters were created with the algorithm and in each set the players were divided into different numbers of clusters. The Cluster set with the highest silhouette score was selected in order to group players most accurately [25].

RESULTS

Correlation of $\Delta\text{CK}_{\text{ABS}}$ and FMP parameters

The total dataset consisted of 757 (24.4 ± 3.8 per player) individual observations (CK and FMP). The average of individual correlation coefficients for the FMP Very Low percentage and duration was negative and moderate to large (-0.43 ± 0.12 ; range: -0.36 to -0.56), but all other examined parameters showed a large positive correlation (0.62 ± 0.12 ; range: 0.53 – 0.69). $\Delta\text{CK}_{\text{ABS}}$ showed higher correlation values with the FMP Duration, than FMP % parameters. The correlation values and the number of significant correlations of all participants ($n = 31$) are illustrated in Table 1.



Table 1. Average correlation distribution of CK change and FMP parameters. In the second column the number (N) of significant correlations ($P \leq 0.05$) are displayed. A clear difference is visible between the Very low intensity and all other FMP parameters regarding the orientation of the relationship. While Very low intensity FMP shows a moderate to large negative correlation with CK change, suggesting a possible regenerative effect, the other FMP metrics display a large positive correlation. Interestingly Duration values have a stronger relationship with CK change, indicating the importance of the actual length of the soccer-specific activity

FMP parameter	N =	r values (mean ± SD)
FMP Very Low Duration %	16	-0.564 ± 0.116
FMP Low Duration %	17	0.556 ± 0.104
FMP Running Medium Duration %	9	0.562 ± 0.076
FMP Running High Duration %	15	0.558 ± 0.131
FMP Dynamic Medium Duration %	15	0.534 ± 0.106
FMP Dynamic High Duration %	20	0.601 ± 0.107
FMP Very Low Duration	1	-0.357
FMP Low Duration	20	0.689 ± 0.108
FMP Running Medium Duration	21	0.613 ± 0.102
FMP Running High Duration	22	0.619 ± 0.121
FMP Dynamic Medium Duration	26	0.638 ± 0.134
FMP Dynamic High Duration	26	0.652 ± 0.140
FMP Running Medium + High	21	0.627 ± 0.106
FMP Dynamic Medium + High	26	0.650 ± 0.141
FMP Running + Dynamic Medium	23	0.656 ± 0.121
FMP Running + Dynamic High	26	0.647 ± 0.134

N: number of significant correlations

Formation of clusters based on the relationship between ΔCK_{ABS} and FMP

On an individual level the correlation coefficients were trivial to very large (Table 2).

After the correlation results were obtained, a PCA was performed first, and player clusters were created. The correlation coefficients of the selected FMP parameters and CK values were utilized for the PCA. The first principal component (PC1) obtained explained 63.8% of the variance in the data, and the second principal component (PC2) explained 19.2%, the two together accounted for a total of 83.0%.

The clustering was performed for several cluster numbers, and the silhouette score was used to determine the proper cluster number. Based on the results, three clusters were created to find the most accurate fit with the lowest possible number of clusters (the Silhouette score for 4 clusters was 0.61).

Figure 1 represents the cluster distribution of the results of the highest Silhouette scores as a result of the principal component analysis. Each player in our dataset was categorized into one of the clusters based on their individual CK responses of the previous day's FMP load distribution.

The average values of the individual correlation coefficients in each cluster are presented in Table 3.



Table 2. Correlation and standard error values for each participant which forms the basis of the clustering process (* $P \leq 0.05$; ** $P \leq 0.01$). Large inter-individual differences reinforce the need for clustering and an individual approach towards CK response to external match and training load

Name	FMP Running		FMP			Clusters	
	FMP Low Duration	Medium Duration	FMP Running High Duration	Dynamic Medium Duration	FMP Dynamic High Duration		
Player1	0.60 ± 0.01**	0.57 ± 0.00**	0.51 ± 0.00*	0.54 ± 0.00**	0.58 ± 0.00**	All responders	
Player2	0.9 ± 0.01**	0.64 ± 0.01**	0.62 ± 0.00*	0.87 ± 0.01**	0.90 ± 0.00**		
Player3	0.70 ± 0.01**	0.71 ± 0.00**	0.56 ± 0.00*	0.75 ± 0.00**	0.75 ± 0.00**		
Player4	0.63 ± 0.00**	0.48 ± 0.00*	0.61 ± 0.00**	0.71 ± 0.00**	0.70 ± 0.00**		
Player5	0.55 ± 0.01**	0.52 ± 0.00**	0.52 ± 0.00**	0.68 ± 0.00**	0.73 ± 0.00**		
Player6	0.78 ± 0.00**	0.80 ± 0.00**	0.68 ± 0.00**	0.79 ± 0.00**	0.8 ± 0.00**		
Player7	0.79 ± 0.01**	0.61 ± 0.00**	0.82 ± 0.00**	0.79 ± 0.00**	0.82 ± 0.00**		
Player8	0.65 ± 0.02**	0.63 ± 0.01*	0.57 ± 0.00*	0.69 ± 0.01**	0.69 ± 0.01**		
Player9	0.69 ± 0.01**	0.63 ± 0.01**	0.77 ± 0.00**	0.78 ± 0.01**	0.79 ± 0.00**		
Player10	0.72 ± 0.01**	0.57 ± 0.01**	0.71 ± 0.00**	0.67 ± 0.01**	0.70 ± 0.00**		
Player11	0.84 ± 0.01**	0.74 ± 0.00**	0.59 ± 0.00**	0.77 ± 0.00**	0.78 ± 0.00**		
Player12	0.83 ± 0.01**	0.72 ± 0.00**	0.87 ± 0.00**	0.81 ± 0.00**	0.86 ± 0.00**		
Player13	0.78 ± 0.01**	0.67 ± 0.00**	0.79 ± 0.00**	0.76 ± 0.00**	0.75 ± 0.00**		
Player14	0.66 ± 0.00**	0.60 ± 0.00**	0.73 ± 0.00**	0.63 ± 0.00**	0.71 ± 0.00**		
Player15	0.66 ± 0.01**	0.52 ± 0.00*	0.60 ± 0.00*	0.62 ± 0.01*	0.57 ± 0.00*		
Player16	0.67 ± 0.01**	0.76 ± 0.00**	0.68 ± 0.00**	0.73 ± 0.00**	0.67 ± 0.00**		
Player17	0.37 ± 0.01	0.59 ± 0.01**	0.29 ± 0.00	0.55 ± 0.01*	0.48 ± 0.01*		Running and Dynamic high responders
Player18	0.31 ± 0.01	0.34 ± 0.01	0.50 ± 0.00*	0.46 ± 0.01	0.55 ± 0.00*		
Player19	0.28 ± 0.01	0.69 ± 0.00**	0.56 ± 0.00*	0.39 ± 0.01	0.42 ± 0.00		
Player20	0.40 ± 0.01	0.45 ± 0.00	0.52 ± 0.00*	0.35 ± 0.01	0.54 ± 0.00*		
Player21	0.62 ± 0.01*	0.44 ± 0.01	0.52 ± 0.00*	0.58 ± 0.01*	0.57 ± 0.00*		Low Intensity, Dynamic medium and high responders
Player22	0.70 ± 0.01**	0.38 ± 0.00	0.42 ± 0.00	0.58 ± 0.00**	0.63 ± 0.00**		
Player23	0.56 ± 0.01*	0.53 ± 0.00*	0.46 ± 0.00	0.48 ± 0.00*	0.58 ± 0.00*		
Player24	0.45 ± 0.01*	0.31 ± 0.01	0.33 ± 0.00	0.54 ± 0.00**	0.58 ± 0.00**		
Player25	0.38 ± 0.01	0.39 ± 0.01	0.23 ± 0.00	0.45 ± 0.01	0.40 ± 0.00	Non-responders	
Player26	0.10 ± 0.02	-0.32 ± 0.00	0.05 ± 0.00	0.12 ± 0.00	-0.06 ± 0.00		
Player27	0.25 ± 0.01	-0.16 ± 0.01	0.34 ± 0.00	0.44 ± 0.01	0.42 ± 0.00		
Player28	0.07 ± 0.01	-0.04 ± 0.00	0.34 ± 0.00	0.14 ± 0.00	0.19 ± 0.00		
Player29	0.39 ± 0.02	0.23 ± 0.01	0.16 ± 0.00	0.48 ± 0.01	0.39 ± 0.01		
Player30	0.07 ± 0.03	-0.24 ± 0.00	-0.16 ± 0.00	0.19 ± 0.01	0.39 ± 0.00		
Player31	0.38 ± 0.02	0.10 ± 0.01	0.24 ± 0.00	0.43 ± 0.01	0.38 ± 0.01		

DISCUSSION

This study examined the relationship between inertial sensor derived Football Movement Profile data and the day-to-day Creatine Kinase change in elite youth national team soccer players. We



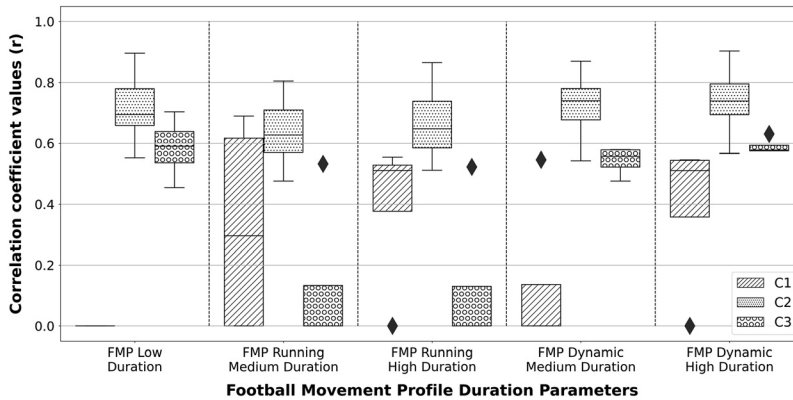


Fig. 1. Distribution of the correlation in the created 4 clusters. While the clustering process resulted in a 4-cluster structure, there are apparent differences within clusters. Even if players may not be perfectly clustered into demarcated groups, trends of individual responsiveness can be identified. The four resultant clusters are characterised as the following: C1, All responders; C2, Running and dynamic high responders; C3, Low intensity, Dynamic medium and high responders. The cluster of Non responders is not presented in the figure as they show no significant correlation values.

Table 3. Average correlation values of CK change and FMP Duration parameters in each created cluster. The participating players ($n = 31$) were clustered into 4 groups based on their CK responsiveness to intensity categories (Low intensity, Medium intensity running, High intensity running, Medium intensity dynamic, High intensity dynamic FMP) created taking into account individual correlation values

Cluster	N =	FMP Running		FMP Dynamic		
		FMP Low Duration	Medium Duration	FMP Running High Duration	Medium Duration	FMP Dynamic High Duration
1	16	0.71 ± 0.09	0.64 ± 0.09	0.66 ± 0.11	0.73 ± 0.08	0.74 ± 0.09
2	4	0.0 ± 0.0	0.32 ± 0.37	0.39 ± 0.26	0.14 ± 0.27	0.39 ± 0.26
3	4	0.58 ± 0.10	0.13 ± 0.27	0.13 ± 0.26	0.54 ± 0.05	0.59 ± 0.03
4	7	0.23 ± 0.15	-0.06 ± 0.26	0.17 ± 0.18	0.32 ± 0.16	0.30 ± 0.18

N: Number of players.

also investigated the feasibility of clustering players based on the individual CK sensitivity to FMP parameter distribution. For this purpose, we used the FMP and CK data of youth national team soccer players, who play regularly at international level. We created 4 clusters representing the FMP-CK response. Our results demonstrate the importance of monitoring the external load and daily CK changes on an individual basis and highlight the utility of new technology for measuring football-specific movements.

In elite sports, creatine kinase is commonly used as an indirect marker of muscle damage and fatigue [6]. Previous studies have described the relationship between soccer load and CK change after training and matches [6, 12, 15, 17]. CK recovery has shown a prolonged time course after demanding soccer matches, while limiting the performance of players [8]. It has recently been found that elevated CK levels corresponded with a reduction in total high-speed distance, very



high-speed distance, accelerations, decelerations, explosive distance, and maximal velocity during training sessions [26]. Players participating in more than 60 min of a soccer game have demonstrated larger increase in CK, hence most studies use this as a cut off threshold when examining the impact of match play on biomarkers, because this might extend the time of recovery, especially in congested schedules [27]. In most CK related studies the data from senior players has been presented, with only a few studies examining the CK characteristics of youth athletes [12, 16, 28]. Therefore, our results provide support for practitioners working with this age group. These findings should be used with caution for adult players, as CK kinetics show age dependency [29].

The relationship between GPS-measured external load parameters and CK has been extensively investigated in the literature [9, 11–16]. Most studies investigated associations between CK change and the locomotor (total distance, high intensity distance, sprint distance) and mechanical (high intensity accelerations and decelerations, changes of directions) load of soccer player [6, 11, 13, 15, 18, 26, 27]. Volume metrics have been the main focus of studies investigating the load-CK relationship [12–14, 17], however intensity parameters have received comparatively less attention [11, 15]. Intensity of soccer-specific movements play a crucial role in players' overall load and can be monitored live, creating opportunity for intervention during training sessions. Therefore, volume and intensity parameters, which are mainly calculated by normalizing volume for one minute, are equally important when defining soccer load. Even though the FMP displays load as a volume measure, it is able to detect and classify soccer-specific movements into intensity categories based on inertial unit data.

In our research we have found moderate to large negative associations between the day-to-day $\Delta\text{CK}_{\text{ABS}}$ and the duration spent in Very Low Intensity ($r = -0.36; P < 0.05$) and Very Low Intensity % FMP parameter ($r = -0.56; P < 0.05$). From this result we can conclude that the distribution of the very low intensity component of movement during training sessions might have a close relationship with recovery, which is represented in the decrease of the next day's CK levels. In national team settings matches are played every 2–3 days, therefore the day after a game is normally a recovery session of very light intensity for the players. In this respect, training sessions are designed to exclude high-intensity movements, promoting the regeneration of players. Although a significant correlation does not demonstrate causation, it is possible that the greater proportion of low-intensity movements (and lower proportion of high-intensity movements) might explain, at least in part, the lower $\Delta\text{CK}_{\text{ABS}}$. Given the correlation values, it seems likely that the reduction of CK is related more to the large percentage of very low intensity activity, than the duration of the session. Therefore, for recovery benefits, reducing the intensity of recovery training may be more important than altering the duration of the session.

While we investigated the relationship between the basic FMP % distribution and other aggregated parameters, they did not provide added value; $\Delta\text{CK}_{\text{ABS}}$ correlated best with the FMP Duration metrics in our dataset. Large correlations were found between $\Delta\text{CK}_{\text{ABS}}$ and the Low ($r = 0.69 \pm 0.11; n = 20$), Medium ($r = 0.61 \pm 0.10; n = 21$) and High Intensity Running ($r = 0.62 \pm 0.12; n = 22$), and Medium ($r = 0.64 \pm 0.13; n = 26$) and High Intensity Dynamic FMP parameters ($r = 0.65 \pm 0.14; n = 26$). This finding partially confirms our hypothesis and supports the trend of previous studies, that high intensity locomotor and mechanical GPS parameters are closely associated with the CK response [11–14]. Our use of inertial sensor-based metrics is of particularly importance as GPS telemetry is largely dependent on satellite



availability, which is influenced by closed stadiums and sessions performed in indoor facilities [30]. Practitioners are increasingly relying on inertial measurement sensor data as it shows smaller measurement error than GPS [4]. FMP represents a practical tool for monitoring the load of soccer-specific movements. FMP parameters also offer an easier method of interpreting soccer-specific load, as it does not use multiple different variables, as is the case with GPS parameters.

Most studies have examined the CK response to external training and match load [11, 13, 14], however the load-CK response appears to be individual-specific. In our previous study with youth soccer players, we found a significant soccer-specific position and training type dependency on the subsequent CK change [16]. Although in our dataset $\Delta\text{CK}_{\text{ABS}}$ showed large correlations with both medium and high intensity dynamic FMP parameters, certain players displayed nearly perfect relationships ($r = 0.90$). These results also show large inter-individual differences, further suggesting an individual responsiveness of CK to soccer-specific activity (Table 3).

The large inter-individual variance in the correlation analysis of FMP variables and $\Delta\text{CK}_{\text{ABS}}$ supports the clustering of players based on their individual responsiveness. The players in our dataset were grouped into 4 distinct clusters, depending on their individual correlations of FMP parameters and $\Delta\text{CK}_{\text{ABS}}$. While the clustering process is not perfect, we aimed to create the lowest possible number of groups into which players could be classified. A 0.61 Silhouette score shows a reasonable structure for this method, supporting the feasibility and importance of such grouping of players. The created clusters are as follows:

1. All responders ($n = 16$): Players' $\Delta\text{CK}_{\text{ABS}}$ have a large correlation ($r = 0.64\text{--}0.74$) with all presented FMP parameters and these values cannot be definitely distinguished. These players seem to be responsive to almost equally any type of load characterized by FMP parameters.
2. Running and dynamic high responders ($n = 4$): these players show the highest, although statistically moderate correlation values with Running parameters and the Dynamic-high parameters ($r = 0.32\text{--}0.39$).
3. Low intensity, dynamic-medium and high responders ($n = 4$): The players in this cluster showed large correlations among $\Delta\text{CK}_{\text{ABS}}$ and Low intensity ($r = 0.58$), Dynamic medium ($r = 0.54$) and high ($r = 0.59$) parameters. The CK response appears to occur as a result of a more dynamic load in these players.
4. Non-responders ($n = 7$): The $\Delta\text{CK}_{\text{ABS}}$ of these players does not show statistically significant associations with FMP values. Further investigations into the type of load that elicits a $\Delta\text{CK}_{\text{ABS}}$ is warranted in these players (Tables 2 and 3).

We conclude that the resultant clusters in our dataset are highly population dependent and even though players can be grouped based on their CK sensitivity to FMP, there are large inter-individual differences which indicate the need for an individual-specific approach. However, our results may help practitioners to better understand training and match load response and manage potential fatigue of players on an individual basis.

Our study has several limitations that warrant discussion. First, in order to increase our sample size, we included 16–21-year-old players; as such, the age of participants has a large variance. Second, as the Football Movement Profile is a specific algorithm developed by a commercial GPS supplier, the exact algorithm is not publicly available. Finally, the CK response of players may be affected by factors other than training and match load, including direct muscle contusions, resistance training and individual neuroendocrine characteristics. In conclusion,



we found a relationship between FMP parameters and the day-to-day CK change but large inter-individual differences exist in the players' response. Closely monitoring the intensity distribution, in addition to traditional volume parameters, may provide a better understanding of the individual CK response to soccer-specific load.

PRACTICAL APPLICATION

Creatine Kinase is commonly used in elite soccer as an objective marker of muscle damage in soccer players, as its elevation is a sign of extensive load on the soft tissues resulting from high-intensity locomotive and mechanical load. Even though it has been found that CK change shows a relationship between the overall volume of several GPS parameters, such as high intensity and sprint distance, as well as accelerations and decelerations, we also suggest tracking the intensity of soccer-specific movements. For this purpose, FMP is a viable option as it classifies activities into specific zones, based on their locomotor orientations and intensity. In addition, as FMP relies solely on inertial sensors, and it is not affected by GPS signal, it can be monitored more accurately. FMP may help coaches and practitioners to better understand load of soccer-specific movements and could potentially decrease the number of parameters used to monitor players' activities. Individual and team physical preparation can be based upon FMP by defining specific target values or thresholds. We can also forecast the players' next day CK response based on their cluster classification and response to different types of soccer-specific load. Consequently, more precise planning of recovery strategies is possible, which is necessary during the congested schedules of national team settings. Despite the positive properties of FMP monitoring, we suggest using it in conjunction with the traditionally used GPS metrics to obtain a more accurate individual profile of CK response to the load of soccer-specific movements.

Conflict of interest: The authors declare no conflict of interest and they have no professional relationships with any company or manufacturer who would benefit from the results of the current study.

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