Quantifying intra-seasonal variations in physical performance measures using player tracking data from an elite football (soccer) academy

Michael Caine*, Varuna De Silva*, James Skinner*, Ahmet Kondoz*, Elliott Axtell^, Matt Birnie^, Tilson Peter^ and Ben Smith^  
*Loughborough University London, UK / ^Chelsea Football Club Academy  
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Background
Maintaining the peak physical performance of elite soccer players is a complex process, one that involves optimizing players’ physical readiness to perform across a competitive season, whilst concurrently minimizing risk of fatigue and injury. These two primary factors, peak physical performance and injury risk, are often in tension, since improving physical performance typically requires adherence to intensive training and conditioning regimes interspersed with competitive match-play, which in aggregate may lead to fatigue, repetitive strain and the potential for chronic injury.

Over the past decade, wearable sensor technologies and multi-view camera systems have been adopted widely, enabling an array of player data to be captured during training sessions and match-play situations. Global positioning system (GPS) based movement tracking is used extensively in professional sports to gain insights into activity demands exerted on players. These insights have the potential to inform the physical performance management of players. Coaches and specialist support staff strive continually to identify better ways to extract actionable performance insights from player tracking datasets.

1. Introduction
Analysis of historical player tracking data across four seasons (2014-2018) at Chelsea Football Club Academy demonstrated that while there are significant positional differences of high-speed running demands (HSRD) during competitive matches, the demands during training sessions do not show comparable positional variations (Figure 1).

To our knowledge, this was the first study in soccer players to investigate differences in activity demands during training sessions and competitive match-play by playing position. The results of our study indicate that while there are significant position-specific differences in activity levels during matches. Such differences are not observed for aggregate data pertaining to the training sessions.

One important factor that may account for the observed difference between competitive match-play and training relates to the coaches ambition to manage the training load of players to minimize fatigue. In periods of the season which are congested with frequent competitive matches, the time between games needs to be managed carefully to mitigate the risk of over-training of the players, which can lead to higher risk of injury. For example, during training sessions in-season, the training load may decrease when approaching a match day [1]. Therefore, granular analysis of training and match loads, for example on a weekly basis, would provide more contextual insights regarding how to adapt training programmes to position specific demands (something coaches often aspire to achieve), while managing the physical loading of players [2].

Informed by these earlier observations, the current study focused on an intra-seasonal analysis of training load to provide greater contextual meaning for the load variations between training and matches. A novel
A statistical technique is presented in this paper to quantify the consistency of exposure to physical activity within a playing season. The objective was to use player tracking data to recognize patterns associated with temporal variation of intra-season physical activity demands and to develop a statistical technique to quantify the activity exposure of players across a period of interest, usually a calendar year or playing season.

![Figure 1: The probability distribution of High speed runs per minute of play (HSR21pMIN) for three different playing positions (CM: Central Midfielders, CF: Centre Forwards and FB: Full Back, during matches and training.](image)

### 2. Methods and data set

#### 2.1. Data Source

Data were collected and analysed from 150 different players, aged between 18 and 23 across four seasons (2014–2018). A summary of the data set is presented in Table 1. For the analysis, three distinct positions of play were selected: Centre Forwards (CF), Central Midfielders (CM), and Full Backs (FB). These different positions were selected because they exhibit different characteristics and because the dataset contained adequate data points for a meaningful analysis. The study was approved by Loughborough University Ethics Committee. The Committee were satisfied that processes implemented by the Football Academy (which did not include obtaining written consent) ensured the Academy players were informed about the collection of the GPS data and the uses to which these data would be put. Data were anonymised and aggregated prior to analysis. It is not possible to link any of the data presented to any given player.

**Table 1.** Number of players, by playing position, across seasons.

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<td>9</td>
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<tr>
<td>Centre Midfielder (CM)</td>
<td>18</td>
<td>22</td>
<td>20</td>
<td>19</td>
<td>10,896</td>
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<tr>
<td>Full Back (FB)</td>
<td>12</td>
<td>15</td>
<td>14</td>
<td>11</td>
<td>5,041</td>
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<tr>
<td>Total</td>
<td>43</td>
<td>51</td>
<td>46</td>
<td>39</td>
<td>20,913</td>
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</table>
2.2. Data Acquisition and Analysis

20,913 data entries were analysed. Each entry corresponds to a summary of performance of one player in one day. While in a given season, a certain player predominantly trains in one squad by age group (e.g. U18) it is common for the player to have training sessions in different squads. For this reason, for some players, the number of data entries per year does not equate to number of entries in a full season of play.

Positional data were obtained from a wearable GPS tracking unit (Model: SPI-HPU) from GPSports, Australia. This system tracked the movements of each player along with their heart rate during all training sessions and competitive matches. The performance of the GPS tracking unit used in this study has been independently validated in numerous studies [3]–[5]. The movement data were then processed to produce metrics of physical performance for each collection period. There is a ‘data entry’ for each player for each session of play (training and competitive matches) during the playing seasons. For the majority of days, there is one session of activity per day, with few entries of two sessions of activity per day. A single data entry consists of multiple fields such as the date, season, training availability, type of day (match or training), duration of play, anonymised player code, position of play, squad, competition, and several physical performance metrics, as described in the next subsection.

2.3. Description of the Physical Performance Metrics

The number of high-speed runs and the high-speed distance (i.e. the distance covered during high-speed runs) are the most commonly utilised physical performance measures reported in recent literature [4],[7],[8]. Furthermore, some studies have profiled running behaviour at different intensities. For example in a previous paper [9], any movement between 21.1 kmph and 24 kmph is considered a high-intensity run, and a movement above 24 kmph is considered a sprint. The current study focused on the differences between high-speed running events during training and match-play sessions. For the purpose of this study, any movement beyond 21 kmph was considered to be a high-speed run (HSR).

Two different types of performance metrics were utilised for the analysis in this paper. They are the number of HSRs above 21 kmph, and the distance covered in high-speed running. Each entry in the data set corresponds to different durations of play, because they correspond to both match-play and training sessions. Therefore, to utilise as much of the data as possible in this analysis, the number of high-speed runs and the distance covered during high-speed runs were normalised by duration of activity, for each day. Therefore, the two metrics used in this work are denoted as HSR21pMIN (for the number of HSRs above 21 kmph per minute of play) and DIST21pMIN (for high-speed distances per minute of play), and can be calculated as follows:

\[
HSR21pMIN = \frac{\text{Number of HSRs on a given day}}{\text{Duration of activity during the day (minutes)}}
\]  
\[
DIST21pMIN = \frac{\text{Distance covered at more than 21kmph on a given day}}{\text{Duration of activity during the day (minutes)}}
\]

By normalising the number of events of high-speed running and the distance covered in HSRs by the duration of activity (training or matches) during a given day, we obtain a measure of the frequency of HSRs in a training session or match.

2.4 Statistical methodology

The statistical method developed comprises two main parts. Firstly, as illustrated in Figure 2, the playing season was segregated into temporally overlapping windows of 30 days (a notional one month period) at a
time. Unlike our previous study [10], where training and match sessions were analysed separately, in this method we consider both types of sessions synonymously. This is because, the match sessions also act as a form of conditioning preparing players for the future sessions. Instead of segregating training sessions and match sessions, we explore activity level distribution using one-month windows. (As illustrated in the Figure 2). We will look at both types of sessions (training and match) as a whole. The entire season is split in to 15 overlapping windows of length 30 days each, and the overlap is 9 days.

![Figure 2: Variation of the average number of high speed runs per minute of play (HSR21pMIN) across 3 months in 2016/17 season](image)

Secondly, the performance data (HSR21pMIN / DIST21pMIN) for all the days within a given window (i.e. a data vector) is compared against all the windows within the season. In simpler terms, we measure how similar the daily activity levels are within a given month (30-day analysis period) to the other months within the season. The Kolmogorov-Smirnov test (KS-test) was utilized to understand the similarity of the two data vectors. An example is provided in Figure 3, where data vectors from 4 windows of CFs are illustrated. The KS-test is a non-parametric test to check if two data vectors have come from the same continuous distribution [11]. The output of the KS-test (i.e. a comparison of activity between two windows) is summarized as a p-value. If p-value is <0.05 we deem that the two activity level vectors have different distributions (i.e. in statistical terms we can reject the null-hypothesis). We utilize a significance level of 5%, with the null-hypothesis that both vectors come from the same distribution. The p-value of KS-Test for each comparison is recorded. This set of p-values can then be used as a guide to measure the consistency of the activity levels that players have been exposed to.

### 3. Results and Discussion

The statistical method adopted measured the consistency of HSRD to which different playing positions are exposed across a season. The p-value tables for CF / CM and FB positions are illustrated in Figure 4. In the figure 4 (a) and (b), W1 to W15 refer to overlapping windows of 30 days, starting 1st of July in a year. The windows W1-W15 covers a duration of 300 days. For example, W1 correspond to days 01/07 to 31/07 and W2 correspond to 22/07 to 21/08.

For the Centre Forward (CF) position, the HSR21pMIN of all temporal windows have statistically similar distributions. Similarly, the DIST21pMIN of all temporal windows of CFs have come from statistically similar distributions. Figure 5 illustrates the mean value of each physical parameter across the windows, and the corresponding confidence interval. Furthermore, individual data points have been placed on top of the bar graphs to show the distribution. As depicted, there is a very little variation of the mean values for both HSR21pMIN and DIST21pMIN across the windows for the CF position.
Figure 3: Example comparison of the distribution of HSR21pMIN variable in different windows

(a) For HSR21pMIN

(b) For DIST21pMIN

Figure 4 - p-value table for similarity of:
(a) HSR21pMIN  (b) DIST21pMIN values across different windows for Centre Forwards (CF)
Figure 5: Comparison of Means for CF position at different windows
For the Central Midfielder (CM) position, the p-value table for HSR21pMIN shows multiple differences, across the season. The key differences are as follows: The window 1 (W1) is significantly different from windows W3 to W5. The window W7, is significantly different from W4 to W6. Furthermore, windows W10-to-W13 is different from W4-to-W6.

![Table of p-values for HSR21pMIN and DIST21pMIN across different windows of Central Midfielders (CM)]

For the CM position, the p-value table for DIST21pMIN shows multiple differences, across the season. The key differences are as follows: The windows W1-W2 are significantly different from windows W3 to W6. The window W15, is significantly different from W3 to W6. Furthermore, windows W10-to-W13 is different from W4-to-W6.

To supplement the results provided in p-value table for CMs, Figure 7 illustrates the mean value of HSR21pMIN and DIST21pMIN variable within different windows.
For the Fullback (FB) position, the p-value table for HSR21pMIN (Figure 8) shows that most windows have originated from a statistically similar distribution, except for windows W1-W3 being statistically different to W7 and W8. The p-value table for DIST21pMIN variable also shows that while most of the windows are statistically similar, the Window W15 is statistically different from several other windows in the season.
Figure 8: p-value table for similarity of (a) HSR21pMIN (b) DIST21pMIN values across different windows of Full Backs (FB)

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<tr>
<th></th>
<th>W1</th>
<th>W2</th>
<th>W3</th>
<th>W4</th>
<th>W5</th>
<th>W6</th>
<th>W7</th>
<th>W8</th>
<th>W9</th>
<th>W10</th>
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<td>0.641</td>
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<td>0.002</td>
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<td>W10</td>
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(a) HSR21pMIN

(b) DIST21pMIN

Figure 9 illustrates the mean values of different windows in the FB training profile. Figure 9(a) illustrates the means of Windows W1-to-W3 and W7 and W8, which are the windows that do not come from statistically similar distributions. As for DIST21pMIN variable, the window W15 shows significant difference from multiple other windows, and the means are illustrated in Figure 9(b). It should be noted that there are only 12 data points in W15 as compared to more than 60 for all other windows in this comparison.
Discussion

This study followed an earlier investigation which demonstrated that high speed running activities differ between training sessions and competitive matches for different playing positions [10]. The current investigation built upon these earlier insights by investigating the consistency of high-speed running activities, during training and match-play, throughout a
given season. We describe a statistical methodology whereby the playing season is segmented into overlapping windows of 1 month to enable the similarity of the activity demands across these windows to be analysed, including by playing position.

The results of this study indicate that, despite a few notable positional variations, the players are exposed to a consistent level of physical activity (in terms of high-speed running) throughout the season. The CFs tend to have the most consistent exposure to high speed running activity. In comparison, the CM playing position experiences increasing levels of activity demands measure by HSR21pMIN as well as DIST21pMIN. The demands during the latter part of the season were higher for CMs. The FB position tends to experience consistent demands of high-speed running activity measured by both HSR21pMIN and DIST21pMIN.

The proposed statistical method described involved pair-wise comparison of windowed performance data. The KS-test compared if the two data vectors originated from a similar data distribution. Comparison of the distribution of data was motivated from our previous study [10] where probability distributions were effectively used to quantify variations in performance data. When comparing the physical demands exerted on players, the comparison between probability distributions is more meaningful than comparison of means, because players would be exposed to varying levels of activity especially dependent on the match situations. Therefore, we propose that the current methodology is more appropriate than ANOVA method or pair-wise t-tests. As illustrated in this investigation, this method can be combined with appropriate visualization methods to quantify the physical activity exposure of players.

4. Conclusions and Impact
Developing training prescriptions that balance the physical, technical and tactical outcomes with risk of injury is a key challenge faced by support staff in elite sports. In keeping with this overarching challenge, we propose a statistical method to quantify physical exposure of the players within a season. In this instance, the method described enabled a discrepancy between measures of high-speed running in training versus competitive matches for some playing positions. The proposed method, in conjunction with match load prediction, has the potential to assist coaching staff to track the physical activity demands exerted on players in training, relative to the demands of match play, thereby enhancing the likelihood of match fitness whilst reducing the risk of injury.

References