THE USE OF CONTEMPORARY COMPUTER BASED ANALYSIS IN EVALUATING THE PHYSICAL AND TECHNICAL DEMANDS OF ELITE SOCCER

ALEXANDER THOMAS SCOTT

A Thesis Submitted In Partial Fulfilment of the Requirements of Liverpool John Moores University For The Degree Of Doctor Of Philosophy

October 2015

This research programme was carried out in collaboration with Liverpool Football Club

Abstract

Soccer is regarded as an intermittent sport with the majority of the activity completed at a sub-maximal intensity that predominantly stresses the aerobic energy system. Within this intermittent profile are frequent unpredictable changes in intensity and direction of movement. Methodologies employed to evaluate these activities within soccer match-play have developed greatly over the last four decades. Recent, advances in semi-automatic computerised tracking technologies, have replaced traditional methods of analysis, and now permit larger and more complicated sets of performance data to be evaluated more quickly and accurately. The proposed aim of this thesis was to investigate the potential for approaches in contemporary performance analysis to provide new insight into the physical and technical demands of elite level soccer.

The aim of Study 1 (chapter 3) was to quantify the within-game variability of a selection of physical variables across a number of time periods (1, 5, 15-minutes) in soccer match-play. Match performance data was produced using a computerised semi-automatic multi-camera image recognition system (Prozone®, Leeds, England). Physical competitive match data were collected from 14 soccer players who played for an elite professional soccer team competing in the English Premier League during the 2010-2011 domestic season ranged from 1 to 31 (14 games ± 8). The physical variables selected for analysis were total distance covered, total high-speed running distance, total high-speed running number, high-speed running distance, high-speed running number, total sprint distance, total sprint number, average speed, total number of accelerations, total number of high accelerations, total number of medium accelerations, total number of low accelerations, total number of decelerations, total number of high decelerations, total number of medium decelerations, total number of low decelerations. Within-game variability (CV%) ranged for 1-minute (7%-261%), 5-minute (16% - 225%) and 15-minute periods (9% - 122%) and was greater than between-game variability values. Average speed and the total distance covered reported variation of <10%. Overall, the high between and within-game variability found indicates player's inability to perform consistent physical actions between and within-games. The data has implications for the interpretation of physical performance. The findings show the 15-minute time periods would be the most appropriate to consider for implementation in future studies (study 3) within this thesis. The physical measures, average speed and total distance, provide potential indicators of physical performance.

The aim of the study 2 (chapter 4) was to quantify the variability associated with a selection of technical performance variables used in elite soccer both between-game and within-game using

time periods of 1,5 and 15-minutes. Technical performance data was again produced using the same computerised semi-automatic multi-camera image recognition system (Prozone®, Leeds, England). Technical competitive match data were collected using the same 14 soccer players as Study 1 (18 games ± 10). Technical variables selected for analysis were pass, successful pass, passing success rate (%), passes received and average time in possession (s). The findings demonstrated that within-game time periods of 5-minutes (27-68%) and 15-minutes (29-78%) reported higher levels of variation than between-game values (21-43%) of variation. The lowest variation was reported to occur in 1-minute periods (9-73%). The high levels of variation found in both between and within-game periods indicate that player's do not perform consistent technical actions between and within-games. The study also showed that it is not only physical performance that is affected by variation between and within-game, but also a player's technical contribution. The high variation reported for the selected technical performance measures has implications for the interpretation of match technical performance. Despite the higher variability found in technical performance measures, average time possession and passing success rate were selected for future work (study 3), as they represent the lowest variation at the 15-minute time periods.

The aim of the study 3 (chapter 5) was to analyse both physical and technical within-game performance using the selected variables from study 1 and study 2 using data from 15-minute time periods. The study also applied a new methodological approach to data analysis to identifying meaningful changes in performance. The findings from study 3 reported that the physical performance measures - total distance and average speed, displayed peak values during the 0-15 min time period of a match (1832m and 2.04m/s respectively). A drop in physical output was found during the 60-75 min period for total distance (1626m) and average speed (1.81m/s). These changes represented meaningful changes in performance and had practical significance. Average time in possession was also significantly lower in the opening period (0-15 min) of the match to the 75-90 min period; this change was a meaningful change. In comparison, technical performance changes within-game were not conclusive. These findings challenge previous assumptions of changes in within-game performance (i.e. accumulation of fatigue) typically represented in the literature.

The aim of study 4 was to determine whether the relationship between blood creatine kinase (CK) and physical match performance in elite male soccer players. Blood samples were collected 48 hrs following a competitive match. Analysis for CK concentration was performed immediately after collection via spectrophotometry using a commercially available reagent kit (Reflotron® Systems, Roche, Mannheim, Germany). Mean ± S.D CK concentration 48 hrs post-match were 520 ± 224 $\mu.mol.l^{-1}$ though large individual variation in the CK response at this time point was observed (184 μ.mol.l^{-1} to 1573 μ.mol.l^{-1}). No significant correlation coefficients were obtained between any of the chosen indicators of physical match performance and CK concentration 48 hrs post match. This data showed that CK concentrations are elevated as a consequence of playing a soccer match though CK may be of limited value in tracking subtle changes in the performance of players during the competitive season.

The aim of study 5 was to investigate elite soccer player's physical match performance data using temporal pattern analysis (T-pattern analysis). The THÈME© 5.0 software package (Magnusson, 1996, 2000) was used to analyse the performance data for `T-patterns' in 5 elite players. The study found that T-patterns of different temporal lengths do occur within football and that these patterns, vary from simple to complex and that these occur cyclically throughout the game. A total of 616 different temporal patterns (including high intensity activities) were identified in the analysis. A greater number of these patterns were seen to occur in the second half of matches compared to the first half (252 v 364). Peaks in the occurrences of pattern sequences were observed between 0-15min, 45-60min and 75-90min. The time periods that contain a high number of pattern sequences may represent "chaotic" phases of play. The findings from the analysis showed the potential of T-pattern analysis to develop our understanding of the physical movements performed in soccer and the physiological demands that are associated with them.

Acknowledgements

Firstly, I would like to take this opportunity to give my sincerest thankfulness to my director of studies Professor Barry Drust, who has supported me throughout the entire 1,677 days that this thesis has taken me to complete. I will be eternally indebted for the time, patience and invaluable advice he has invested in me throughout this journey. I cannot express how challenging the journey to the completion of my PhD thesis has been for me. The unique working environment that is elite professional football and writing a PhD thesis has pushed me to limits that I did not know I could before. I would not have done this without your support and for that I am very grateful.

I would also like to thank my PhD supervisors, Dr. Darren Burgess and Dr. Warren Gregson. I will always be grateful to Darren for the opportunity to experience working within the sport science department at Liverpool FC and allowing me to develop my theoretical and applied understanding of player fitness and conditioning in elite football. I am also thankful for the academic input provided by Warren, who particularly at the latter stages of the thesis provided valuable feedback under great time constraints.

I would like to express my gratitude to the members of staff who were associated to Liverpool Football Club during my 3-year internship. A special mention to Alan McCall, Billy Parry, Dr. Fergus Connolly, Glen Driscoll, Dr. James Morton, Dr. Peter Brukner and Ryland Morgans for all of their guidance and support. A particularly special mentioned goes to Dr. James Malone and soon to be Dr. Dave Rydings, whom were two fellow interns working alongside me at Liverpool FC. A great friendship was formed between us during this period and don't think without the camaraderie between us three I would have enjoyed the experience as much as I did. A special thank you also goes to Andy Scoulding, of the performance analysis department, who has provided me with invaluable support and advice. The unique nature of working as a performance analyst has been remarkably difficult, particularly alongside my PhD thesis, and grateful for you believing in my ability throughout it all and constantly challenging me to better myself.

Outside of the world of football and academia, it is very important that I write a very special thank you to all of my friends who have helped me through this significant period of my life. I cannot thank you enough for your support, motivation and understanding. My sincerest gratitude also goes to all of housemates at Penny Lane, Roding Road and Cotleigh Road who have excused me on countless occasions from cooking, cleaning and allowing me to turn social and fun areas of the house into rooms of solitude and silence.

Finally, a special thank you goes to my family. Mum, Dad and Jonno, you've had the worst of it all. I cannot thank you enough for putting up with the countless phone calls and trying to understand my moods and frustrations throughout this journey.

CONTENTS PAGE

List of Abbreviations

Analysis of Variance (ANOVA)
Attackers (ST)
Average Speed (AVE)
Bloomfield Movement Classification (BMC)
Central Defender (CD)
Central Midfielder (CM)
Coefficient of Variation (CV)
Comma-separated Values File (CSV)
Confidence Intervals (CI)
Creatine Kinase (CK)
High-Intensity Running Distance without Possession (HIRWP)
High-Intensity Running with Possession (HIRP)
High-Speed Running Distance (HSRD)
High-Speed Running Number (HSRN)
Minimum Criterion Change (MCC)
Recovery Time (REC)
Smallest Worthwhile Change (SWC)
Temporal Pattern (T-pattern)
Thiobarbituric Acid Reactive Substances (TBARS)
Total Antioxidant Status (TAS)
Total Distance Covered (TD)
Total High-Speed Running Distance (THSRD)
Total High-Speed Running Number (THSRN)
Total Number of Accelerations (TAC)
Total Number of Decelerations (TDEC)
Total Number of High Accelerations (HACC)
Total Number of High Decelerations (TDEC)
Total Number of Low Accelerations (LACC)
Total Number of Low Decelerations (LDEC)
Total Number of Medium Accelerations (MACC)
Total Number of Medium Decelerations (MDEC)
Total Sprint Distance (TSD)
Total Sprint Number (TSN)
Wide Defender (WD)
Wide Midfielder (WM)

List of Units of Measurement

Coefficient of Variation (CV)

Hours (hrs)

Kilometres (km)

Kilometres Per Hour (km/h^{-1})

Metres (m)

Metres Per Second (m/s)

Micromoles/Litre (µ.mol.l^{-1})

Minimum Criterion Change (MCC)

Minute (min)

Number of (n)

Seconds (s)

Standard Deviation (SD)

List of Tables

List of Figures

Chapter 5

1.0 General Introduction

1.1 Background

There is a large literature base that has investigated the physiological demands of soccer (Ekblom, 1970; Reilly, 2007; Drust et al., 2007; Di Salvo et al., 2009). This information denotes that soccer is a complex intermittent sport and elite player's will generally perform a wide variety of soccer-specific actions in a match and cover a total distance of 10-12km (Drust et al., 2007). The majority of this distance in a game is performed at low-intensities in the form of walking, jogging and running actions and requires relatively small amounts of aerobic energy turnover (Bangsbo et al., 2006). Additionally, the anaerobic system is involved in supporting the activity of the most decisive actions (cruising, sprinting, and jumping for headers). An elite player will perform 150-250 of these brief intense actions during a game (Mohr et al., 2003). These actions are particularly important as they are considered to be associated to match winning moments (i.e. sprinting to a ball, kicking the ball, jumping for a header) (Stolen et al., 2005). On top of this activity are the tactical requirements and technical actions placed on players. These technical involvements with the ball are limited in elite soccer with less than 2% of the total distance covered in a match being in possession of the ball (Reilly & Thomas, 1978). These actions include actions such as passes, shots, and tackles (Carling et al., 2008; Drust et al., 2007). This technical ability, though limited in its frequency in a game, is clearly a key factor in the performance of an elite player (Bangsbo, 1994) as they reflect specific individual actions and decisions towards the total team effort. This element of soccer performance is contextualised by a player's tactical knowledge, game intelligence and decision-making, so that actions are tactically relevant to the outcomes of the game (Williams & Reilly, 2000).

Semi-automatic tracking systems provide the capability to develop a detailed activity profile of a player during a game. Such activity profiles from within the game are an important alternative method of looking at a player's match performance compared to looking at the total physical output during a match. Through the use of 5, 15 and/or 45-minute time intervals, it is possible to analyse fluctuations in movements that may be related more closely to key incidents or occurrences within competition (i.e. score-line, fouls, goals scored, and shots on goal). For example, Mohr et al., (2003) reported that the amount of high-intensity running in professional players decreased substantially in the final third of games as well as observing that the 5-minute period immediately after the most intense 5-minute interval in a match included less high-intensity running than that observed during the average 5-minute period. Similar data has also been replicated with technical information though in a more limited way. Studies in these areas have reported differences in technical performance and skill-related proficiency between each 45 min half thereby indicating changes in the skill profiles (i.e. pass success, number of touches, percentage of duels won, touches per possession) exhibited by players during a game (Rampinini et al., 2009; Carling & Dupont, 2011). Information from such investigations, while useful, is limited by both the relatively small sample sizes that have been used and the length of the time interval used to examine the data (Krustrup et al., 2002; Mohr et al., 2003, 2005; Rampinini et al., 2007). These factors prevent a clear understanding of the dynamics of within-game changes in activity pattern/technical skill being obtained. One novel development in semi-automatic computerised tracking technologies has been the ability to utilise small time periods (e.g. 1-minute time periods) to analyse both the physical and technical data from matches. This capability to use finer time periods for analysis has the potential to enable more comprehensive insights to be made into the both physical and technical elements of a player's performance. Such information may provide the platform for the development of strategies to improve the physical and technical skills of players.

Methodologies employed to evaluate the activity within soccer match-play have developed over the last four decades as requirements for valid and reliable information have increased (Drust et al., 2007). Recent advances in semi-automatic computerised tracking technologies have replaced previously used methods of analysis that provided relatively simple data for small numbers of players (Reilly & Thomas, 1976; Bangsbo, 1994; Di Salvo et al., 2009). Such computerised, semi-automatic computerised tracking technologies provide real time movement information, as well as allowing for simultaneous analysis of all players and officials during match-play for both physical and technical actions (Di Salvo et al., 2009; Carling et al., 2008; Krustrup et al., 2005; Drust et al., 2007). This has meant that larger and more complicated sets of performance data can be evaluated more quickly and accurately than in previous investigations (Drust et al., 2007; Di Salvo et al., 2009).

The physiological implications of the physical and technical demands of soccer match-play are also not well understood. The modern elite soccer player will compete in a large number of games (>60) during a domestic season often playing multiple games within a week. The potential for residual fatigue to impact on high-intensity activity in congested match periods is therefore potentially high (Odetoyinbo et al., 2008). As a consequence, it is important that players attempt to maximise their recovery between games in an attempt to minimise the fatigue and/or muscular overload that may ultimately impair performance (Smith, 2000; Brancaccio et al., 2010). One of the enzymes commonly used as a proxy marker for exercise-induced muscle damage is Creatine Kinase

(CK). For example, Lazarim et al., (2009) used plasma CK values for the early detection of muscle overload in soccer players suggesting that such relationships could form the basis of reducing the risk of injury by informing changes in the training load. CK analysis in relation to soccer has received very little attention in the available research literature. The data from this research may be limited as a consequence of the short study (5 months) and therefore the small number of CK samples collected. Additionally, the study also failed to attempt to evaluate any relationships between the activities performed in games and the CK concentrations. Such relationships would seem to be important in determining if physiological measures such as CK are good indicators of the demands placed on soccer players in competitive situations.

New approaches to data collection may also provide a more comprehensive understanding of the complex inter-relationships between discrete events that could potentially determine the performance of games (Borrie et al., 2002; Bloomfield et al., 2005). Temporal Pattern Analysis is an analytical approach to examining data that looks at time-based events and real-time behaviours in a sporting context. The approach is based on a time pattern called a 'T-pattern' that is detected using a specialist software package called THÈME. The use of 'T-patterning' has been successful in discovering a high number of temporal interactive playing-patterns in soccer matches that highlight that sports behaviour is more synchronised than the human eye can detect (Borrie et al., 2002; Bloomfield et al., 2005). Sarmento et al., (2011) found a total of 787 T-patterns ranging from simple to complex when analysing the technical performance in 12 games for a Spanish soccer team. The data provided characterised a particular strength of the team's success from counter-attacking plays. Such patterns would not have been detected by more traditional frequency based approaches to analysis, as the actions would have been identified as discrete events. The current research base relating to T-patterns has focused exclusively on technical actions. As a consequence very little is known about the existence of such patterns in a player's activity profile. Such information has the potential to provide a greater understanding of the physical and technical interrelationships within elite soccer matches and aid in the development of soccer specific training methods.

1.2 Aims & Objectives of the Thesis

The proposed aim of this thesis is to investigate the potential for approaches in contemporary performance analysis to provide new insight into the physical and technical demands of elite level soccer. The aims of this thesis will be met by the following objectives:

1. Determine the between and within-game variability of physical and technical variables relevant to performance in elite soccer.

2. To analyse the within-game physical and technical performance demands in elite soccer using 15-minute time periods for analysis.

3. Evaluate the relationship between Creatine Kinase and physical performance measures during competitive matches.

4. Apply temporal pattern analysis to within-game data from elite Premier League players to investigate the existence of temporal patterns in the activity profile of players.

2.0 Literature Review

The opening section of this literature review will provide an overview of soccer performance and detail the key components associated with the physical and technical demands of the sport. The review will then look to identify the different approaches that have been used to analyse soccer performance. This section will also review the contemporary methods used to analyse physical and technical performance in matches. In addition, a critique of our current understanding of match related fatigue and variability in performance will also be included within this section.

2.1 Fundamentals of Soccer Performance

Performance in soccer is a consequence of a myriad of factors that include technical, tactical, physical, physiological and mental components (Bangsbo, 1994). Each one of these elements of soccer performance is closely linked with the other factors. For example, players with lower fitness levels may compensate by having greater capabilities in other areas important to soccer, such as technical skill (Bangsbo, 1994). From a physical perspective, soccer is regarded as an intermittent sport with the majority of the activity completed at a sub-maximal intensity that predominantly stresses the aerobic energy system (Bangsbo, 1994; Ekblom, 1986; Reilly 2006). Within this intermittent profile are frequent unpredictable changes in intensity and direction of movement (Reilly, 2003; Mohr et al., 2003; Drust et al., 2007). Superimposed on this activity profile are actions that directly relate to the involvement in a match. These include technical skills such as kicking, throwing, dribbling, heading the ball and physical challenges with opponents to contest possession (Bangsbo et al., 2006; Di Salvo et al., 2009). The impact of match-play on individual players is therefore a consequence of both direct and indirect involvements in the game. Such direct involvement occurs when responding to attacking and defensive movements of opposing players as well as individual decision-making of when to become engaged in play (Reilly & Thomas, 1978). As a consequence of these factors, soccer performance is highly variable from game-to-game; this can make the quantification of performance problematic (Gregson et al., 2010).

2.2 The Physical & Technical Demands Of Soccer

Methodologies employed to evaluate soccer performance have developed over the last four decades through the greater requirement for valid and reliable information from competitive matches (Drust et al., 2007). Earliest investigations used motion analysis methods to asses a variety of performance factors such as different environmental conditions (Ekblom, 1986), work rate

(Reilly & Thomas, 1976), styles of play (Drust, 1999; Rienzi et al., 2000) and levels of competition (Florida-James & Reilly, 1995; Mohr et al., 2003). This type of method was traditionally limited to a specific player whose activities were recorded for the entire 90 minutes of the game (Bangsbo et al., 1991). However, some studies used multiple cameras to focus on more than one individual player per game (Rienzi et al, 2000). Recent advancements in semi-automatic computerised tracking technologies, which have replaced traditional methods of analysis, now permit more complicated sets of performance data to be evaluated more quickly and accurately (Drust et al., 2007; Di Salvo et al., 2009). These methods of analysis provide information on the total distance covered, the total time spent and the frequency of occurrence of relevant activity classifications. There is a large literature base that has investigated the physiological demands associated with soccer (Ekblom, 1970; Bangsbo, 1994; Mohr et al., 2003; Drust et al., 2007; Reilly, 2003; Di Salvo et al., 2009, Bradley et al., 2011). Such investigations have shown that player's typically cover 8 - 13 km during a game with the majority of the activity being performed at low-intensity (i.e. walking and jogging) (Bangsbo, 1994; Di Salvo et al., 2007; Reilly, 2003; Mohr et al., 2003, Bradley et al., 2010). A particular focus in recent investigations has been the high-intensity bouts of exercise included in the game such as jumping and sprinting (Bangsbo et al., 2006). These high-intensity efforts are thought to be critical to the outcome of a match as they frequently relate to the actions that can result in winning or losing, such as, movements to win the ball and actions with agility to go past defending players (Stolen et al., 2005). Previous research has reported that high intensity activity is affected by league position with less successful teams covering significantly greater distances in both high-intensity running distance and sprinting than teams considered more successful (Di Salvo et al., 2009). Recent studies have also found that players in lower standards of English soccer reportedly covering more total distance and high-intensity running during matches compared to those in the highest standard (Bradley et al., 2013, Di Salvo et al., 2013). Overall, these findings highlight the absence of an established physical measure to differentiate between levels of performance or competition in soccer match-play.

Previous studies have used total and high-intensity running distance to represent the physical demands of soccer match-play (Bradley et al., 2009; Di Salvo et al., 2009). Whereas, a more recent study by Barnes et al., (2014) highlighted high-speed running distance as a better measures to represent the physical demands of soccer match-play as it correlates well with physical capacity (Bradley et al., 2011) and discriminates between competitive standard and gender (Bradley et al., 2013; Mohr et al., 2008). Despite a plethora of research, the difficulty in establishing a criterion measures to distinguish performance in elite soccer matches can be a result of the simplistic nature of the investigations analysing high-speed physical measures in isolation. Previous research has typically used a reductionist approach whereby match-running performance is examined in detail without any integration of external factors (i.e. match importance, score line and recovery days), and ultimately leads to a 1-dimensional insight into match performance (Bradley et al., 2013). Paul et al., (2015) recently suggested that it would be advantageous to analyse the contextual interplay between physical, psychological, technical, and tactical factors. It is therefore vital that future research provides a greater insight into the complexity of match play and the influence of contextual and tactical factors on high-speed physical performance measures before making inferences on performance data.

In comparison, studies investigating technical and tactical elements of the sport have benefitted in recent years due to the development of semi-automatic computerised tracking technologies so that greater detail can be provided into the demands of soccer (Russell et al., 2012; Rampinini et al., 2009; Bradley et al., 2009). It is important to investigate technical performances of an elite player as they reflect the specific individual contributions and decisions made towards the total team effort (Bangsbo, 1994; Reilly, 2003). Previous research has primarily focused on team technical performance using comparative analysis to investigate the success of team performance (Hughes & Franks, 2005; Rampinini et al., 2009; Lago-Ballesteros & Lago-Peñas, 2010). For example, Lago-Ballesteros and Lago-Peñas (2010) reported that teams ranked higher in the Spanish La Liga had a higher average of goals for total shots and shots on goal than middle and bottom teams. In comparison, investigations analysing individual technical actions of elite players are somewhat limited in comparison (Bradley et al., 2010; Barnes et al., 2014; Dellal et al., 2010; 2011). It is reported that a player will typically complete between 50 and 110 technical involvements within a game and that the number of ball contacts, dribbling and short passes are the most important characteristics of technical activity during match-play (Bloomfield et al., 2007; Dellal et al., 2011). These technical actions have been found to increase since 2006 to 2013 in elite English soccer players (Barnes et al., 2014). Barnes et al., (2014) found that players performed -40% more passes, with a greater percentage of successful passes occurring in 2012–13 (84%) compared to 2006–07 (76%). This increase in the number of passes is suggested to be a result of an increased passing tempo, resulting in greater involvement with the ball (Barnes et al., 2014). It is also important to acknowledge the tactical role (i.e. defensive or attacking responsibilities) and situational effects with individual playing positions (i.e. a player might be required to operate in a specific areas of the pitch) as they can also alter the relationship with physical activity (Bradley et al., 2011; Castellano et al., 2011).

The findings have also led to the suggestion that technical factors are better able to differentiate between competitive standards in elite soccer than physical measures (Bradley et al., 2013). Despite research reporting information on the technical contribution to soccer performance in isolation, there are a limited number of studies that have investigated the interaction between technical and physical components in combination within match play. Bradley et al., (2013) reported that ball possession did not influence teams overall activity profile with and without possession, but did impact on the composition of high-intensity running efforts and some technical elements of performance (i.e. successful passes, received passes and tackles). Whereas, Carling & Dupont (2011) reported a decline in total and high-intensity distance in the latter stages of a game, but was not accompanied by a drop in skill-related performance (i.e. shots, shots on target, passes and successful passes). Despite these findings providing new information, they also highlight the need for a greater level of analysis into the way technical and physical performance interacts with one another. This will enable a greater understanding of the complexities to elite soccer performance and match play.

2.3 Factors Affecting Physical & Technical Performance

Player's physical and technical performance is highly dependent on their positional role within the team (Di Salvo et al., 2007; Mohr et al., 2008). Differences have been observed in high-intensity running, number of sprints, headers, tackles and the total distance covered between different positional roles (Bradley et al., 2009; Dellal et al., 2010; Di Salvo et al., 2007; Di Salvo et al., 2009). The midfielders are reported to cover the greatest high-intensity distances when compared to central defenders, fullbacks, and attackers (Rampinini et al., 2008; Di Salvo et al., 2009). When the technical demands are analysed in detail it has been reported that fullbacks have the highest frequency of technical involvements (i.e. number of actions, number of touches per possession, time per possession and time in possession) compared to other positions (Carling, 2010). These differences in performance can be attributed to the tactical role each player has within the team and as such are a consequence of playing style (Drust et al., 2007; Dellal et al., 2011; Reilly, 2003). For instance, teams that adopt a direct style of play are required to cover greater distances given the ball travels further when attacking, whereas, teams that implement a passing style are required to make short movements to pass and generate space (Reilly, 2003; Di Salvo et al., 2009). Bradley et al., (2011) found that playing formation impacted a player's overall high-intensity running performance according to whether the teams were with or without ball possession. Technical demands have also been found to fluctuate depending on the opponent's formation, where a greater number of passes were reported in a 4-4-2 formation compared to a 4-2-3-1 or 4-3-3 (Bradley et al. 2011; Carling, 2011).

The amount of high-intensity running distance has previously reported to be a distinguishing characteristic between players at different performance levels (Mohr et al., 2003; Bradley et al., 2013). Notable differences in high-intensity running distances covered by soccer players have been reported between leagues and playing divisions in various countries (English: Bradley et al., 2013; Di Salvo et al., 2009; Italian and Danish: Mohr et al., 2003; Swedish: Andersson et al., 2008; Spanish: Di Salvo et al., 2007). High-intensity running has been reported to be 10–15% higher in the English FA Premier League than in the Danish (Mohr et al., 2003) and Swedish Premier Leagues (Andersson et al., 2007), but similar to the Italian Serie A (Mohr et al., 2003) and the Spanish La Liga (Di Salvo et al., 2007). Whereas international elite level players have been found to perform 28% more high-intensity running and 58% more sprint distance than players at a lower standard (Mohr et al., 2003). Despite the small number of investigations, technical differences have also been found to occur in heading, tackles and time in possession of the ball across playing positions between La Liga (Spain) and Premier League (England) players (Dellal et al., 2011).

2.4 Within-Game Performance

Despite the many external factors that can affect performance, the player's capability to regulate their own physiological load (i.e. aerobic and anaerobic activity) can impact upon an individual's game metrics. Reilly (2005) suggested that the self-imposed demands chosen by players reflect their commitment to the team's efforts and their own abilities to pace themselves throughout the game. Changes in physical performance have not only been found to occur from game-to-game but also during matches (Bangsbo, 1994; Mohr et al., 2003; Rampinini et al., 2007; Rienzi et al., 1998; Lovell et al., 2013). Several studies have shown declines in physical performance during a match, particularly during the second half for sprinting, high-intensity running and total distance covered (Bangsbo, 1994; Mohr et al., 2003; Krustrup et al., 2005; Rampinini et al., 2007). The work-rate of an elite soccer match has also been shown to represent a positive pacing strategy during each half (Weston et al., 2011), wherein the proportion of high-speed running performed in the first 15-minutes of each half has been reported to be the greatest (Bradley et al., 2009; Mohr et al., 2003; Lovell & Weston, 2013). Technical performance and skill-proficiency (i.e. involvements with the ball, short passes) have also been found to be affected by these physical differences with a reported deterioration in the second halves of matches in involvements with the ball, short passes and successful short passes (Rampinini et al., 2009; Carling & Dupont, 2011). These declines within a game have been linked to match related physical fatigue (i.e. transient and accumulated) (Bangsbo et al., 2006; Mohr et al., 2005).

In soccer, where performance must be sustained for a prolonged period of time (45 minutes), fatigue is represented by the inability to sustain the required work-rate within match-play (Reilly et al., 2008). This decline in physical capability coincident with the onset of fatigue has been defined as a reduced capacity to generate the required level of force (Edwards, 1983). Investigations identifying the occurrence of fatigue in soccer have been made more possible due to the development in computerised semi-automatic tracking systems. These tracking systems enable larger data samples to be analysed that allows for a greater statistical power and therefore provides a more comprehensive analysis of fatigue in soccer performance. Several studies using within-game data samples of 5-minutes have investigated the occurrence of transient and accumulated fatigue in soccer (Bradley et al., Mohr et al., 2010; Di Mascio & Bradley et al., 2013). These previous studies have found decrements in high-intensity running after the most intense period of activity within the game and towards the end of the match for both domestic and international players (Mohr et al., 2003; Bradley et al. 2009). This evidence would suggest that players experience temporary and accumulative fatigue within soccer match-play. Despite such findings, the current within-game research has been reluctant to quantify the variation in the time periods and performance measures that have been used in these investigations. Establishing the variability across the different time periods is important for predicting statistical power in research as well as how worthwhile a certain intervention is for performance (Atkinson, 2003). Previous research has shown that large variation does occur in high-intensity performance measures between-games (Gregson et al., 2010). Such changes in the within-game activity profile could be a consequence of the inherent variability associated with these performance measures or time periods across the game. For example, a reduction in high-speed running distance after the most intense period could in fact be a consequence of variation in the data rather than deterioration in performance due to physiological changes that could result in temporal fatigue. A greater understanding of soccer performance within-game has the potential to provide new insight into the intricacies of soccer player's work-rate patterns as well as possible factors that can affect performance.

2.5 Variation In Soccer Match Performance

Like all measures of sporting performance, physical and technical actions in soccer match-play are not stable properties but are subject to large variation between successive matches. As previously highlighted, the sources of variation in soccer performance may be due to a myriad of factors related to both internal factors (fitness status, psychological motivation) and external factors (opposition, tactics, measurement systems and environment) (Mohr et al., 2003; Rampinini et al., 2007; Gregson et al., 2010; Weston et al., 2011; Kempton et al., 2014). As a consequence of these factors, the variability in performance measures in soccer is likely to be relatively large (Gregson et al., 2010). Despite the importance of this information, there is presently a limited understanding of the typical variability associated to performance measures in elite soccer. This is uncommon when compared to other sports. Previous work investigating individual events such as cycling and swimming consider the variability in a top athlete's performance from competition-to-competition to be one of the key factors when the athlete's prospect of a medal is under consideration (Hopkins, 2001). Research quantifying athlete's timed performances in cycling and swimming, where athletes are frequently required to perform relatively simple timed bouts of maximal exercise have reported levels of variability of 1-5% (Hopkins 2001, 2005). These small levels of variability have enabled practitioners to gauge the impact of factors that affect medal-winning performance and detect real systematic changes in performance that accompany interventions (Hopkins, 2001; 2005; Paton & Hopkins, 2006).

In contrast to cycling and swimming research, soccer performance is a construct where a multitude of different performance components or indicators interact together at both the level of the player and team (Atkinson, 2002). For example, Gregson et al., (2010) found considerably high variation in high-speed activities (i.e. high-intensity running distance and sprint distance) from game-to-game and between players across positions in the English Premier League. Total high-speed running distance was found to be as high as 17% whilst total sprint number was reported to have the highest variation at 30%. Similar levels of variation have also been found to occur for high-intensity activities in other team sports such as, rugby league (Kempton et al., 2013) and Australian rules football (Kempton et al., 2014). Of the physical performance measures that have been analysed, total distance has been reported to be a relatively stable physical measure in soccer (Rampinini et al., 2007) and in the different football codes (Kempton et al., 2013), particularly when total distance was expressed relative to time spent on the field (m/min^{-1}) (Kempton et al., 2014). However, it is important for further investigations to continue to analyse a wide selection of physical performance measures in soccer, such as total distance, to determine whether similar levels of variation occur across different levels of competition. In comparison, investigations analysing technical performance variability, have yet to be analysed in soccer, despite recent research highlighting the importance of technical performance measurements (Bradley et al., 2013; Russell et al., 2012). Currently, the only team sport that has investigated variability in technical actions is in Australian rules football (Kempton et al., 2014). This data reported that key technical measures (i.e. possession, kicks, handballs and player data rankings), though appearing as sensitive performance measures, displayed high levels of match-to-match variation (33-55%). It is therefore important for technical performance measures to be quantified to better understand the potential variation that surrounds individual measures. Determining the variability associated with both physical and technical performance components in soccer would enable greater understanding for research such as in field tests (i.e. Loughborough intermittent shuttle test, Yo-Yo intermittent endurance test) (Nicholas et al., 2000) and predicting statistical power in research (Atkinson, 2003).

While match-to-match variation in physical performance measures have been reported for soccer (Rampinini et al., 2007; Gregson et al., 2010) there have been no studies that have investigated the variability in physical and technical performance within-game for elite soccer players. This is despite the growing research that uses semi-automatic computerised tracking technologies to examine match-related fatigue (Mohr et al., 2010), develop tactical strategies (Bradley et al., 2011) and analyse work-to-rest ratios (Mascio & Bradley, 2013). The single investigation that has analysed technical and physical measures in combination has been by Weston et al., (2011), who used Premier League referees and reported low variability for mean distance from fouls and mean distance from ball (m). Researchers who select performance measures without understanding the associated variability can lead to the misinterpretation of performance changes due to the 'noise' surrounding a true signal. As a result, intervention work can have a negative impact if the information is incorrect. It is therefore important for practitioners and researchers to understand the variability associated with physical and technical performance measures to better inform decision-making and performance related objectivity.

2.6 Biological Measurements & Performance Data

Elite soccer players are subject to a high number of competitive fixtures per season, including domestic, continental and international matches (>60). As a consequence teams will often play multiple games within a week (Nedelec et al., 2012). During periods where the schedule is particularly congested (i.e. two matches per week over several weeks), the recovery time allowed between two successive matches is only 2–3 days, which may be insufficient to restore normal homeostasis within players (Nedelec et al., 2012). If the recovery time between games is limited there is an increased risk of muscle "overload" that can result in muscle damage, underperformance and ultimately injury (Lazarim et al., 2009). Such statements are supported by studies that have reported that >72 hours are required to achieve pre-match values in a subsequent game for physical measures (muscle soreness, isokinetic knee extension, countermovement jump), as well as normalizing muscle damage and inflammation among elite (Andersson et al., 2008; Ispirlidis et al., 2008), and sub-elite players (Ascensão et al., 2008; Magalhães et al., 2010). Ekstrand et al., (2004) showed that players who 'underperformed' at the 2002 FIFA World Cup had played a mean of 12.5 matches during the 10 weeks before the event. In comparison, those who performed above expectations had only played nine matches over the same period. In addition, Dupont et al., (2010) reported a 6.2-fold higher injury rate in players who played two matches per week compared with those who played only one match per week. Developments in the theoretical approach and practical delivery of player monitoring strategies is therefore vital in ensuring players are recovering appropriately between training and matches.

The intermittent nature of soccer matches requires elite players to perform frequent unpredictable changes in intensity that range from static pauses to maximal sprints (Drust et al., 1998). The muscular overload associated with these demands puts an obvious strain on the neuromuscular and metabolic systems (Bangsbo, 1994; Andersson et al., 2008; Lazarim et al., 2009). The impact of match-play on the neuromuscular system is partly associated with the eccentric muscle contractions required for performance. These have the potential to lead to micro-trauma in both the muscle and connective tissue (Byrne et al., 2004; Howatson et al., 2009; Lazarim et al., 2009; Nedelec et al., 2013). The severity of the muscle damage can vary from micro-injury to a small number of fibres to disruption of a whole muscle (Lazarim et al., 2009). The demands of training and match-play have also been found to affect biochemical parameters such as, uric acid and urea concentration, with reported increased levels after a soccer match (Bangsbo, 1994). In addition, muscle glycogen, which is considered one the most important substrates for energy production, has also been found to be depleted in muscle fibres after matches (Bangsbo et al., 2006; Krustrup et al., 2006; 2011). The reduced availability in muscle glycogen has been linked to the reductions in sprint performance (2% slower post game) (Mohr et al., 2002); jump performance (reduced by 4% post game) (Rastaad et al., 2002); and isokinetic knee extension and flexion (reduced by 9% post game) (Andersson et al., 2002) that occur immediately after training and matches (Andersson et al., 2008; Ispirlidis et al., 2008). Additionally, oxidative stress markers and antioxidants are reported to increase following a soccer match (Ascensao et al. 2008; Magalhaes et al. 2010). A clearer understanding of the impact and time course of these physiological changes induced by the elite level soccer demands will help the designing and development of more effective strategies to accelerate recovery (Andersson et al. 2008).

Research protocols that aim to study recovery in soccer have suggested that specific performance variables, hormonal, subjective wellness scales and muscle damage markers are all potentially important components of a highly efficient monitoring of recovery (Bishop et al. 2008). Previous studies that have monitored neuromuscular fatigue have used countermovement jumps (Andersson et al., 2008; Mohr et al., 2010), single sprints (Rampinini et al., 2007; Ispirlidis et al., 2008) and repeated-sprint ability to measure the time course of recovery (Nedelec et al., 2012). Findings from such investigations have suggested elite soccer players recover more quickly than non-elite players, who have a larger range of performance decrements (e.g., strength, jump and sprint performance) and longer recovery periods (Ascensao et al. 2008; Fatouros et al. 2010;

Magalhães et al. 2010). Research analysing hormonal and muscle enzyme measures also have the potential to assist in the assessment of both the immediate and the longer term response of the body following intense exercise (Brancaccio et al., 2007). Changes in hormone levels have been reported following a soccer match with an increased catabolic state (i.e. cortisol levels) observed throughout the first 48 hrs of the recovery period (Ispirlidis et al. 2008; Kraemer et al. 2004). Additionally, the use of oxidative stress markers and antioxidants has also been used as a monitoring tool following a soccer match (Ascensao et al. 2008; Magalhaes et al. 2010). However, comparisons across studies are difficult as the markers employed in each investigation have been different (i.e. total antioxidant status (TAS) and Thiobarbituric acid reactive substances (TBARS)) (Nedelec et al., 2012). The enzymes and proteins commonly analysed after exercise-induced muscle damage include creatine kinase (CK), lactate dehydrogenase, aspartate transaminase and myoglobin (Ehlers et al., 2002; Baird et al., 2012). Of these markers, plasma CK activity is considered to be the best indicator of exercise severity and its effect on tissues (Chevion et al., 2003; Lazarim et al., 2009).

Creatine Kinase is a compact enzyme that is found in both the cytosol and mitochondria of tissues where energy demands are high (Baird et al. 2012). Following muscle damage, increased membrane permeability results in the release of CK from the muscle cell into the plasma (Brancaccio et al., 2007). The plasma levels reflect total circulating CK, with post-exercise increases believed to be representative of CK release from damaged muscle tissue (Hunkin et al., 2013). As result of this, Creatine Kinase has received interest within applied research in sport due to CK levels remaining elevated for several days following exercise. This is in comparison to other proteins (i.e. myoglobin) that normalize before 24 hours post-exercise (Ascensão et al., 2008; Magalhães et al., 2010). This prolonged elevation of CK is thought to enable the marker to be used as a potential tool to monitor player recovery status between soccer matches (Coehlo et al., 2011; and Lazarim et al., 2009). For example, previous findings have reported that CK concentration can rise to between 70% and 250% above baseline, with a peak in concentration at 24–48 hours after a match and a return to baseline between 72 and 120 hours after (Andersson et al., 2008; Ispirlidis et al., 2008; Nedelec et al., 2012; Lazarim et al., 2009). It is suggested that increases in plasma CK are related to the intensity, duration and type of exercise (e.g. Apple and Rhodes, 1988; Guzel et al., 2007). Furthermore, Coehlo et al., (2011) and Lazarim et al., (2009) have suggested that CK can be used as an early indicator of player fatigue and therefore a potential tool to monitor player recovery status within soccer. This is despite other research suggesting that the physiological understanding of the reasons for increases in CK following training or matches are not fully understood in elite soccer (Andersson et al., 2008). At present, a considerable proportion of CK investigations have observed non-elite male populations (Ascensao et al. 2008; Fatouros et al. 2010; Magalhaes et al. 2010;

Andersson et al., 2008) with fewer studies in elite male soccer (Silva et al., 2013; Lazarim et al., 2009). The current understanding of CK response in elite soccer highlights the importance for further research to be conducted in such soccer populations to evaluate the effectiveness of CK as a monitoring tool.

Research in elite team sports has been somewhat limited with previous investigations analysing CK damage using pre and post match testing methods (Nedelec et al., 2012). Direct attempts to link physical performance indicators to CK concentrations are very limited in the literature (Hunkin et al., 2013; Johnstone et al., 2013). This is despite the developing access to semi-automatic computerised tracking technology capabilities in elite soccer (Bradley et al., 2009). At present there has only been a single study that has investigated physical performance indicators in soccer with creatine kinase (Thorpe & Sunderland, 2012). The study by Thorpe & Sunderland, (2012) found significant correlation between CK and the number of sprints performed during a semi-professional soccer match. While providing useful information, the study was limited to a single match and observed a non-elite population who have lower resting CK values in comparison to elite athletes (Brancaccio et al., 2007; Nedelec et al., 2012). It is also reasonable to assume that the physiological stress imposed by a lower-standard match will not replicate the stress of an elite soccer match (Silva et al., 2013). Research in other team sports analysing CK and performance measures have reported mixed findings. For example, Smart et al., (2007) suggested that high levels of CK in rugby union players (926.8 ± 204.2 IU) are most likely related to high-intensity activities that are included in match-play. Contrastingly, research by McLellan et al., (2010), showed no significant relationships between total distance in rugby league players either following one half of play or over the full match. Whereas, alternative performance measures such as the coach's performance ratings in Australian Rules football were found to significantly decrease with elevations in pre-match CK (Hunkin et al., 2013). These findings highlight the importance for practitioners and scientists to have valid performance measures that can be used in player monitoring systems to guide future training and recovery (Hunkin et al., 2013). At present there are no studies within elite soccer that have shown a relationship between the activities completed within a soccer match using physical performance measures and CK concentrations post-match. There is therefore, a growing requirement for longitudinal studies to analyse an elite soccer population to examine the relationships between physical performance measures and blood CK to provide greater understanding on the demands placed on elite soccer players.

2.7 Pattern Analysis

Traditional methods of analysis have typically used frequency of event occurrences (e.g., number of passes made in a certain area of the field or how many times a team committed an error) as an indicator of performance (Borrie et al., 2002). Analysing the event frequency of a performance variable has provided valuable insights into understanding the interactions between different technical, tactical, mental and physiological factors associated to soccer (Drust et al., 2007; Carling et al., 2009). Research has not only been able to produce information on typical physical and technical activity profiles of elite soccer players, but provide insights into the effect of ball possession on physical and technical profiles (Bradley et al., 2013), the effect of substitute players (Bradley et al., 2014) and also the use of entries into the penalty area as a performance indicator (Ruiz-Ruiz et al., 2013). The findings have provided, and will continue to provide, important information for coaches, athlete's and researchers (Sarmento et al., 2010). However, if one accepts the argument that sport performance consists of a complex series of interrelationships between a wide variety of performance variables, then simple frequency data may only provide superficial information and cannot necessarily capture the full complexity of a performance (Borrie et al., 2002). There is thus a growing requirement for a more rigorous approach to the collection of data that can provide quantifiable evidence that details the complex interrelationships that make up a soccer performance (Camerino et al., 2012; Jonsson et al., 2006). Furthermore, if performance analysis is to continue to advance the understanding of sports performance, then it must continue to explore different methods of collecting and analysing data (Sarmento et al., 2010).

One particular aspect of soccer performance that has yet to receive much interest is the study of temporal structures and the interrelationships between the discrete events that make up a performance (Borrie et al., 2002). This form of analysis was developed and tested extensively, outside of sport, in research focusing on human behaviour and social interaction (Jonsson, 1997, Magnusson, 1996, 2000). The analysis is conducted using an observational software package called THÈME© (Magnusson, 1996, 2000) that uses a specifically developed algorithm to determine repeated temporal and sequential structures in real-time behaviour records (Borrie et al., 2002). The method is based on the assumption that complex streams of human behaviour have a sequential structure that cannot be fully detected through unaided observation or with the help of standard statistical and behaviour analysis methods (Jonsson et al., 2006). A temporal pattern (T-pattern) is essentially a combination of events in which the actions occur in the same order with the real-time differences between consecutive pattern components remaining relatively invariant (Borrie et al., 2002). This form of analysis has been able to capture important characteristics of the temporal organisation of a number of behavioural streams. For example, Magnusson (2000) identified patterns in 'head tilts', 'glances' and 'commands' within human behaviour. Additionally, Anguera (2007) reported that the THÈME© software is able to filter data sets to find relevant T-patterns according to the allocation of qualitative or quantitative criteria and the objectives in the study. Research using T-pattern analysis has also been used effectively in sport to analyse tactical and technical performance in basketball (Fernandez et al., 2009), judo (Gutierrez et al., 2011), swimming (Louro et al., 2010) and karate (Lapresa et al., 2011). For instance, work by Prieto et al., (2014) identified technical errors in student's technique performing a specific judo movement and was able to provide recommendations on technique improvement based on the student's sequential actions. Whereas, Louro et al., (2010) reported that the swimmers who presented greater stability in swimming patterns could obtain better performance results. Overall, the results illustrate the relevance of T-pattern analysis and its potential to enhance our understanding of elite soccer performance by providing new insights into the complexities of soccer match-play.

Soccer specific research that has used T-pattern analysis is somewhat limited in comparison to other sports. Studies that have investigated soccer performance have primarily focused their attention on tactical components of the game (Borrie et al., 2002; Lapresa et al., 2013; Sarmento et al., 2010). Camerino et al., (2012) identified a reoccurring attacking sequence of play used by an elite Spanish football team that consisted of the central defensive zone starting the play, before shifting to the wide right and wide left midfield areas, and then entering the offensive zone. Furthermore, Sarmento et al., (2011) revealed the existence of 787 different T-patterns from a sample of 12 soccer games for the same Spanish club analysing counter attacking play. The findings from this research show that soccer performance contains a large number of temporal patterns (Borrie et al., 2002). Yet despite such findings highlighting the huge potential of the analysis, there remains very little interest in using such approaches to investigate physical performance. There is currently only a single pilot study that has investigated the physical activity of an elite level soccer player using THÈME© (Bloomfield et al., 2005). Within this study Bloomfield et al., successfully identified a number of different patterns of movement in an English Premier League player. For example, the study identified a complex pattern of skips sideways left at low intensity (perhaps preparing for another high intensity burst), turns left and jogs forward at low intensity and gradually increases pace into a run changing direction by moving diagonally left. The findings from the study led Bloomfield et al., to suggest the potential impact this research could have on the applied setting for specific physical conditioning practices. The limitations to this study, however, were that the study only collected data for a single 15-minute period and only selected one player for analysis. In order to provide insights on the patterns associated to the physical activity of elite soccer players then a comprehensive data set would be required for analysis. This would therefore provide a better representation of the physical movements that elite players perform in matches and would further research into establishing the physiological demands, and also assist in the enhancement of coaching and physical conditioning practices.

2.8 Summary

In summary, this section described the advancements in semi-automatic computerised tracking technologies, which now permit more complicated sets of performance data to be evaluated more quickly and accurately. These technological developments provide greater insights into the physical and technical demands of soccer match-play using both between and within-game data points. The importance of quantifying the variation surrounding physical and technical performance measures using these periods have also been highlighted to ensure accurate data analysis. Such technological advancements used in combination with biological markers or new forms of performance analysis have the potential to provide new insights into the complexities of soccer performance and will be investigated in the current thesis.

3.0 An Investigation into the Variation in Elite Soccer Player's Physical Match Performance

3.1 Introduction

The emergence of semi-automatic computerised tracking systems has enabled more complicated sets of performance data to be evaluated quickly and accurately (Drust *et al.,* 2007; Di Salvo *et al.,* 2009). There have been a number of studies that have, as a consequence of this ability, described the match activity of elite soccer players (Di Salvo *et al.,* 2006; Krustrup *et al.,* 2005). It is well established in the literature that an average player will cover between 8 - 13 km during a match (Di Salvo et al., 2009; Bradley et al., 2009) with brief high-intensity actions accounting for 8-10% of this distance. These specific actions are considered a crucial element of soccer performance (Bradley *et al.,* 2010; Carling et al., 2012). Physical performance variables in soccer match-play are not stable properties and are subject to large within (player) and between-match variation (Atkinson, 2003; Gregson et al., 2010). This can be as a consequence of changes in the tactical role of players (Mohr et al., 2003; Rampinini *et al.,* 2007) and the self-regulation of physical efforts (Drust *et al.,* 2007; Di Salvo *et al.,* 2009).

Research analysing match-to-match variability in English Premier League soccer players has reported values of 16.2% for high-speed running and 30.0% for the total number of sprints (Gregson et al., 2010). The variability in performance has previously been quantified in other sports such as swimming and distance running events. These types of events are simply, competitive timed bouts of maximal effort. The low coefficient of variation (CV) values reported (1.2-4.2%) in these sports has enabled researchers and practitioners to detect real systematic changes in performance (Hopkins, 2001; 2005). The multitude of different components that interact in soccer performance mean levels of variation will be considerably higher. The implications of such large variation in soccer means that meaningful changes in performance are harder to detect. This would suggest that multiple observations and large data samples would be required to accurately determine an individual's maximal capacity to perform (Batterham & Atkinson, 2005).

While the match-to-match variation in physical activity measures have been reported for soccer there have been no studies that have investigated the variability of physical performance using within-game time periods (1, 5, 15-minutes). This is despite several studies focusing on within-game data samples to investigate the occurrence of transient and accumulated fatigue (Bradley et al., Mohr et al., 2010; Di Mascio & Bradley et al., 2013). These previous studies have found decrements in high-intensity running after the most intense period of activity within the game and at the end of the match for both domestic and international players (Mohr et al., 2003; Bradley et al. 2009). This suggests that players experience temporal and accumulative fatigue within soccer match-play. Such changes in the within-game activity profile may also be a consequence of the inherent variability associated with these performance measures. For example, a reduction in high-speed running distance after the most intense period could in fact be a consequence of variation in the data rather than deterioration in performance due to temporal fatigue. Such misinterpretation of physical performance measures in soccer match-play could have implications for both an understanding of performance and for physical training programmes.

The aim of this investigation was therefore, to quantify the within-game variability of a selection of physical variables across a number of time periods in soccer match-play.

3.2 Methods

The following section of the methodology has been divided into five sub-sections in order to provide the reader with the necessary background and methodological information for the chapter. The opening two sections will provide the reader with information regarding the subjects and the data collection process used in the investigation. The third section will describe how the Prozone® system collects performance data from soccer matches and is produced. The fourth section, will then provide detail on the validity and reliability of the Prozone® system. The final section will then give information on the statistical analysis employed for the study.

The most common approaches used to analyse soccer performance are indirect methods, due to the restricted access to elite players and the rules and regulations upheld by club's respective soccer governing bodies (Impellizeri, 2005; Reilly, 2003). Previous research has used work-rate or motion analyses to investigate the physiological demands of soccer (Reilly & Thomas, 1978; Drust et al., 1998; Krustrup et al., 2005). This method of analysis is traditionally limited to a specific player for the duration of a game and therefore limits the researcher's potential data collection process as multiple player analysis is highly time consuming. More recently, commercial systems in use within the professional game have employed multiple cameras placed at strategically elevated positions in the stands; and provide a comprehensive collection of physical, technical and tactical data from all players at each game (Drust et al., 2007). This form of analysis is associated with significant costs and prohibits these techniques to be employed by an individual research scientist. In order to collect a suitable data sample this investigation utilised the respective elite professional soccer team's commercial system (Prozone®, Leeds, England). A limitation of using the 3rd party commercial system was that Prozone® collected the data and then systematically analysed it using proprietary software to provide an interactive coaching and analysis tool. This meant that the data collection process was completed by a third party, i.e. Prozone® and was not under the control of the researcher. The data was only available postproduction.

3.2.1 Subjects and Match Data

Match performance data was produced using a computerised semi-automatic multi-camera image recognition system (Prozone®, Leeds, England). Physical competitive match data were collected from 14 soccer players who played for an elite professional soccer team competing in the English Premier League during the 2010-2011 domestic season. A total of 212 individual match observations were undertaken on outfield players. Analysis was only undertaken on outfield players due to the specialised role of the goalkeeper. The number of games completed by players in the squad over the 2010-2011 season ranged from 1 to 31 (14 games ± 8). In an attempt to provide a true representation of an elite level squad only players who were considered a part of the 'first team' by the respective coaches were accepted for inclusion in the study. The minimum number of completed matches by a 'first team player' were >7 completed matches (i.e. 90-minutes). Due to the occurrence of injuries, substitutions and suspensions through the data collection period the overall sample size was restricted. The study conformed to the ethical standards of the researcher's university ethics committee. Head of the Sport Science and Medical Departments granted informed consent on behalf of the players at the respective club.

3.2.2 Data Collection and Analysis

Players were assigned to the same playing positions as those identified in previous literature (Di Salvo et al., 2009; Gregson et al., 2010). The specific breakdown of the data between positions were; central defender (3 players - 66 match observations); wide defender (3 players - 37 match observations); central midfielder (4 players - 59 match observations); wide midfielders (2 players – 29 match observations) and attackers (2 players - 21 match observations). Players' activities were coded into the following categories and speed thresholds: standing (0-0.6 km/h^{-1}), walking (0.7-7.1 km/h^{-1}), jogging (7.2-14.3 km/h^{-1}), running (14.4-19.7 km/h^{-1}), high-speed running (19.8-25.1 km/h^{-1}), and sprinting (>25.1 km/h^{-1}). The speed categories are the same as previous investigations using semi-automatic tracking systems (Di Salvo *et al.,* 2009; Gregson *et al.,* 2010). The following physical variables were selected for analysis: 1. Total Distance Covered (TD), 2. Total High-Speed Running Distance (THSRD) (running speed 19.8 km/h and greater over a 0.5s time interval), 3. Total High-Speed Running Number (THSRN) (running speed 19.8 km/h and greater over a 0.5s time interval), 4. High-Speed Running Distance (HSRD) (running between 19.8 to 25.2km/h), 5. High-Speed

Running Number (HSRN) (running between 19.8 to 25.2km/h), 6. Total Sprint distance (TSD) (average running speed > 25.2 km/h^{-1} over a 0.5s interval), 7. Total Sprint number (TSN), 8. Average Speed (AVE) is calculated by the mean per second speed of a player. Average speed was included in the investigation as it provided a novel measure to compare between the volume of physical effort and rest periods. Accelerations and decelerations were also selected for analysis as these parameters may represent additional energetically demanding movements. These may also be important and novel indicators of high-intensity physical performance. The acceleration and deceleration thresholds selected for analysis were: 9. Total number of accelerations (TAC) (1+ m/s^2), 10. Total number of high accelerations (HACC) (4+ m/s^2), 11. Total number of medium accelerations (MACC) (2.5-4 m/s^2), 12. Total number of low accelerations (LACC) (1-2.5 m/s^2), 13. Total number of decelerations (TDEC) (1+ m/s^2), 14. Total number of high decelerations (TDEC) (4+ m/s^2), 15. Total number of medium decelerations (MDEC) (2.5-4 m/s^2), 16. Total number of low decelerations (LDEC) (1-2.5 m/s^2).

3.2.3 Prozone® System Overview

The Prozone® system is a 3rd party post-match analysis service provider that collects match performance data using computerised semi-automatic multi-camera image recognition technology. Each match is captured by eight colour cameras that are positioned in each of the stadiums that use the Prozone® system. The data is collected and processed independently by Prozone® and uses predefined Prozone® thresholds to generate the match performance data. This process can take >24 hours post-match to finalise. Due to the procedure being completed internally, match performance data is only available in the Prozone® post-production format that reports data at a minimum unit of 0.5 seconds and only provides raw data exports at 1, 5 and 15-minute time periods. The functionality of the Prozone® products also limits the researchers ability to manipulate the data through the production tools capabilities (Prozone 3®, Matchviewer® and Prozone Trend®).

The formats of post match files were dependent on the technological installation at the stadia where the game took place. In the event of a stadia not having the required technological installation, only technical performance data was available for post-match analysis and would be provided in a Prozone Matchviewer® compile. This compile would integrate video and technical performance data together. Matches that were played in a Prozone® installed stadium would receive a Prozone 3® compile, which would also include physical performance data. Both files, once downloaded, could be accessed via Prozone Desktop® software that were installed on a Windows® (Microsoft, Redmond, USA) supported laptop or computer. In addition, Prozone® also provided a comprehensive database software package called Prozone Trend® that stored all Prozone 3® and

Matchviewer® data from the season. These software tools enabled the researcher to access the match performance data via an interactive combination of game footage, physical and technical data, full-pitch animation and multi layer graphics. All match performance data were exported using the Prozone Trend® database at both total game and within-game periods (1, 5, 15-minute) through a series of data filtering options. The exports were in a Microsoft Excel® CSV format and were then analysed using customised Microsoft Excel spread sheets (Microsoft, Redmond, USA).

The validation and reliability testing of the Prozone® system could not be independently performed for the purposed of this thesis. This was due to the large costs associated to the renting of the system as well gaining access to an elite professional soccer stadium. The Prozone® system has previously been validated by Di Salvo et al., (2006), who quantified the displacement velocities during match-related activities relative to data obtained using timing gates. More recently, Di Salvo et al., (2009) further analysed the same data set using a more detailed methodology (mixed model repeated measures analysis and the percentage coefficient of variation) to provide an overall indication of the systematic and random error between the two methods of observation. A 0.4% coefficient of variation (CV) was observed indicating that Prozone® serves as a highly accurate system for quantifying match-related displacement velocities in soccer. In addition, Di Salvo et al., (2009) tested for reliability and objectivity of the Prozone® system by analysing two outfield players on two separate occasions by two different quality control personnel from Prozone®. The coefficients of variation and associated 95% confidence intervals (95% CI) that were reported showed that the Prozone® system was a reliable system for measuring match activity in soccer (Gregson et al., 2010).

3.2.4 Prozone® Video Capture & Physical Data Process

The Prozone® system and capturing process used in this thesis is consistent with previous investigations analysing match physical performances of English Premier League players (Bradley et al., 2009; 2010; Di Salvo et al., 2006; 2009; Gregson et al., 2010). All outfield players' movements were captured during each game by eight colour cameras (Vicon® Surveyor Dome SVFT-W23, Oxford, UK) that were positioned in each of the stadiums at roof height. Each of the cameras were individually positioned, fixed for optimal zoom, and field of vision to guarantee long-term stability of the capture system. The position of the cameras allowed for every area of the pitch to be covered by at least two cameras to address issues of accuracy, occlusion, resilience, and resolution.

The 8 individual video files created from the cameras were then analysed using match-analysis software (Stadium Manager, Prozone® Sports Ltd, Leeds, UK) to determine image co-ordinates and continuous trajectories for each player. The data were then combined to produce a single data set and used Kalman (1960) filters to ensure object speed; directional data and erroneous objects (i.e. debris on the field) were corrected or removed. Every 0.1 second period of each player's trajectory were then delimited by x and y co-ordinates measured in meters from the centre spot on the pitch. Using Pythagoras theorem Prozone® then calculated the distance covered within each 0.1 seconds trajectory with the average velocity across the 0.5 seconds period computed from the distance covered over time (Di Salvo et al., 2009).

In the final stage, a Prozone® quality control process checks were conducted on each player (by start position, position during game and correspondence with an outside broadcast feed) to ensure that the tracking software did not confuse different players in moments of congestion within small areas (e.g. set pieces, goal celebrations). The percentage of trajectories that was derived from automated tracking (without manual correction) were dependent on the amount of occlusion, which can range from 38% to 97% of a match (average around 58%) (Di Salvo et al., 2009). The completed match physical performance data were then compiled onto a Prozone 3® application and made available for export at a minimum reporting unit of 0.5 seconds. Data from Prozone 3® files could also be exported from Prozone Trend®. A detailed description of how the technical data is process can be found in 4.2.3 of the thesis.

3.2.5 Statistical Analysis

The within-game data was collected using the three within-game time periods (1, 5, 15-minutes) available for export from the Prozone Trend® system. Within-game data were arranged by physical variable (see page 3.2.2 for list), player (subject), playing position, time period to calculate the percentage coefficient of variation (%CV; Hopkins, 2004) and associated 95% confidence intervals (CI) were calculated for each variable. Between-game data were also collected from Prozone Trend® system and then arranged by physical variable, playing position and player (subject) to calculate CV values. Data were initially log transformed and a constant of 10 was added to all of the data. Each player's data was analysed through a one-way within ANOVA using SPSS version 21 (Chicago, Illinois, USA) to find the square root of mean squares error from the ANOVA output table and then back-transformed to get a ratio CV. The coefficient of variation values for each individual player were then grouped and presented as the mean ± standard deviation. Confidence Intervals (CI's) at 95% CI were calculated using the inverse chi square distribution from the one-way within ANOVA output and then back transforming the values into a percentage.

3.3 Results

The following results are structured into three sub-sections. The first sub-section provides the overview of variables previously reported in the literature such as High-Speed Activity & Total Distance Covered. The second and third sections provide insight into two novel areas of research, Accelerations & Decelerations, and iii) Average Speed.

3.3.1 High-Speed Activity & Total Distance

Table 3.1 Between-Game Variation (CV%) and 95% CI in Distance Covered and Activity Frequency (n=14).

Physical Performance Variables	%CV	95% CI
Distance Measurements:		
Total Distance	3.2 ± 1.5	2.8% - 3.8%
Total High-Speed Running Distance	25.1 ± 9.1	21.3% - 30.4%
High-Speed Running Distance	23.2 ± 9.1	19.9% - 28.2%
Total Sprint Distance	36.5 ± 14.5	30.9% - 44.7%
Number Measurements:		
Total High-Speed Running Number	21.5 ± 8.5	18.4% - 26.0%
High-Speed Running Number	21.2 ± 7.8	18.1% - 25.6%
Total Sprint Number	32.9 ± 12.8	27.9% - 40.1%

Total high-speed running distance = (≥5.5m/s); Total high-speed running number = (≥5.5m/s); High-speed running distance = (>5.5 – 7m/s); High-speed running number = (5.5 - 7m/s); Total sprint distance = (≥ 7m/s) Total Sprint Number (≥ 7m/s) (mean ± SD).

The lowest between-game variation was observed for the total distance (Table 3.1). Higher degrees of variation were observed for high-speed activities (21.2-36.5%). The variables that described the most explosive actions (total sprint distance and total sprint number) were found to have the highest variation between-game with values of 36.5% and 32.9% respectively. Distance and frequency measures showed similar levels of variation for all high-speed activities.

Table 3.2 Within-game Variation (CV%) and 95% CI in High-Speed Activity & Total Distance Covered (n=14).

Physical Performance Variables	**1-minute Periods (n=14)**	**5-minute Periods (n=14)**	**15-minute Periods (n=14)**
Distance Measurements:			
Total Distance	41.2 ± 10.9 (40.7% - 41.7%)	15.6 ± 4.0 (15.2% - 16.0%)	8.7 ± 1.5 (8.4% - 9.1%)
Total High-Speed Running Distance	254.6 ± 25.2 (250.0% - 259.3%)	115.6 ± 31.7 (111.9% - 119.5%)	51.6 ± 15.5 (49.0% - 54.4%)
High-Speed Running Distance	212.9 ± 20.0 (209.2% - 216.6%)	103.7 ± 28.4 (100.4% - 107.1%)	46.2 ± 13.8 (43.9% - 48.6%)
Total Sprint Distance	160.8 ± 29.8 (158.3% - 163.4%)	222.8 ± 24.7 (214.3% - 231.8%)	122.0 ± 52.1 (114.9% - 130.0%)
Number Measurements:			
Total High-Speed Running Number	70.9 ± 12.3 (69.9% - 71.8%)	115.6 ± 12.8 (111.9% - 119.5%)	43.4 ± 10.6 (41.3% - 45.7%)
High-Speed Running Number	76.2 ± 12.8 (75.2% - 77.3%)	79.8 ± 12.3 (77.4% - 82.3%)	46.2 ± 10.2 (43.9% - 48.6%)
Total Sprint Number	30.5 ± 7.7 (30.2% - 30.9%)	84.0 ± 11.9 (81.5% - 86.7%)	81.8 ± 21.9 (77.4% - 86.7%)

Total high-speed running distance = (≥5.5m/s); Total high-speed running number = (≥5.5m/s); High-speed running distance = (>5.5 – 7m/s); High-speed running number = (5.5 - 7m/s); Total sprint distance = (≥ 7m/s) Total Sprint Number (≥ 7m/s) (mean ± SD).

Table 3.2 shows the within-game variation found across the high-speed activity categories and total distance for different within-game time periods. Within-game variation in high-speed activity across the three different time periods was greater than that observed between games. Total high-speed running distance, high-speed running distance, and total distance showed an increase in variation as the time periods became smaller. Total high-speed running number, total sprint distance and total sprint number demonstrated greater variation at 5-minute than at 1-minute. Variables that measured the number of actions (i.e. sprint number) were found to be lower in variation compared to variables measuring distance covered (i.e. sprint distance). The lowest variation for high-speed activity was found for total sprint number at 1-minute time periods (30.5%). Total high-speed running distance (<254.6%) and total sprint distance (<228.8%) were found to have the highest variation for all high-intensity variables at 1 and 5-minute periods respectively. Total distance showed the lowest variation across all time periods and was lowest at

15-minutes (8.7%).

3.3.2 Accelerations & Decelerations

The TACC, LACC, TDEC and LDEC and showed <10% variation between-games (Table 3.3). The highest level of variation between games was observed for HACC and HDEC with values of 39.7% and 60.0% respectively. The second highest variation reported in a measure was found in MACC (17.1%) and MDEC (21.2%). The lowest speed thresholds (LACC and LDEC) were associated with the lowest variation of 7.3%.

Table 3.3 Between-Game Variation (CV%) and 95% CI in Acceleration & Decelerations Profiles (n=14).

Physical Performance Variables	CV%	95% CI
Total Number of Measurements:		
TACC	8.7 ± 1.5	7.5% - 10.4%
TDEC	8.7 ± 1.6	7.5% - 10.4%
High Threshold Measurements:		
HACC	39.7 ± 10.6	33.6% - 48.7%
HDEC	60.0 ± 16.1	50.2% - 74.6%
Medium Threshold Measurements:		
MACC	17.1 ± 4.4	14.7% - 20.6%
MDEC	21.2 ± 4.1	18.1% - 25.6%
Low Threshold Measurements:		
LACC	7.3 ± 1.1	6.3% - 8.7%
LDEC	7.3 ± 1.6	6.3% - 8.7%

TAC = Total number of accelerations; HACC = Total number of high accelerations; MACC = Total number of medium accelerations; LACC = Total number of low accelerations; TDEC = Total number of decelerations; HDEC = Total number of high decelerations; MDEC = Total number of medium decelerations; LDEC = Total number of low decelerations (mean ± SD).

Table 3.4 Within-Game Variation (CV%) and 95% CI in Acceleration & Decelerations Profiles (n=14).

Physical Performance Variables	1-minute Periods (n=14)	5-minute Periods (n=14)	15-minute Periods (n=14)
Total Number of Measurements:			
TACC	72.1 ± 5.9 (71.2 - 73.1%)	30.5 ± 3.4 (29.8% - 31.4%)	18.6 ± 2.1 (17.7% - 19.5%)
TDEC	75.6 ± 5.0 (74.6% - 76.6%)	32.2 ± 4.0 (31.4% - 33.1%)	19.9 ± 2.3 (19.0% - 20.9%)
High Threshold Measurements:			
HACC	11.1 ± 0.02 (10.9%- 11.2%)	49.7 ± 0.06 (48.4% - 51.2%)	87.6 ± 0.08 (82.9% - 93.0%)
HDEC	6.5 ± 2.0 (6.5% - 6.6%)	30.0 ± 4.9 (29.3% - 30.8%)	71.7 ± 12.8 (67.9% - 75.8%)
Medium Threshold Measurements:			
MACC	62.5 ± 7.0 (61.7% - 63.4%)	75.1 ± 5.8 (72.9% - 77.4%)	39.3 ± 6.6 (37.5% - 41.4%)
MDEC	53.7 ± 7.8 (53.1% - 54.4%)	84.5 ± 4.7 (82.0% - 87.2%)	46.3 ± 9.6 (44.1% - 48.8%)
Low Threshold Measurements:			
LACC	65.9 ± 5.5 (65.0% - 66.7%)	27.8 ± 3.1 (27.1% - 8.5%)	16.8 ± 2.2 (16.0% - 17.6%)
LDEC	69.4 ± 4.6 (68.5% - 70.4%)	29 8 ± 3.5 (29% - 30.6%)	18.2 ± 2.1 (17.4% - 19.1%)

TAC = Total number of accelerations; HACC = Total number of high accelerations; MACC = Total number of medium accelerations; LACC = Total number of low accelerations; TDEC = Total number of decelerations; HDEC = Total number of high decelerations; MDEC = Total number of medium decelerations; LDEC = Total number of low decelerations (mean ± SD).

Table 3.4 shows the different within-game time periods for the acceleration and deceleration profiles. The overall variability was generally high across each of the within-game time periods with the greatest variation generally found at 5-minute in MDEC (84.5%). In comparison, both HACC (11.1%) and HDEC (6.5%) had lower levels of variation at 1-min. At the 15-minute periods TACC, TDEC, LACC and LDEC showed <20% variation. Variation in MACC and MDEC were greater at 5-minutes, whereas HACC and HDEC were found to be highest at 15-minute. A noticeable trend in both the acceleration and deceleration profiles were the doubling in size of the variability with every speed threshold increase except MACC and MDEC.

3.3.3 Average Speed

Table 3.5 Between-Game Variation (CV%) and 95% CI in Average Speed (n=14).

Physical Performance Variables	CV%	95% CI
Average Speed	4.6 ± 0.8	3.9% - 5.4%

Total Distance = (>0m/s); Average Speed = (m/s) (mean ± SD).

Between-game variation for average speed (4.6%) was lowest amongst all physical variables. Within-game variations for average speed was higher (<37.8%), particularly for the different time periods. The variability was found to be lowest at 15-minutes (8.7%) and highest at 1-minute intervals (37.8%).

Table 3.6 Within- Game Variation (CV%) and 95% CI in Average Speed (n=14).

Physical Performance Variables	1-minute Periods (n=14)	5-minute Periods (n=14)	15-minute Periods (n=14)
Average Speed	37.8 ± 7.6 (37.4% - 38.3%)	15.6 ± 4.0 (15.2% - 16.0%)	8.7 ± 1.5 (8.4% - 9.1%)

Total Distance = (>0m/s); Average Speed = (m/s) (mean ± SD).

3.4 Discussion

The aim of the present study was to investigate the variability associated with a range of physical performance variables both within and between games. Findings demonstrated that within-game time periods (1,5 and 15-minutes) had higher levels of variability when compared to between-game values. The variation found across the within-game periods ranged for 1-minute (6.5%-254.5%), 5-minute (15.6% - 231.8%) and 15-minutes (8.7% - 122.0%). The lowest variation within-game was found at 15-minutes periods. Within this 15-minute time period, average speed and total distance covered reported variation of <10%. The highest reported variation within the 15-minute period was 122.0% for total sprint distance. Overall, the high between and within-game variability found in this sample indicates player's inability to perform consistent physical actions between and within-games. This data has implications for the interpretation of physical performance in match-play and also the use of indicators of performance in future investigations. The high levels of variability reported in this study indicate the difficulty of analysing physical performance within-game and making assumptions about the changes in activity across the match. From these findings, it can be suggested that the 15-minute time period showed the lowest level of variation and would seem to be the most appropriate time period to consider for implementation in future studies within this thesis. The physical measures that displayed the lowest variation within this period, average speed and total distance, provide potential indicators of physical performance.

The variation reported in the current study for between-game periods was found to be of equal size to previous research by Gregson et al., (2010). This is despite differences in the sample sizes in the two investigations. The sample used by Gregson et al., included 485 players, from multiple teams and spanning a number of distinct seasons. The current investigation used 15 players from one elite English soccer team for one full season. Previous findings have suggested that a smaller sample sizes is likely to contribute to higher variability (Kempton et al. 2013; Gregson et al., 2010). The data from the current investigation would seem to indicate that despite the smaller sample size used in the current study, the data would seem to be representative of a larger and more diverse data set. This may increase the confidence of the findings from this study been generalizable to other populations.

The levels of variability reported by Gregson et al., (2010) who analysed high-speed activities found slightly lower coefficient of variation (CV) values in total high-speed running distance in comparison to the current investigation (Gregson et al., = 18% v Current Investigation = 25.1%); high-speed running distance (16% v 23.2%); total sprint distance (31% v 36.5%); and total sprint number (30% v 32.9%), respectively. A study by Rampinini et al., (2009), who used a similar semi-automatic computer tracking software (SICS®, Bassano del Grappa), reported considerably smaller variation in high-speed running distance than that observed in the current investigation (7% v 23.2%); total high-speed running distance (14% v 25.1%); and total distance (2% v 3.2%), respectively. A possible suggestion for the difference in reported values between Rampinini et al., (2009) and the current data could be due to the methodological approach employed to collect the data on which the coefficient of variation was calculated. The approach used by Rampinini et al., (2009) only tested for variation using two consecutive matches that were played within the same week. The current study and work by Gregson et al., (2010), used an approach that utilised an entire season's data set for each variable to calculate the variation. The short-term time periods used by Rampinini et al., (2009) would result in markedly reduced variation, as factors such as, the time of season when the data is collected and changes in player fitness levels, which have been reported to impact the data, would be small (Di Salvo et al., 2009; Gregson et al., 2010; Weston et al., 2011). It is therefore suggested that this type of research is conducted using a longitudinal approach as this provides a more realistic indication of an individual players performance.

Analysis of between-game periods identified that total distance and average speed represented the lowest variation (4%) out of all physical performance measures used in the investigation. This suggests that these measures are not sensitive to analyse performance. Previous research has also reported that total distance is a relatively stable marker of performance (Rampinini et al., 2007). The highest variation reported between-game was found to occur in the actions HACC and HDEC (33.6% and 50.2% respectively). To the author's knowledge, this is the first study to evidence the variability surrounding acceleration and deceleration profiles. The current study also reported high variability in other high-speed activities, particularly, sprint number and sprint distance (36.5%, 32.9%, respectively). This analysis highlights that the most explosive and demanding actions in soccer performance would seem to be the least stable physical performance parameters. This has been supported in other research on high-speed activities in soccer (Gregson et al., 2010; Rampinini et al., 2007) and Australian football rules (Kempton et al., 2014). Previous research has stated that high-speed activities are considered significant physical performance indicators due to their reported ability to discriminate between playing levels and positional roles in a team (Di Salvo et al., 2009). The observation of such high variation has implications for the use of such variables in future research examining performance related interventions, as well as attempting to interpret meaningful performance information. In these cases, a large sample size is required to overcome these limitations. Batterham and Atkinson (2005) highlighted the issue using a nomogram to determine appropriate sample sizes. In order to detect a worthwhile change of 10% using a performance measure that had a coefficient of variation of 30%, it would require a sample size of approximately 200 soccer players. In the available published literature only Gregson et al., (2010) used a sample size large enough to detect a 10% smallest worthwhile change (SWC) in high-intensity efforts, while Rampinini et al., (2007) sample could only determine a 10% SWC in total distance covered. The implications of this finding highlight the difficulty of analysing high-speed activities in future work within the thesis. It is therefore, beneficial in future work to analyse physical performance measures that represent the lowest levels of variation in an attempt to detect worthwhile change in performance.

The variation in physical variables were also analysed for within-game time periods of 1, 5 and 15-minutes. To the author's knowledge, this is the first study to report that physical performance measures using within-game periods have a higher level of variability than those observed between-games. One of the key findings from this study was that smaller time periods of 1-minute and 5-minute were associated with considerably higher variation than 15-minute time periods. Previous research analysing between-game variation have attributed the variability to the influence of the team having possession of the ball (Gregson et al., 2010), playing position (Di Salvo et al., 2007; Mohr et al., 2008), strength of opposition (Di Salvo et al., 2009) or the player's ability to self-regulate their own activity (Drust et al., 2007). The increase in variability as the duration of the reference period decreased is an expected outcome and has been reported in previous research (Kempton et al., 2014). As the size of the observation period increases, the parameters may be more likely to stabilise due to the addition of more data points. For example, the highest variation recorded within-game was for total high-speed running distance (254.6%) and high-speed running distance (212.9%) at 1-minute time periods. Whereas, the variation for the same parameters at 15-minutes were 51.6% and 46.2%, respectively. The reduced variation can be attributed to the greater number of potential measurement points included in a 15-minute period than compared to 1-minute periods. It is therefore, recommended that the 15-minute time periods are considered for future studies to analyse physical performance measures within-game, due to the considerably lower levels of variation.

The variation reported in this study for total high-speed running distance (115.6%) at 5-minute periods, also has potentially important implications for previous research that have analysed the occurrence of temporal and accumulative fatigue. For example, Mohr et al., (2003) suggested the drop in high-intensity effort in the 5-minutes proceeding the highest period within match-play, was due to temporal fatigue. Similar findings have also been reported using computerised semi-automatic multi-camera systems, which have utilised larger data samples (Bradley et al., 2009; Di Salvo et al., 2009; Mohr et al., 2010). However, the current findings suggested that the 115.6% variation reported for total high-speed running distance means the values reported by Mohr et al., of a 52% drop from the peak 5-minutes to the next 5-minutes could to some extent reflect the random error inherent in the variable rather than a performance decrement mediated through fatigue. The size of the variation associated to such physical measures makes interpretation of performance changes very difficult to make when limited by sample size. This further highlights the importance of selecting physical measures that have low measurement error in order to detect meaningful change.

In summary, this was the first study to provide data on the variation that surrounds physical performance measures in within-game time periods (1,5 and 15-minute). The data reported in this study shows that physical performance is highly variable both between and within-games. The within-game variability was found to be greater than between-games, particularly, at the finer periods of time (1 and 5-minutes). Average speed and total distance variables reported <10% variation between and within-game (at 15-minutes) demonstrating that these seem to be relatively stable performance measures. High-speed activities, however, showed much higher variation at both the between and within-game periods. This highlights implications for both interpretation of match physical performance and as an indicator of performance in future investigations within the thesis. Due to the high levels of variability reported in this study, it is recommended that 15-minute time periods be used for future analysis as they represent the most stable time period. Physical performance measures, average speed and total distance, are also recommended for future analysis within-game at 15-minutes for their <10% variability. While high-intensity efforts have been reported in the literature to be a significant performance measure, it is also critical for physical measures to have a low measurement error in order for future studies to analyse meaningful performance changes. As a result of a limited sample size to overcome this issue, it is therefore decided, that high-intensity efforts will not be included for future analysis.

4.0 An Investigation into the Variation in the Technical Match Performance of Elite Soccer Players

4.1 Introduction

Technical and tactical abilities are considered to be key components of success in elite soccer (Bangsbo, 1994; Rampinini et al., 2009). While high physical fitness allows elite soccer players to remain involved in match-play and to perform more high-intensity activities (Di Salvo et al., 2009; Bangsbo, 1994; Bangsbo et al., 2006), the overall the performance of technical actions (i.e. soccer skills) can determine success in soccer match-play (Di Salvo et al., 2007; Russell et al., 2012). Previous research into technical performance in soccer has primarily focused on descriptive studies of the English (Bradley et al., 2013; Russell et al., 2012), and European domestic leagues (Dellal et al., 2011; 2013; Rampinini et al., 2009). This type of research has reported that a player will typically complete between 50 to 110 technical involvements within a game (Bloomfield et al., 2007; Carling, 2010). Of those involvements, ball possession, dribbles and short passes are considered the most important aspects of the technical activity during match-play (Bloomfield et al., 2007; Dellal et al., 2011; Bradley et al., 2013). These technical performance measures are affected by the level of play (Rampinini et al., 2007), team formation (Bradley et al., 2011), match location, quality of opposition and score line (Lago & Martin, 2007; Bradley & Noakes, 2013).

Variation in physical performances has previously been quantified for measures such as high-speed activities (Gregson et al., 2010). The complex interplay between individuals on the same and opposing teams has found high-speed activity to be unstable properties that shows large variation between matches (Rampinini et al., 2009; Gregson et al., 2010; chapter 3.0 of the thesis). The sources of variation in match performance within-subjects (players) over successive matches have been related to both internal (i.e. fitness status, motivation) and external factors (i.e. opposition, tactics, measurement system and environment) (Gregson et al., 2010; Drust et al., 2007). These findings have important implications for applied research, as variables that demonstrate large variation require large data sample sizes to accurately detect meaningful change (Batterham & Atkinson, 2005).

Recent research has suggested that technical factors are better to differentiate between competitive standards in elite soccer (Bradley et al., 2013). However, such interpretations of technical performance measures in soccer match-play require a greater understanding of the variation surrounding technical data. Quantifying the variability associated with technical measures will provide a greater understanding of the sensitivity of technical parameters and help to determine key technical performance indicators (Atkinson, 2003). Despite this, no study to date has examined the variability of key individual technical performance measurements in soccer. Therefore, the aim of this investigation was to quantify the variability associated with a selection of technical performance variables used in elite soccer both between-game and within-game using time periods of 1,5 and 15-minutes.

4.2 Methods

In order to quantify the variation associated with technical performance in soccer match-play, the same methodological procedures used in study one were applied to the current investigation. In order to collect a suitable data sample the investigation utilised an elite professional soccer team's data provided by a commercial system (Prozone®, Leeds, England). The data was only available postproduction. This meant that the data collection process was completed by Prozone® and therefore removed the researcher from the capturing and data collection/manipulation process. For more detail on the Prozone® capturing process please see section 3.2.3 of study one.

4.2.1 Subjects and Match Data

Match performance data was produced using a computerised semi-automatic multi-camera image recognition system (Prozone MatchViewer®, Leeds, England) (please see section 3.2.3 for detailed description of system). Technical competitive match data were collected from 14 soccer players who played for an elite professional soccer team competing in the English Premier League during the 2010-2011 domestic season. A total of 263 individual match observations were undertaken on outfield players. Analysis was only undertaken on outfield players due to the specialised role of the goalkeeper. The number of games completed by players in the squad over the 2010-2011 season ranged from 1 to 38 (18 games ± 10). In an attempt to prevent a small number of games influencing the data a threshold of >7 completed matches (i.e. 90-minutes) per player were required for inclusion in the study. The study conformed to the ethical standards of the researcher's university ethics committee and the Head of Sport Science and Medical Departments granted informed consent on behalf of the players at the respective club.

4.2.2 Data Collection and Analysis

Players were assigned to the same playing positions as used in Chapter 3.0. The specific breakdown of the data between positions were; central defender (3 players - 81 match observations); wide defender (3 players - 47 match observations); central midfielder (4 players - 73 match observations); wide midfielders (2 players – 36 match observations) and attackers (2 players - 26 match observations). Technical data from each match was supplied by Prozone® (Prozone MatchViewer®, Leeds, England). The technical actions chosen for this investigation were selected using a three-stage review process. This process was to ensure that the selected variables used for analysis best described a soccer player's technical contribution to match-play. At stage one, a comprehensive review of the literature was performed to identify key technical performance variables (Hughes & Bartlett, 2002; Taylor *et al*., 2008; Rampinini *et al.,* 2009; Russell & Kingsley, 2011; Dellal et al., 2012). A total of 49 different technical actions were identified in the review. During stage two, the comprehensive list of technical variables were then compared to the list of technical actions that were coded and collected by the Prozone® tracking system. Technical variables that were not collected by Prozone® were removed from the selection process. The measures that were collected were then assigned a definition using Prozone® categorisations. At stage three, the head performance analyst, who worked for the respective soccer team, reviewed the refined list for coherency and the suitability of each variable. The review process considered whether the technical variable were i) a meaningful measure of the club's football playing style; ii) considered insightful by the coaching staff at the respective club; iii) the suitability of the variable when measured in combination with physical performance measures. A total of 5 technical performance variables were selected for analysis following this procedure (please see table 4.1 for technical actions and definitions). The technical variables that were selected after stage three of the process were principally based on the club's playing philosophy of controlling possession and maintaining a high quality of passing throughout a match.

Table 4.1 Technical variables selected for analysis with Prozone® defined definitions.

Technical Variables	Definition
Pass	Any attempt by a player to play the ball to a team-mate
Successful Pass	A successful pass by a player to a team-mate
Passing Success Rate (%)	The number of successful passes divided by the number of attempted passes
Passes Received	A pass is successfully received by a player from a team-mate
Average Time in Possession (s)	The average time in possession of the ball

4.2.3 Prozone® System Overview

The collection of technical performance data for the current study used the same capturing process as previously highlighted in section 3.2.3 and 3.2.4 for physical match performance data. A detailed review of the Prozone® system capturing process can be found in section 3.2.4. The Prozone® system provides technical performance data in both the PZ3® and MatchViewer® file formats. All technical performance data were exported using the Prozone Trend® database for both total game and within-game periods (1, 5, 15-minute) through a series of data filtering options. The exports were in a Microsoft Excel® CSV format and were analysed using customised Microsoft Excel spread sheets (Microsoft, Redmond, USA).

4.2.4 Prozone® Video Capture & Technical Data Process

The Prozone® system and capturing process used in this thesis is consistent with previous investigations analysing match technical performances of English Premier League players (Bradley et al., 2011; 2011). Prozone® technical performance data provides a detailed account of every on-the-ball event that occurs during match-play. The technical actions are coded using 5 key categories; i) event, ii) time of event, iii) player 1 involved, iv) player 2 involved (if applicable) and v) pitch location (x and y co-ordinates). The process of compiling the technical data follows 4 stages. At the stage one, the 'setup operator' inputs the game footage (using the single camera angle) using Prozone® Manager software to create the fixture details. The 'setup operator' then distributes equal units of game footage to a team of 'observers'. At stage two, the team of observers code all of the events that occur in the allotted segment of the game using Prozone®

Events software. This software displays only the specific users segment of game footage, along with the pre-populated information from Manager and Prozone® technical event category list. The Events software permits the observer to follow systematically and linearly through the match footage every 0.1-seconds until an event occurs. Events are coded following the sequential coding process of; event, time of event, player 1 involved, player 2 involved (if applicable) and pitch location (x and y co-ordinates). The software assists the observer at every event by listing only permissible events for that 0.1-second time instance based on the previously coded event. This process has been found to reduce input errors and coding time (Bradley et al., 2007). Observers are not required to input the outcome (i.e. successful or unsuccessful pass), the direction (forwards, sideways or backwards) or length (short, medium or long) of events. The software from the sequential coding process calculates these permutations automatically. At stage three, 'team leaders' using Events software perform a quality control process and assess the events logged by the observers. The team leader then uses the same methods, as described in stage two, to make corrections to events if necessary. At the final stage, the second team leader performs a final quality control process. Once all of the units are completed and checked the setup operator compiles the data together onto a MatchViewer or PZ3® file.

Bradley et al*.,* (2007) tested for reliability and objectivity of the Prozone MatchViewer® system by comparing two event coding groups for inter-observer agreement. It was found that absolute error of event time was 0.007 seconds and the inter-observer agreement for event type, player and second player involvement showed very good strength using kappa statistics (κ = < 0.995). The results indicate that Prozone MatchViewer® system is a reliable analysis tool when operated by observers that have undergone the recommended quantity of end-user training.

4.2.5 Statistical Analysis

The within-game data was collected in three time periods (1, 5, 15-minutes) from Prozone Trend® system. Within-game data were arranged by technical variable, player (subject) and time period in order to calculate coefficients of variation (CV) and associated 95 % confidence intervals (CI). Every technical variable, for every player and every period (1, 5, 15-minutes) were analysed. Between-game data were also collected from Prozone Trend® system and then arranged by technical variable, position and player (subject) to calculate CV values. Coefficients of variations were calculated following the method of Hopkins (2004). Whereby, each data set was log transformed and a constant of 10 was added to all of the data. Each player's data was run through a one-way within ANOVA to find the square root of the mean squares error from the ANOVA output table and then back-transformed to get a ratio CV. The coefficient of variation values for each individual player were then grouped and presented as the mean ± standard deviation. Confidence Intervals (CI's) at 95% CI were calculated using the inverse chi square distribution from the one-way within ANOVA output and then back transforming the values into a percentage.

4.3 Results

The between-game variation was high across all technical variables with the highest and lowest variation found in passes received (41.6%) and passing success rate (23.0%) respectively (Table 4.2).

Table 4.2 Between-Game Variation for General Technical Actions (CV%) and 95% CI (n=14).

Technical Variables	CV%	95% CI
Total Number of Successful Passes	38.7 ± 12.0	32.7% - 47.4%
Total Number of Passes	32.9 ± 9.5	27.9% - 40.1%
Passing Success Rate (%)	23.0 ± 5.4	19.6% - 27.9%
Passes Received	41.6 ± 14.0	35.1% - 51.1%
Average Time in Possession (s)	10.0 ± 3.8	8.5% - 11.9%

(mean ± SD).

Table 4.3 shows the within-game variation for technical actions. The overall variability can be seen to be highest for 5-minutes (26.2% – 74.0%) and 15-minutes (28.0% – 81.5%) periods. The variability was lowest at 1-minute periods (<23.9%), except for average time in possession (73.7%). The lowest variation was found at 1-minute for passing success rate (9.4%). Both total number of successful passes and passes received had a <25% variation at the same time period. Passing success rate showed the lowest variability across the 3 different time periods (<28.0%).

Table 4.3 Within-Game Variation on General Technical Actions (CV%) and 95% CI (n=14).

Technical Performance Variables	1-minute Periods (n=14)	5-minute Periods (n=14)	15-minute Periods (n=14)
Total Number of Successful Passes	20.6 ± 6.0 (20.4% - 20.8%)	67.3 ± 13.8 (65.4% - 69.4%)	81.5 ± 12.5 (77.1% - 86.3%)
Total Number of Passes	23.9 ± 6.1 (23.7% - 24.2%)	74.0 ± 12.2 (71.9% - 76.3%)	76.8 ± 14.9 (72.8% - 81.4%)
Passing Success Rate (%)	9.4 ± 2.2 (9.3% - 9.4%)	26.2 ± 5.6 (25.5% - 26.9%)	28.0 ± 7.9 (26.7% - 29.4%)
Passes Received	19.9 ± 5.1 (19.7% - 20.1%)	64.9 ± 11.8 (63.0% - 66.8%)	79.6 ± 12.0 (75.4% - 84.4%)
Average Time in Possession (s)	73.7 ± 6.1 (72.8% - 74.6%)	66.8 ± 10.6 (64.9% - 68.9%)	29.5 ± 5.9 (28.2% - 31.0%)

(mean ± SD).

4.4 Discussion

The main aim of the study was to investigate the between game and within-game variability of key technical performance variables in elite soccer players. To the author's knowledge this is the first study to provide information on the variability associated with technical performance for an elite soccer team. The findings demonstrated that within-game time periods of 5-minutes (26.2-74%) and 15-minutes (29.5-81.5%) reported higher levels of variation than between-game values (10-41.6%) of variation. The lowest variation was reported to occur in 1-minute periods (9.4-73.7%). Passing success rate reported the lowest variation (9.4-28.0%) out of all the technical variables analysed across the different time periods. Overall, the high levels of variation found in both between and within-game periods indicate that player's do not perform consistent technical actions between and within-games. These findings highlight the difficulty of interpreting technical performance changes within match-play. The reported variation associated with technical performance measures has implications on future investigations that are focussed on within-game and between-game analysis in this thesis.

A possible reason for such high levels of variability in technical performance measures could be due to the available sample size used for analysis. It is acknowledged that the sample size used in the current investigation is considerably smaller than what has previously been published for investigations on physical performance variation (Gregson et al., 2010). This study was restricted to a single season's worth of match data for a total of 14 soccer players as a consequence of the restrictions of the population sample being from a single soccer team competing in the English Premier League. However, the sample size used in the current investigation also had a relatively high number of repeated observations, which enhances the power of the study (Batterham and Atkinson, 2005). Previous findings have suggested that a smaller sample sizes is likely to contribute to higher variability (Kempton et al. 2013; Gregson et al., 2010). However, data from the previous investigation analysing physical performance would seem to indicate that despite the smaller sample size, the data from the current study could be representative of a larger and more diverse data set. Such assumptions however, are beyond the scope of the current investigation, as there is no comparative technical data in the literature at present to compare with our findings. Due to the limited number of subjects, a possible suggestion to reduce the variation could have been the addition of data from multiple seasons. This method would also have small implications (i.e. cross-season variability), but the influence of time of season has been found to be relatively small compared to the other factors that may influence performance within-games (Gregson et al., 2010). The larger data sample would improve the statistical power in a study and therefore increase sensitivity to detect changes in performance (Drust et al., 2007).

Another possible explanation for the large variation observed is the failure to examine position specific estimates of variability. This could have resulted in greater variation since a player's technical profile is influenced by position. For example, central defenders have been found to perform fewer passes than central midfielders during matches (Carling, 2010; Bloomfield *et al.,* 2007; Reilly, 2003). The high variability observed in other match performance variables (e.g. physical performance measures) has been explained by factors such as the team's possession of the ball (Gregson et al., 2010), playing position (Di Salvo et al., 2007; Mohr et al., 2008), strength of opposition (Di Salvo et al., 2009) or the player's ability to self-regulate their own activity (Drust et al., 2007). Other possible factors that can be attributed to the inherent variability associated with the game, such as possession of the ball and tactical changes (i.e. formation changes), that have been suggested for between-game variation in physical performance (Di Salvo et al., 2009; Rampinini et al., 2009; Gregson et al., 2010) could also be explanatory factors. It can be suggested that the major contributing factor in variability within the current investigation was due to a change in management and coaching staff at the selected club. During the data collection period (2011-2012 season) there was a change that will have had an impact on the style of play and formation during the season. This could have affected certain playing position's technical involvements as previously suggested in the literature (Reilly, 2003).

Analysis of between-game periods in this study reported high variability across all selected technical performance measures except average time in possession (10%). A possible explanation as to why the variation was lowest with this variable could be due to the values being expressed as an average. Previous research into technical performance in soccer has suggested that ball possession is a key performance indicator due to its strong association with success (Hughes & Bartlett, 2002; James et al., 2004; Lago & Dellal, 2010; Lago & Martin, 2007). The low variability within average time possession highlights it's potential as a useful performance measure between-games. In comparison to other measures in the current study, such as total number of passes, the high variability reported between-games (32.9%) has serious implications for sample size estimation in research examining performance pre and post intervention, as well as, for applied practitioners attempting to interpret meaningful performance changes (Gregson et al., 2010; Kempton et al., 2014). Batterham and Atkinson (2005) highlighted the issue using a nomogram to estimate the effects of measurement repeatability. For example, to detect a meaningful difference of 10% in a technical performance measure that had a coefficient of variation of 30%, a sample size of approximately 200 soccer players would be required. This finding emphasizes the difficulty of using any of the selected technical performance measures here to detect worthwhile change or to provide an accurate indication of an individual's ability to perform. It is therefore, suggested that additional technical performance measures are analysed for variability in future research to explore whether other technical actions can be used to detect worthwhile change.

The variation associated to technical measures were also analysed using within-game time periods of 1, 5 and 15-minutes. To the author's knowledge, this is the first study to report that technical performance measures using within-game periods of 5 and 15-minute have a higher level of variability than compared to between-game periods. One of the key findings from this study was that the smallest time periods of 1-minute were associated with the lowest variation compared to other within-game periods. This finding differs to the findings reported in study 3.0 was greater variation in physical performance was observed at finer time periods. The reduced variation can be attributed to the fewer number of measurement points included in 1-minute data periods than compared to 5 and 15-minutes. Despite the lower variation in 1-minute periods, the fewer number of measurement points included in 1-minute data would also seem to limit its use for future investigations. However, the large variability reported for technical performance measures using within-game time periods highlights the implications for future research. Previous studies have used within-game periods to suggest the occurrences of fatigue associated with physical activity.

For example, Rampinini et al., (2009) reported a decrease in the number of involvements with the ball as well as a decrease in the total number of short passes and number of successful short passes. This finding lead to the conclusion that match-related fatigue had a greater influence on a player's ability to get involved with the ball than it does on player's skill proficiency. However, this study failed to identify the variability surrounding the selected technical performance measures. This could therefore be misinterpreting unstable technical measures that have large levels of variability as a meaningful signal of performance change. The size of the variation associated with such technical measures makes interpretation of performance changes very difficult to make with a limited sample size. This further highlights the importance of detecting technical measures that have low measurement error in order to detect meaningful change.

In summary, this was the first study to provide data on the variation that surrounds technical performance measures both between game and within-game time periods (1,5 and 15-minutes). Present findings indicate that technical performance is highly variable both between and within-games. The within-game variability at 5 and 15-minutes periods was found to be greater than that between-games. Passing success rate reported <10% variation within-game at 1-minute periods and average time in possession (10%) between-games demonstrating these particular technical variables are relatively stable performance measures in elite soccer performance, though this is limited by the number of observations used in the study. Overall, the current study showed that it is not only physical performance that are affected by variation between and within-game, but also a player's technical contribution. The high variation reported for the selected technical performance measures has implications for the interpretation of match technical performance. Despite the higher variability found in technical performance measures, average time possession and passing success rate have been selected for future work as they represent the lowest variation at the 15-minute time periods.

5.0 An examination of the Within-game Physical and Technical Match Performance of Elite Soccer Players

5.1 Introduction

Chapters 3.0 and 4.0 within the current thesis have reported high variability in activity data both between and within-games for physical and technical performance measures. The high-intensity activities exhibit the highest variability in physical performance (<263%). This has also been reported in previous research (Gregson et al., 2010). The lowest variability was found for average speed (<40%) and the total distance covered (<43%). In comparison, technical performance measures showed high variability across all time periods (<78%) with the smallest variability occurring in average time in possession and passing success rate (<30%). The high variation associated with these physical and technical performance measures has significant implications for research analysing soccer activity. These implications primarily relate to the interpretation of physical and technical performance data in both a scientific and practical context.

Previous research analysing both physical and technical performance within a soccer game has primarily focused on a comparative analysis of data associated with various time periods and temporal divisions (e.g. time periods when peak activity is measured and the subsequent 5 min period) (Mohr et al., 2003, 2010; Bradley et al., 2010). Such data has been suggested to provide information on match-related fatigue. This type of analysis has largely been carried out without an acknowledgement of the variability associated with the selected performance measure and time periods used in the analysis. Evidence within the current thesis provides clear information that high-speed running, is subject to large variability using both 5 and 15-minute periods. This suggests that there is a possibility that data from any within-game analysis linked to the identification of "match-related fatigue" could be misinterpreted. Furthermore, previous research designs analysing within-game periods have typically applied Null-hypothesis significant testing (NHST) to determine whether a performance measure or time period is statistically significant or non-significant. Batterham and Atkinson (2006) acknowledged that this method of analysis, particularly for applied research could be misleading, as it is dependant on the magnitude of the statistic, error of measurement and sample size. As a result, Batterham and Atkinson recommended a new methodological approach to interpreting performance changes in applied research using magnitude-based inferences. Applying a more intuitive and practical approach to analysis could provide the researcher with a greater statistical context to the data when interpreting performance changes, and reduce the likelihood of misinterpreting data to factors such as high variability.

Currently, this approach has yet to be applied to elite soccer despite it's potential to assist greatly in the interpretation of within-game performance data. Applying a methodological approach such as this would provide stronger statistical understanding when analysing changes in performance within a game.

The aim of the investigation is to therefore, analyse both physical and technical within-game performance using data from 15 min periods. The study will also look to apply the new magnitude-based inferences approach to data analysis when identifying performance changes. Such approaches may hopefully provide new understanding associated with elite performance within-game.

5.2 Methods

The following section of the methodology will look to firstly provide information on the participants and data procedures, as well as the video capture process used in the current investigation. The proceeding section will then look to provide a detailed breakdown of the statistical analysis used in the current study. The methodological approach implemented in the investigation was designed as an explanatory study to help inform applied researchers of the benefits of using a more intuitive magnitude based inference approach rather than via the dichotomy of traditional NHST methods. Stage 1 highlights the traditional approach to inferential statistics that have previously been performed to analyse within-game performance that is known as null-hypothesis significance testing (NHST). This stage will identify whether there are significant differences ($p < 0.05$) found in the performance data for the selected physical and technical measures across 15-min time periods. Stage 2 then uses a magnitude based inference approach using Smallest Worthwhile Change (SWC) to analyse the within-game performance data to identify whether the significant differences identified at stage 1 using the NHST are in fact meaningful changes in performance and have practical relevance.

5.2.1 Participants and Match Data

Match performance data was produced using a computerised semi-automatic multi-camera image recognition system (Prozone®, Leeds, England). Physical and technical competitive match data were collected from 14 soccer players who played for an elite professional soccer team competing in the English Premier League during the 2010-2011 domestic season. A total of 98 individual match observations were undertaken on outfield players. Analysis was only undertaken on outfield players due to the specialised role of the goalkeeper. The number of games completed by players in the squad over the 2010-2011 season ranged from 1 to 31 (14 games ± 8). In an attempt to provide a true representation of an elite level squad only players who were considered a part of the 'first team' by the respective coaches were accepted for inclusion in the study. This was to limit the potential variability in physical and technical performance measure data. Due to the occurrence of injuries, substitutions and suspensions through the data collection period the sample used here was further restricted. For the purposes of selecting the largest number for the study, a total of 7 completed matches (i.e. 90 min) per player were chosen. This was to ensure that a player with a greater number of matches would not create a bias to the data. The study conformed to the ethical standards of the researcher's university ethics committee and the Heads of Sport Science and Medical Departments granted informed consent on behalf of the players at the respective club.

5.2.2 Data Collection & Analysis

Players were assigned to the same playing positions as those identified in previous literature (Di Salvo et al., 2009; Gregson et al., 2010). The specific breakdown of the data between positions were; central defender (3 players - 21 match observations); wide defender (3 players - 21 match observations); central midfielder (4 players - 28 match observations); wide midfielders (2 players – 14 match observations) and attackers (2 players - 14 match observations). Players' activities were coded into the following categories and speed thresholds: standing (0-0.6 km/h^{-1}), walking (0.7-7.1 km/h^{-1}), jogging (7.2-14.3 km/h^{-1}), running (14.4-19.7 km/h^{-1}), high-speed running (19.8-25.1 km/h^{-1}), and sprinting (>25.1 km/h^{-1}). The speed categories are the same as previous investigations using semi-automatic tracking systems (Di Salvo *et al.,* 2009; Gregson *et al.,* 2010). The physical and technical variables chosen for the investigation were selected based on the data examining the coefficient of variation (CV) of physical and technical parameters analysed in chapters 3.0 and 4.0. The selected variables were chosen on the basis of having the lowest reported CV for both physical and technical performance measures. The following physical and technical performance variables were selected for analysis: 1. Total Distance Covered (m); 2. Average Speed (AVE) (Calculated by the mean per second speed of a player); 3. Passing Success Rate (%) (The number of successful passes divided by the number of attempted passes); and 4. Average Time in Possession (sec) (the average time in possession of the ball). The decision to excluded high-intensity activity in the current investigation despite being a crucial element of soccer performance (Stolen et al., 2005) was to identify whether variables with smaller variability could identify meaningful changes in performance due to the greater strength of the signal-to-noise ratio.

5.2.3 Prozone® Video Capture & Physical Data Process

The Prozone® system and capturing process used in this thesis is consistent with that used in previous investigations that have analysed the physical and technical match performances of English Premier League players (Bradley et al., 2009; 2010; Di Salvo et al., 2006; 2009; Gregson et al., 2010; see chapter 3.0 and 4.0). For a detailed review of the physical and technical data process please see Chapters 3.2 and 4.2. The chosen within-game time period was 15 min as it represented the lowest variability in comparison to the other within-game periods of 1 and 5 min (see chapters 3.0 and 4.0 within the thesis). The 15-minute time periods were collected from the Prozone Trend® system as previously described in chapters 3.0 and 4.0. Physical and technical data were arranged in separate Microsoft Excel® spread sheets (Microsoft, Redmond, USA) and categorised by the variable and time period (0-15 min, 15-30 min) in order to calculate coefficients of variation (CV) and Smallest Worthwhile Change (SWC).

5.2.4 Statistical Analysis

5.2.4.1 Stage One - Differences Between Physical and Technical Within-game Performance

To explore if significant differences existed for physical and technical performance variables across time periods (0-90 min), a one-way ANOVA with repeated measures was used. This form of analysis was selected as previous studies have used similar NHST methods when analysing data for statistical differences in performance measures across time periods within a game (Mohr et al., 2003; Bradley et al., 2009). The sphericity assumption for the repeated measure variables and the interaction effects were checked using Mauchly's test of sphericity. When a violation of the sphericity assumption was apparent, the Greenhouse-Geisser correction procedure was used to adjust the degrees of freedom (Schutz & Gessaroli, 1987). Observed significant differences were followed up using Bonferroni post hoc tests. The level of significance was set at $p < 0.05$. The ANOVA statistical analyses were computed using SPSS 19.0 software (SPSS Inc., Chicago, USA).

5.2.4.2 Stage Two – Identifying Smallest Worthwhile Change in Physical and Technical Within-game Performance

Time periods that were identified as 'significantly different' ($p < 0.05$) during stage one of the analysis were then selected for further analysis at stage two. The traditional ANOVA analysis (i.e. NSHT) reported at stage one identifies whether any of the mean differences between the time periods for each performance measure was significantly different from zero (Field, 2000). The limitation to this form of statistical analysis is that a change, although significantly different from zero, may not necessarily be practical when looking at performance changes within match-play for elite soccer players (Batterham & Atkinson, 2006). This approach is also unable to consider the magnitude of the statistic, error of measurement or sample size. Therefore, the new analytical method used at stage two, attempts to apply a more intuitive approach that uses magnitude-based inferences as suggested by Batterham and Atkinson (2006) to consider whether the mean difference change between time periods demonstrates a smallest worthwhile change in performance. This approach uses 95% confidence intervals to inspect the magnitudes of pairwise mean differences between each time period to define the likely range of the true difference. To provide a practical relevance to the differences in time periods the Smallest Worthwhile Change (SWC) is then used. The SWC is defined as the smallest change in a measurement likely to be relevant in performance terms, to the average of all players (Kempton et al., 2014). This value determines whether the selected difference between time periods is greater than the SWC and can be considered a meaningful performance change. If the mean difference showed a positive change, a positive SWC would be used to determine if the change was meaningful, whereas a difference that showed a negative change would use a negative SWC. For a difference to be considered a meaningful performance change, the 95% confidence interval range must not overlap the SWC line.

The smallest worthwhile change (SWC) for each variable was calculated by multiplying 0.2 by the between-subject standard deviation of the selected variable's 0-15 min period value observed in game. The 0-15 min period was selected on the basis that it provided a baseline measurement since there was no effect of fatigue. As the data set in the current study were different to studies 1 and 2 the coefficient of variations (CV) were calculated for each of the variables following the Hopkins (2004) method (for a full description of the process please see section 3.2.2 of chapter 3.0). The CV calculation was selected to provide the measurement of the typical error and determine the width of the confidence intervals (CI). The coefficients of variation for each variable included in the analysis can be found in table 5.1 below.

Table 5.1 Coefficient of Variation (CV) and Smallest Worthwhile Change (SWC) calculations.

Performance Measures	0-15min Period Mean Values	CV%	SWC
Average Speed (m/s)	2.06 (m/s)	7%	0.03 (m/s)
Total Distance (m)	1851.0 (m)	6%	24.9 (m)
Ave. Time in Poss. (s)	2.36 (s)	18%	0.06 (s)
Passing Success Rate (%)	83.6 (%)	29%	0.02 (%)

The selected performance outcomes following the initial statistical analysis were analysed using one-sample *t*-tests comparing the differences between paired observations using Microsoft Excel® spread sheets (Microsoft, Redmond, USA). Specifically, this analysis was to determine whether the mean difference was significantly different from the SWC at the 0.05 significance level. The findings were then plotted as figures to highlight the mean difference value with its 95% confidence interval and the SWC as previously suggested by Batterham and Hopkins (2006).

5.2.4.3 Interpreting the presentation of the Smallest Worthwhile Change (SWC)

This section provides a description of how to interpret the Smallest Worthwhile Change figures that are included in the results section of the study.

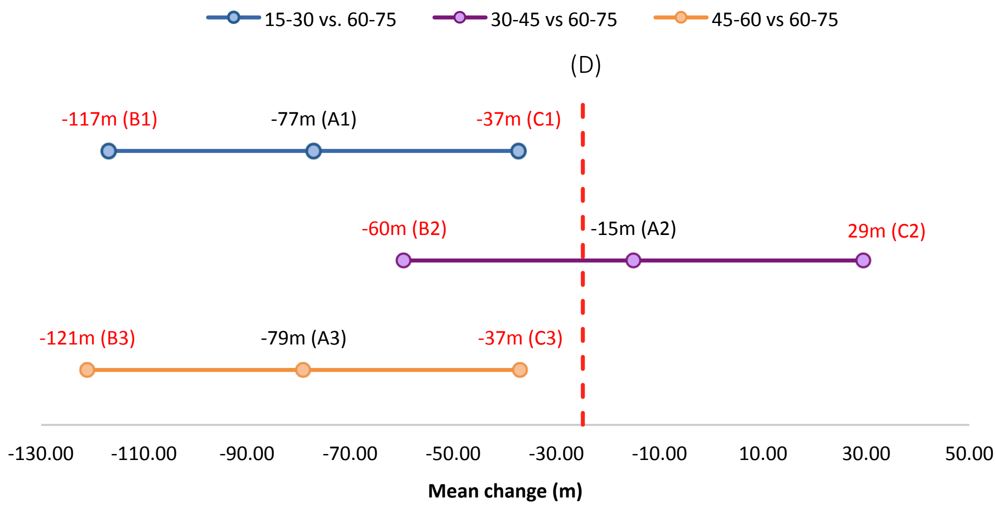


Figure 5.1 An example of the Smallest Worthwhile Change (SWC) for Total distance (m) comparing the 60-75 min time period to 15-30 min (blue line), 30-45 min (purple line) and 45-60 min (orange line) periods. Symbols (A1), (A2) & (A3) highlight the value for each pairwise mean difference between time periods. Symbols (B1), (B2) & (B3) shows the lower limits of the 95% Confidence Intervals (CIs) for the mean difference and (C1), (C2) & (C3) for the upper limits. The lower and upper limits are shown in red font. (D) Shows the SWC line for Total Distance (m) difference between time periods of the match. The vertical line represents the SWC at - 25 meters. For a difference to be considered meaningful in this figure the mean difference, lower limit and upper limit of the 95% CI's need to be bigger than the - 25m SWC threshold line. Period 60-75 to 15-30 min (blue line) and 60-75 to 45-60 min (orange line) show a mean difference that is lower than zero and the SWC. Period 60-75 to 30-45 min (purple line) shows a mean difference that is lower than zero but not bigger than the SWC as the confidence interval range (B2 and C2) crosses the - 25m SWC.

Figure 5.1 provides an example illustration of the differences in total distance covered (m) between 3 time periods (15-30 min, 30-45 min and 45-60 min) compared to the 60-75 min of a match. It can be seen in the figure that the 15-30 min (blue line) and 45-60 min (orange line) periods were lower than the 60-75min period of the match. This can be identified in the figure by the mean differences (A1) & (A3) for both periods being lower than zero and the 95% CIs (B1, C1 and B3 and C3) not crossing the Smallest Worthwhile Change (SWC) line of - 25m (D). The average mean difference between periods 60-75 min to 15-30 min was -77m (A1) and for 60-75 min to 45-60 min was -79m (A3). The example figure above shows that the 60-75 min to 15-30 min period (blue line) has the most precise estimation of the mean in the example data set, which can be identified by the size of the 95% confidence intervals (-117m to -37m) (see B1 and C1). In comparison, 60-75 min to 45-60 min (orange line) displayed wider 95% CI showing a range of -121m to -37m (B3 and C3), this indicates a less precise estimation of the mean difference. This is probably due to higher variability.

The 60-75 min to 30-45 min (purple line) period represents a comparative time period where the change in performance was not significantly bigger than the SWC line of - 25m (D). Despite the period reporting a mean difference of -15m (A2), which is bigger than the SWC line (D), the purple line shows a 95% confidence interval range of -60m to 29m (see B2 and C2). The majority of the interval range (B2 and C2) crossed the SWC 25m line (D). As a result, a time period that crosses the SWC line (D) with the 95% CI interval (B1, B2, B3) or (C1, C2, C3) or with the mean difference (A1, A2 or A3) indicates that some of the data does not constitute a smallest worthwhile change in performance. This period would then be reported in the results section to have no worthwhile performance change between the time periods at stage two of the analysis.

5.3 Results

5.3.1 Total Distance

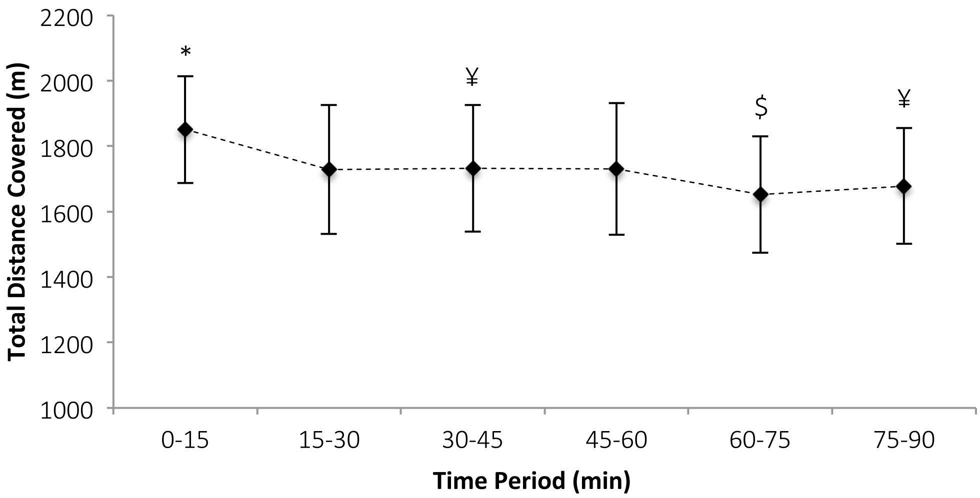


Figure 5.2. Stage one analysis of total distance covered (m) across separate 15 min time periods within-game (Mean ± SD). * = Significantly greater than all other time periods (P = 0.00); ¥ = 30-45 min is significantly greater than 75-90 min (P = 0.024); $ = Significantly lower than all other periods except 75-90 min (P < 0.05).

Figure 5.2 shows that the highest total distance covered in the match occurred in the opening period (0-15 min); this distance was 6-11% greater (P < 0.05) than all other time periods. The total distance covered at certain time periods in the second half showed a significant drop when compared to the opening 0-15 min; more specifically the 60-75 min period (11% lower, P < 0.05) and 75-90 min (9% lower, P < 0.05) than the initial period in the game. The final 15 min period of the first half (30-45 min) was 8% greater in terms of the total distance covered (P < 0.05) than the final period (75-90 min) in the second half. All of the differences between the 0-15 min period and the other five time periods were significantly higher than - 25m (SWC) at the 95% confidence level (see figure 5.3). The differences between the 60-75 min time period versus 15-30 min, 30-45 min and 45-60 min were also found to be significantly higher than the SWC at the 95% confidence level (see figure 5.4). It was found that the difference between time periods 30-45 min and 75-90 min was not significantly different from the SWC (see figure 5.5).

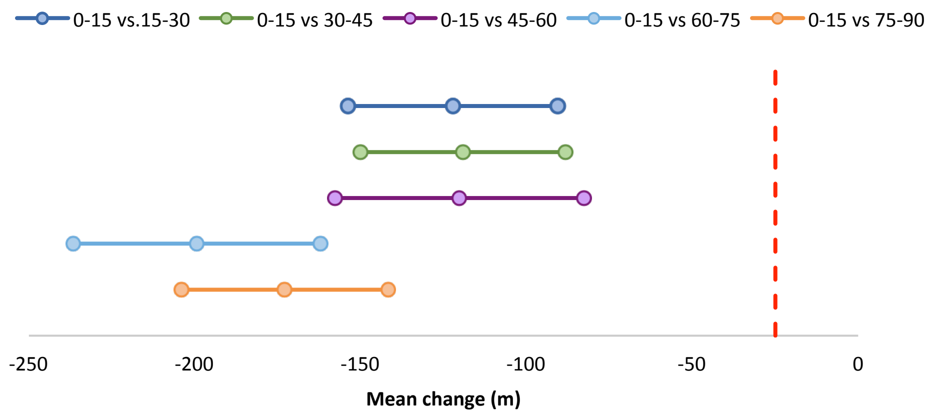


Figure 5.3. Stage two analysis showing mean differences (and 95% CIs) of total distance (m) between the 0-15 min period and the other five 15 min time periods of the match. The vertical line represents the SWC (-25m). The figure shows that the differences between the 0-15 min time period and all the other periods were significantly bigger than the SWC as none of 95% CIs crosses the SWC line.

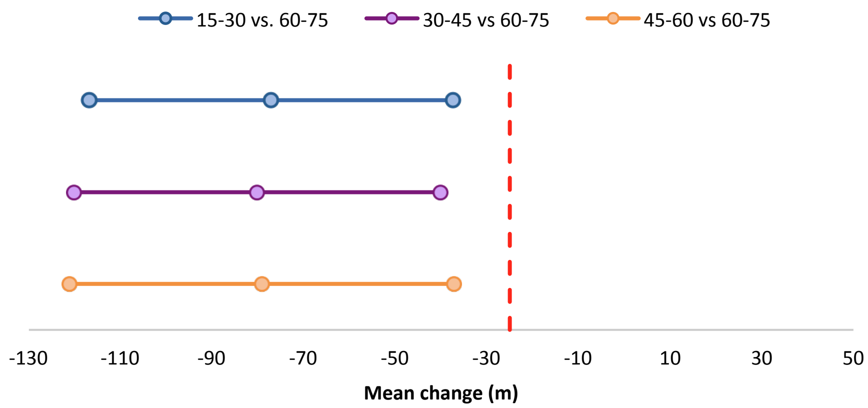


Figure 5.4. Stage two analysis showing mean differences (and 95% CIs) of total distance (m) between the 60-75 min period and three other time periods of the match. The vertical line represents the SWC (-25 m). The figure shows that the differences between the 60-75 min time period and all the other periods were significantly bigger than the SWC as none of 95% CIs crosses the SWC line.

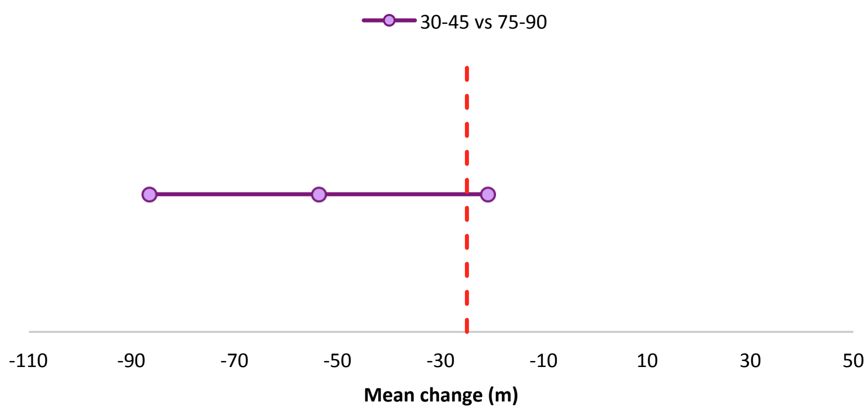


Figure 5.5. Stage two analysis showing mean differences (and 95% CIs) of total distance (m) between the 30-45min period and 75-90 min time periods of the match. The vertical line represents the SWC (-25 m). This period shows no difference significantly bigger than the SWC between the selected time periods as the 95% CIs crosses the SWC line.

5.3.2 Average Speed

Figure 5.6 shows that the highest average speed was also reported in the opening period of the match (0-15 min). The 0-15 min period was 6-10% greater (P < 0.05) in terms of average speed when compared to all other time periods in the game. In a similar way to the total distance, the 60-75 min period had the biggest drop in average meters' covered compared to 0-15 min (10% lower, P < 0.05).

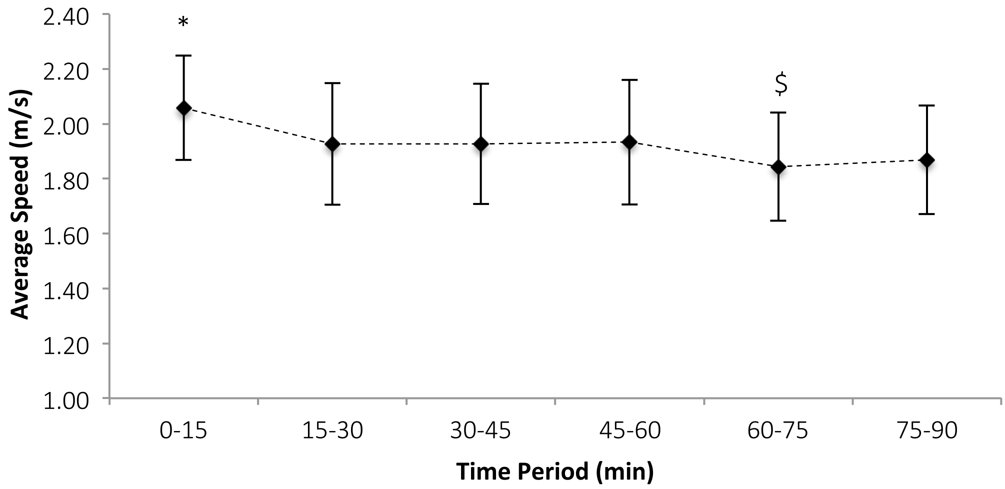


Figure 5.6. Stage one analysis of average speed (m/s) within-game using 15 min time periods (Mean ± SD). * = Significant greater than all other time periods (P = 0.00); $ = Significantly lower than all other periods except 75-90 min (P < 0.05).

All of the differences between the 0-15 min period and the other five time periods were significantly bigger than 0.028 m/s (SWC) at the 95% confidence level (see figure 5.7 and 5.8). The average speed in the 60-75 min period was significantly bigger when compared to all the other time periods, except the 75-90 min of the game. All these differences were also significantly bigger than the SWC. The first half periods of 0-15 and 30-45 min also reported an increased average distance when compared to the same stages of the second half (45-60 & 75-90 min). These increases were 6% and 3%, respectively.

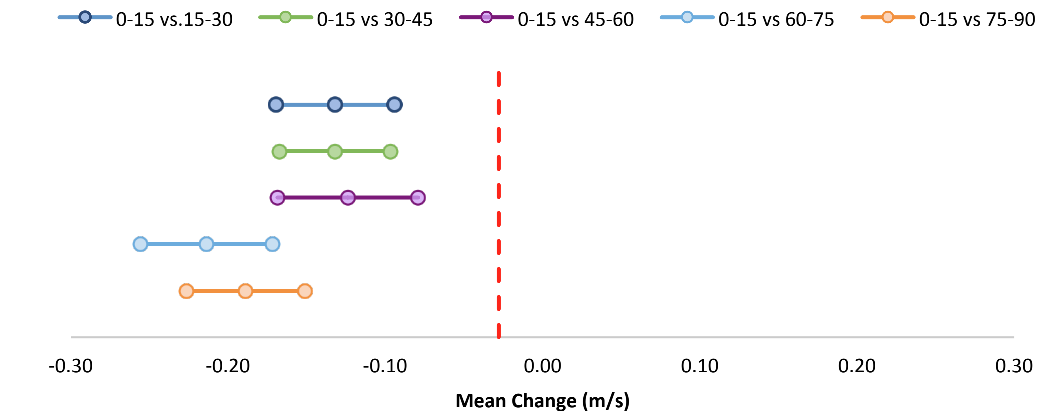


Figure 5.7 Stage two analysis showing mean differences (and 95% CIs) of average speed (m/s) between the 0-15 period and the other time periods of the match. The vertical line represents the SWC (- 0.028 m/s). The figure shows that the differences between the 0-15 min time period and all the other periods were significantly bigger than the SWC as none of 95% CIs crosses the SWC line.

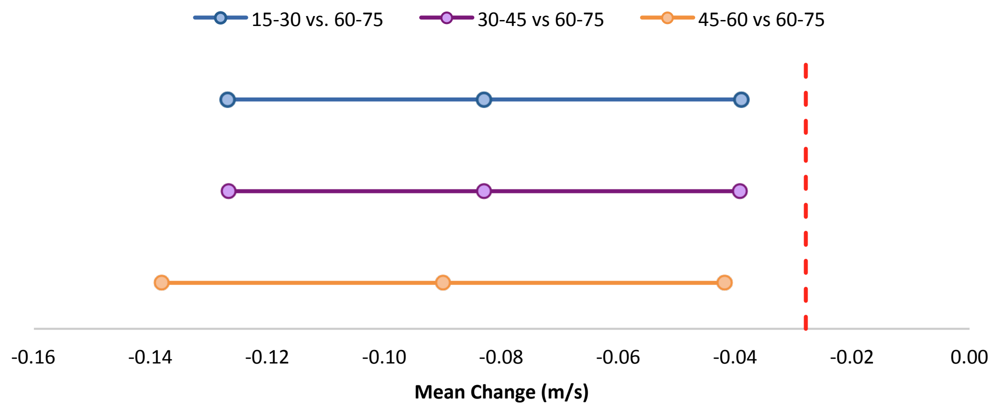


Figure 5.8 Stage two analysis showing mean differences (and 95% CIs) of average speed (m/s) between the 60-75 period and three other time periods of the match. The vertical line represents the SWC (- 0.028 m/s). The figure shows that the differences between the 60-75 min time period and all the other periods were significantly bigger than the SWC as none of 95% CIs crosses the SWC line.

5.3.3 Average Time in Possession

Unlike the physical performance measures, average time in possession was found to be lowest in the opening time period (0-15 min, 2.37s) when compared to the rest of the match (see figure 5.9). Average time in possession increased by 11% ($P < 0.05$) from the opening 0-15 min to the final period of the match (75-90 min, 2.63s). Figure 5.9 shows that average time in possession increased throughout the second half compared to the first half. The time in possession at the start of the second half (45-60 min) was 2% higher when compared to 0-15 min while the 75-90 min period was 5% higher than at the end of the first half (30-45 min). The difference between the 0-15 min vs. 75-90 min periods was significantly higher than 0.061 % (SWC) at the 95% confidence level (see figure 5.10).

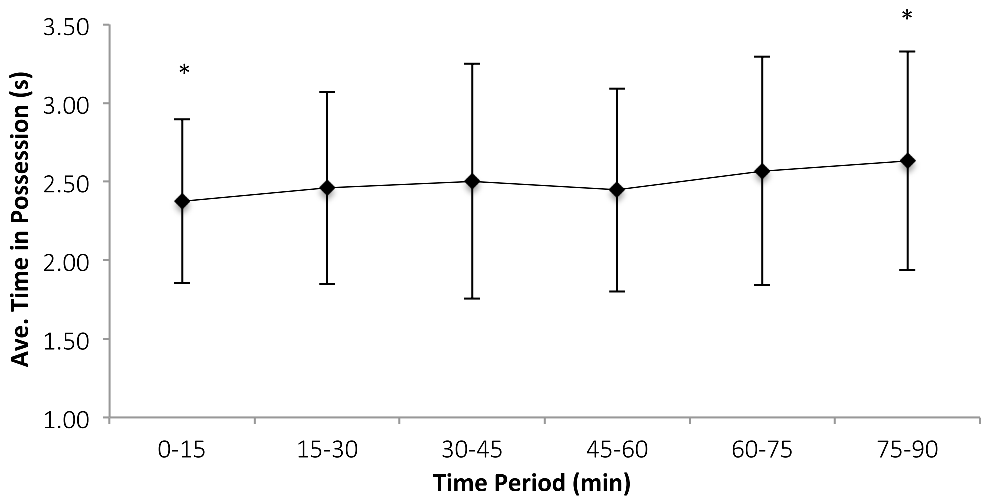


Figure 5.9 Stage one analysis of average time in possession (s) within-game using 15 min time periods (Mean ± SD). * = 75-90 min period is significantly greater than 0-15 min ($P = 0.016$).

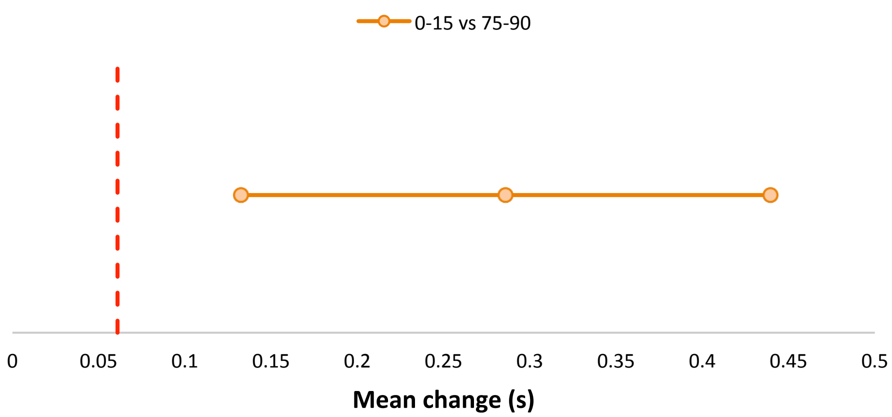


Figure 5.10 Stage two analysis showing the mean difference (and 95% CIs) of average time in possession (s) between the 0-15 min period and the 75-90 min period. The vertical line represents the SWC (0.061 s). The figure shows that the differences between the 0-15 min and 75-90 min time period was significantly higher than the SWC as none of 95% CIs crosses the SWC line.

5.3.4 Passing Success Rate

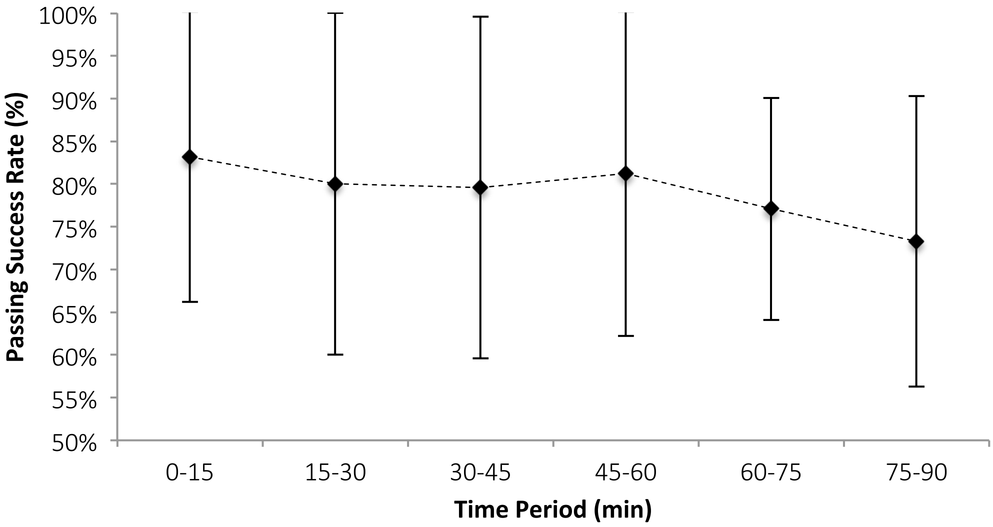


Figure 5.11 Stage one analysis of passing success rate (%) within-game using 15 min time periods (Mean ± SD). No significant differences were found.

Passing success rate was highest in the opening 0-15 min period (83%) compared to all other time periods (see figure 5.11). The drop in physical variables reported at 60-75 and 75-90 min periods were also evident in this aspect of technical performance with 77% and 73% success rates observed in each of these periods respectively. These values represent a 7-12% drop when compared to the opening period of the match. The second half showed a drop in passing success rate when compared to the first half. The final period of the 1st half (30-45 min) was 7% greater than when compared to the final period of the 2nd half (80% v 73%). As there were no significant differences found in the one-way ANOVAs with repeated measures there was no further analysis for this variable.

5.4 Discussion

The aim of the investigation was to examine both the physical and technical within-game performance of elite soccer players using data from 15 min time periods. The current study also attempted to apply new methodological approaches to data analysis to determine whether significant differences in time periods were associated with meaningful performance changes within a game. The findings from the study reported that the physical performance measures, total distance and average speed, displayed peak values during the 0-15 min time period of a match (1832m and 2.04m/s respectively). The analysis also identified a drop in physical output during the 60-75 min period for total distance (1626m) and average speed (1.81m/s). This period was also found to be the lowest reported in any of the 15 min periods within-game. The new statistical approach used in the study suggested that these periods (peak at 0-15 min and drop at 60-75 min periods) represented meaningful changes in performance and therefore indicate differences that are of practical significance. In comparison, technical performance changes within-game were not as conclusive. Average time in possession was significantly lower in the opening period (0-15 min) of the match in comparison to the 75-90 min period; this change was also found to be meaningful. The average time spent in possession showed an increase throughout the match in each successive 15 min period but was not identified as either a significant or meaningful change within-game. Passing success rate did not change meaningfully within the game. From these findings, it can be suggested that 15 min time periods and the physical performance measures (average speed and total distance) can be used to identify performance changes within a game.

The findings from the current study identified that the opening time period of the match (0-15 min) demonstrated a significantly greater physical performance (total distance and average speed) than all other time periods within the game. Similar findings have also been reported in previous research for other variables such as high-speed running and sprint distance in elite soccer players (Mohr et al., 2003; Bradley et al., 2009; Weston et al., 2009). These findings when looked at collectively may reflect a 'chaotic' nature of the start to the match where player's activity profiles are indicative of an attempt to gain tactical control of the game through the use of increased physical output. Reasons for the increased physical output during this period have previously been suggested to be the 'frantic' nature of players wishing to 'engage' and 'register their presence' with the opposition (Bangsbo, 1991; Lovell et al., 2013). This evidence in combination with the findings from the current study on technical performance strengthens such claims. Average time in possession was significantly lower in the opening period of the game when compared to the final period of the match (75-90 min). This reduction in possession may also be indicative of an increased focus of players on setting the physical tempo for the match. The evidence from this study therefore suggests this chaotic start to a game may have implications to applied research examining within-game performances. Previously, research has used the opening 0-15 min period of the match as baseline to compare performance within-game, but the information provided from this study supports previous evidence by Lovell et al., (2013) that this time period might perhaps be an unrealistic baseline. The finding challenges traditional theorem on within-game performance, and highlights the need for a truer representation of the physical and technical demands in match-play, such as the use of averaged data, or a more generalised based line measurement. Such inferences however are beyond the scope of this study.

A novel finding in the study was the identification of a drop in physical performance at the 60-75 min period. Both total distance (1626m) and average speed (1.81m/s) were observed to be lowest during this period of the match. This observation conflicts with previous research findings that have reported the biggest decline in physical performance to occur at the 75-90 min period (Carling & Dupont, 2011, Mohr et al., 2003; Bradley et al., 2009). These findings when viewed with the current study suggest a possible onset of physical fatigue that has accumulated throughout a match and is affecting players towards the end of the game. Previous investigations have supported the theory that the fatigue is accumulated throughout a match and has a deleterious effect on end-game physical performance in the 75-90 min period (Bradley et al., 2009; Mohr et al., 2003). However, the results from the current study suggest that changes in this period might not solely be related to fatigue, as technical performance measures did not show the same decline. For example, average time in possession, despite not showing a significant difference, reported the 2nd highest time in possession during the 60-75 min period and increased again during the 75-90 min period. Whereas, passing success rate showed no affect of performance detriment during the 60-75 min period. From these findings it can be proposed that the physical drop at 60-75 min does not affect technical performance, and instead suggests the concept of players having an ability to manage their physical load during the second half by retaining greater possession of the ball through more touches. Previous findings have also suggested the concept of players consciously or unconsciously adopting pacing strategies to control physical exertion in an attempt to reduce energy expenditure (Carling et al., 2013). Attempts to provide further context to the drop in physical performance using the subsequent time period (75-90 min) is somewhat difficult, as this period has been reported to involve a number of external factors that can affect the stability of the time period for comparison. For example, the introduction of substitutions would have an impact on average physical data, as well as the outcome of the match having potentially not been decided (Bradley et al., 2009). The difficulty to ascertain a more conclusive finding in the current data sample therefore suggests that a larger population could provide the statistical power to analyse the occurrence of players adopting pacing strategies in the second half of matches. Alternatively, the finding also questions the effectiveness of whether final periods (75-90 min) of matches can be used as a stable time comparison when looking at performance within-game.

The novel statistical analysis performed in the current study highlighted a new approach to investigating within-game performance data in soccer for applied researchers. As highlighted in the method section of the study, the null-hypothesis significance testing (NHST) used by previous researchers to analyse within-game time periods are somewhat limited in their ability to identify meaningful changes in performance that can impact 'real world' practices. These traditional methods are able to identify whether any of the mean differences between time periods for each performance measure are significantly different from zero (Field, 2000). However, a limitation to this form of statistical analysis is that a change in performance, although significantly different from zero, may not necessarily be practical when looking at performance changes within match-play for elite soccer players. Instead, the new statistical approach considers the smallest worthwhile change required to observe a practically meaningful change in performance. For example, the mean difference for total distance covered at 30-45 min was found to be significantly lower than the 75-90 min time period using the traditional ANOVA method of analysis. This can also be seen in figure 5.5, as the mean difference is lower than zero. However, when analysed using the SWC it was found that the 95% confidence intervals crosses the SWC line, which implies that the change is of little practical importance because the difference is not greater than the threshold of smallest worthwhile change of -25m. This finding shows that the novel statistical analysis aids in the interpretation of results for researchers who are interested in the impact of interventions or analysis for 'real world' practises. This particular issue raises potential implications for previous within-game findings using physical performance measures, such as, the occurrence of transient fatigue in high-speed running distance. The initial findings by Mohr et al., (2003), as well a more recent analysis by Bradley et al., (2009) still show a significant difference from zero, but may not in fact be considered a meaningful change in performance. Unfortunately, examples from these investigations are unable to be calculated due to the limited statistical information provided in each study. The ambiguity from the findings does however highlight the need for new analysis to identify whether these changes are indeed meaningful changes in performance. Such findings would have considerable impact in applied research as the findings can assist in training practices, player selection, and player management within-games (i.e. substitutions).

It is important to clarify that the methodological approach implemented in the current investigation was designed as an explanatory study to inform applied researchers of the benefits of using a more intuitive magnitude based inference approach rather than via the dichotomy of the traditional null hypothesis significance testing method. The rational for the use of a two-stage analysis was to acknowledge at stage one, that the NHST method using an ANOVA could identify significant differences between periods from zero, but were unable to provide practical inferences or factor the magnitude of the statistic, error of measurement or sample size. Then at stage two, the analysis attempted to use the new inference based approach to identify whether the differences found at stage one were greater than the smallest worthwhile change, and whether the measurement error was a factor when attempting to identify changes in performance across time periods. It can be disputed that the more intuitive method used at stage 2 is a more stringent approach, as it is statistically impossible for a mean difference to be significantly bigger than a SWC of 1.4, or any number, if it is not different from zero. It could therefore be suggested that a less stringent approach could be applied in future research, such as the use of smaller SWC. The current study applied 0.2 x the between-subject standard deviation of the selected variable's 0-15 min period value observed in game as previously used by Kempton et al., (2013) in Australian football. Alternatively, a value of 0.1 could be applied, or the between-subject standard deviation could be taken from an overall average for all time periods, as the frantic nature of the opening period of the game would result in higher values (Lovell et al., 2013). Alternatively, smaller confidence intervals could also be applied when interpreting inferences for applied research. Batterham and Atkinson (2006) suggested that a 90% CI could be used as the 95% CI level is too conservative when adopting an inference based approach. Batterham and Atkinson also acknowledged that making an inference about magnitudes is not an easy task and requires justification of the smallest worthwhile effect, extra analysis that stats packages do not yet provide by default, a more thoughtful and often difficult discussion of the outcome. This study therefore hopes to provide useful information that can stimulate further discussion on applied research and the uses of inference based analysis in soccer performance.

The current study also highlighted the importance of selecting low variability measurement tools for analysis. A key finding from the study showed that average speed and total distance were able to identify performance changes within-game despite the relatively small sample in comparison to previous research studies that have used 350+ players (i.e. Bradley et al., 2009). This finding has important implications to applied research, as it highlights physical measures that can be used when monitoring a soccer team or individual player with a limited data sample. Technical performance measures however, require a greater data set in order to reduce the error of measurement when attempting to identify change in performance. Additionally, the SWC analysis used in this investigation provided an insight into how sample size can affect the interpretation of changes in performance, particularly when performance measures show high variability. It can be seen from the findings within the results section (see section 5.3) that a limitation to the current study is the size of the data sample used for the investigation. Previous research by Gregson et al., (2010) reported that a greater sample size improves the statistical power when interpreting data, and is further evidenced in the current study. The SWC figures show that within the current data sample (n=15) the 95% confidence intervals are considerably wide, especially In the case of the technical performance measures. A greater data sample would potentially reduce the size of the confidence intervals, thus making it easier to identify meaningful changes in performance. Obtaining precise indicators of performance are important to formulate applied research studies to examine the impact of interventions that could potentially affect the success of a player or team (Atkinson & Nevill, 2000).

In summary, this was the first study to identify a drop in physical performance at 60-75 min period and suggests either a fatiguing effect or highlights the possibility of a player's ability to manage their physical activity during a game through an increased time in possession of the ball. It was also reported that the opening period of the match (0-15 min) represented a somewhat chaotic start with the highest distance covered and lowest average time in possession. These findings potentially challenge previous assumptions of within-game performance (i.e. accumulation of fatigue) and highlight new considerations to the interpretation of within-game performance. In addition, the use of new methodological approaches to analysing elite soccer performance within-game has shown the potential these findings can have in applied research. This form of analysis provides the researcher with a greater statistical context to the data when interpreting performance changes, and reduces the likelihood of misinterpreting data to factors such as high variability. Together these findings provide useful information to applied researchers that attempt to identify key performance changes within-game. Furthermore, the identification of average speed and total distance as performance measures that can identify changes in performance highlight the potential for their use in future studies.

6.0 Creatine Kinase Concentration is not Related to Indicators of Physical Match Performance in Elite Premier League Soccer Players

6.1 Introduction

Soccer is an intermittent sport. The activities completed during matches involve frequent unpredictable changes in intensity that range from static pauses to maximal sprints (Drust et al., 1998). Lazarim et al., (2009) has suggested that the muscular overload associated with the demands of matches and training can lead to micro-trauma in both the muscle and connective tissue. Such changes have been linked to the reductions in performance that are observed following training sessions and matches (Andersson et al., 2008; Ascensao et al., 2008; Ispirlidis et al., 2008). The demands of the competitive schedule at the elite level require players to frequently play matches with relatively short recovery durations. The time periods associated with important recovery processes (e.g. glycogen repletion) would suggest that at times players are required to perform whilst at sub-optimal levels of physiological function. This may not only reduce the likelihood of a successful performance outcome but also increase the risk of injury (Lazarim et al., 2009). The development and implementation of strategies that monitor an individual's recovery from intense training or competitive match-play is therefore of interest to both practitioners and scientists.

Effective monitoring strategies require the tracking of variables that are sensitive to the changes associated with the stress of exercise. The available research would suggest that various hormonal and muscle enzyme measures have the potential to assist in the assessment of both the immediate and the longer term response of the body following intense exercise (Brancaccio et al., 2007). Creatine kinase is an enzyme that is found in both the cytosol and the mitochondria in muscle that has been generally considered to be an indirect marker of muscle damage (Ehlers et al., 2002; Baird et al., 2012). Numerous papers have examined the increase in CK following exercise indicating that the increase in serum CK is related to the intensity, duration and type of exercise (e.g. Apple and Rhodes, 1988; Guzel et al., 2007). Coehlo et al., (2011) and Lazarim et al., (2009) have suggested that CK can be used as an early indicator of player fatigue and therefore a potential tool to monitor player recovery status within soccer. Few studies have, however, been completed in an elite athletic population, especially soccer players, to evaluate such proposals.

Smart et al., (2007) has suggested that high levels of CK are most likely related to high-intensity activities that are included in match-play. Direct attempts to link "actual" performance indicators to CK concentrations are very limited in the literature (Hunkin et al., 2013; Johnstone et al., 2013). Creatine kinase is related to the coaches subjective performance ratings in Australian Rules Football (Hunkin et al., 2013) but not the total distance covered in rugby league (McLellan et al., 2010). This may, however, be a consequence of the overriding influence of the physical collisions and the blunt force trauma that occurs in such sports as Australian rules football and rugby league, as opposed to their movement demands (Johnston et al., 2013). Only one study has, so far, examined the relationship between the activities completed within a soccer match and CK concentrations post-match (Thorpe and Sunderland, 2012). This data indicated a relationship between post-match salivary CK concentration and both number of sprint efforts and distance in semi-professional soccer players. Such data, while useful in providing initial information on the potential relationships between CK and indicators of physical match performance may be limited. These limitations are associated with the technology that was used to evaluate the activities of players within the match; the standard of player included in the sample and most importantly the small sample size (a single match) on which these relationships are developed. The aim of this investigation is therefore to examine the relationships between blood CK and the physical match performance of an elite soccer playing population across a regular season period.

6.2 Methods

6.2.1 Experimental Approach to the Problem

This investigation was completed as part of the on-going scientific support strategy implemented at a professional soccer club. As a consequence of this approach a traditional scientific experimental design was not employed for the investigation (please see 6.2.3 for more details). The research aim was fulfilled by collecting data on the match activity profiles and post-match CK concentrations of a group of elite soccer players across a competitive English Premier League (EPL) season. Following this data collection the available information was analysed using statistical techniques that examined the relationships between important physical match performance variables and CK measured 48 hrs post-match.

6.2.2 Procedures

Data was collected from a total of 15 elite soccer players (mean ± S.D.; age, 26 ± 4 years; height, 1.8 ± 0.6 m; body mass, 84 ± 6 kg). All participants played for an elite professional soccer team competing in the EPL. Data was collected during the 2011-2012 domestic season. Goalkeepers were excluded from the sample due to their specialised role within the team. Only outfield players were therefore included in the sample. The positional breakdown for the sample of players included was: 3 wide defender (WD), 3 central defenders (CD), 2 wide-midfielders (WM), 4 central midfielders (CM) and 3 forwards (ST). In an attempt to control the potential influence of differences in the number of observations on each player impacting the data a threshold of > 6 completed matches per player were used for subject inclusion in this investigation. The study conformed to the ethical standards of the local university ethics committee though was not locally approved. This was a direct consequence of the data collection being a condition of the player's employment at the football club in question. Such situations have been recognised by Winter and Maughan (2009) as influencing the normal conditions for ethical approval. Every effort was made for the data collection to adhere to recommendations of best practice so as to protect the interests and welfare of both the participants and the researchers. This included the Informed consent of both the Head of Sport Science and Medical Department at the club in question and the players.

6.2.3 Subjects

Match performance data was collected across the entire 39 weeks of the competitive season. Match performance data were produced using a semi-automated multi-camera recognition system (Prozone®, Leeds, England) installed at the home stadium of the study team. This system enabled data to be collected on all players in the 18 home league matches played in the EPL season. Kick-off times were between 12:45 and 20:00 depending on the fixture schedule and/or the requirements of the live television provider. A greater level of flexibility was required for the data collection process due matches and kick-off time being re-scheduled for television broadcast purposes, which would also affect the training session schedule. All matches were preceded by a training session completed on the day before the match and was followed by a recovery day in which all players were not required to report to the club's training facilities.

The generation of physical match performance data using Prozone® is based upon the development of a continuous movement trajectory for each individual player during match-play (Di Salvo et al., 2006). Recent studies have evaluated the validity and reliability of Prozone® (Di Salvo et al., 2006; Di Salvo et al., 2009). To develop the players' activity profiles movements were coded into the following categories and speed thresholds: standing (0-0.2 $m.s^{-1}$), walking (0.2-2 $m.s^{-1}$), jogging (2-4 $m.s^{-1}$), running (4-5.5 $m.s^{-1}$), high-speed running (5.5-7 $m.s^{-1}$), and sprinting (>7 $m.s^{-1}$) as in previous investigations (Di Salvo et al., 2009; Gregson et al., 2010).

The physical measures selected to explore the links between CK and movement profiles were based upon important match performance indicators in previous research (Mohr et al., 2003; Krustrup, 2006; Di Salvo et al., 2009) and variables selected by the club's Sport Science Department. The following measures were selected for analysis: 1. Total Distance Covered (Total Distance); 2. Total High-Intensity Running Distance (THIRD) (running speed >5.5 $m.s^{-1}$ over a 0.5s time interval); 3. Total High-Intensity Running Number (THIRN); 4. High-Intensity Running with Possession (HIRP) (high-intensity running distance covered when the players' own team was in possession of the ball); 5. High-Intensity Running Distance without Possession (HIRWP) (the subtraction of high-intensity running distance with possession of the ball from total high-intensity running distance); 6. Total Sprint Distance (TSD) (average running speed > 7 $m.s^{-1}$ over a 0.5s interval) and 7. Total Sprint Number (TSN); 6. Average Speed (Ave. Speed) (average speed is the mean value (metres per second) of the speeds that have been completed by a specific player for specific time periods; and 8. Recovery Time (Rec. Time) (average time in seconds between high intensity activity bouts >5.5 $m.s^{-1}$).

Blood samples were taken from each participant's fingertips at a time point approximately 48 hrs post-match. All samples were taken between the hours of 09:00 and 10:00 prior to the start of training. The samples were collected in a standing position using a sterile lancet (Roche, Mannheim, Germany) in combination with a spring-loaded Accu-Chek lancet device (Roche, Mannheim, Germany). Every effort was made to control a range of factors that have the potential to impact CK concentration. These included the time of day and the immediate nutritional intake prior to the sample collection. Other potentially important variables such as post-match nutrition, activity not associated with official training sessions and climate could not be rigidly controlled during data collection due to the nature of this investigation. Such factors are however unlikely to impact upon the data to any large extent as a consequence of the similarity in individual players routines following each match. Creatine kinase samples were analysed immediately after collection via spectrophotometry using a commercially available reagent kit (Reflotron® Systems, Roche, Mannheim, Germany). Capillary blood analysed using this method displays an intra-assay reliability of <3% coefficient of variation (Howatson et al., 2009).

6.2.4 Statistical Analyses

Statistical analysis for the investigation followed two stages. Stage one calculated mean data values for each subject's CK score and each of the Prozone® physical match performance variables across the available sample of matches for each individual. The second stage involved statistical analysis to determine within-subjects correlation coefficients between each players CK values and the individual's physical match performance output collected during the match. These correlation coefficients were calculated from outputs from the general linear models (Jones et al., 2013) according to the approach of Bland & Altman (1995) using SPSS version 17 (SPSS Inc., Chicago, Illinois, USA). The data reported in the manuscript are represented as mean ± S.D. For all statistical analysis, $p < 0.05$ was considered significant.

6.3 Results

Table 6.1 shows the physical match performance data relating to distance covered for the sample of players from the matches that were associated with the data collection for blood CK concentrations used in the investigation. These values are similar to those previously reported for elite players in the literature (Di Salvo et al., 2009; Gregson et al., 2010). The THIRN and TSN (140 ± 43 and 46 ± 19 respectively) also seem representative of this type of data (Di Salvo et al., 2009; Bradley et al., 2009). The REC and the AVE are broadly representative of the overall intensity of effort of individual players across the match. The REC was 44 ± 18s with the AVE calculated as 1.9 ± 0.1 $m.s^{-1}$.

Table 6.1. Mean ± SD Physical match performance data by position for the distance covered in the games selected for analysis.

Position	Total Distance (m)	THIRD (m)	TSD (m)
CD	9672 ± 389	534 ± 122	133 ± 51
WD	10507 ± 428	1035 ± 189	339 ± 102
CM	11454 ± 763	1161 ± 279	326 ± 123
WM	10663 ± 975	1331 ± 254	451 ± 150
ST	10476 ± 647	1180 ± 275	338 ± 136
Overall	**10574 ± 854**	**1030 ± 358**	**312 ± 154**

Total Distance = Total Distance Covered; THIRD = Total High-Intensity Running Distance; TSD = Total Sprint Distance (Average ± SD). CD = Central Defender; WD = Wide Defender; CM = Centre Midfielder; WM = Wide Midfielder, ST = Striker.

Table 6.2. Creatine Kinase values by position in the games selected for analysis (mean ± SD, minimum, maximum values).

Position	Ave. CK Value	Min. Value	Max. Value
CD	437 ± 200	203	1250
WD	511 ± 110	296	758
CM	566 ± 310	184	1573
WM	612 ± 169	365	1110
ST	513 ± 220	210	1360
Overall	**520 ± 224**	**184**	**1573**

Total Distance = Total Distance Covered; THIRD = Total High-Intensity Running Distance; TSD = Total Sprint Distance (Average ± SD).

Table 6.3. Table showing the relationship between creatine kinase and physical match performance variables.

Variables	R Value	Sig. (p < 0.05)	95% Confidence Intervals	
			Lower Bound	Upper Bound
Total Distance (m)	0.076	0.34	-0.072	0.221
HSRD (m)	0.045	0.57	-0.103	0.191
HSRN (No.)	0.051	0.52	-0.097	0.097
THIRD (m)	0.083	0.30	-0.065	0.228
THIRN (no.)	0.018	0.82	-0.13	0.165
HIRP (m)	0.058	0.47	-0.09	0.204
HIRWP (m)	0.002	0.98	-0.145	0.149
TSD (m)	0.108	0.71	-0.04	0.251
TSN (m)	0.084	0.29	-0.064	0.229
Ave. Speed (m/s)	0.146	0.64	-0.001	0.287
Rec Time (s)	0.057	0.47	-0.091	0.203

Total Distance = Total Distance Covered; HSRD = High-Speed Running Distance; HSRN = High-Speed Running Number; THIRD = Total High-Intensity Running Distance; THIRN = Total High-Intensity Running Number; HIRP = High-Intensity Running with Possession; HIRWP = High-Intensity Running Distance without Possession; TSD = Total Sprint Distance; TSN = Total Sprint Number; Ave. Speed = Average Speed; Rec Time = Recovery Time.

Average CK concentration for the sample of players 48 hrs post-match was 520 ± 224 µ.mol.l^{-1} (see table 6.2). Individual player values showed great variation in the CK response to matches. This variation ranges from 184 µ.mol.l^{-1} to 1573 µ.mol.l^{1}. The R-values obtained from the correlation coefficients signify the strength of the relationship between CK and the selected Prozone® variables (see table 6.3). No significant relationships were observed between any indicator of physical match performance and CK concentration measured 48 hrs post-match (see figure 6.1).

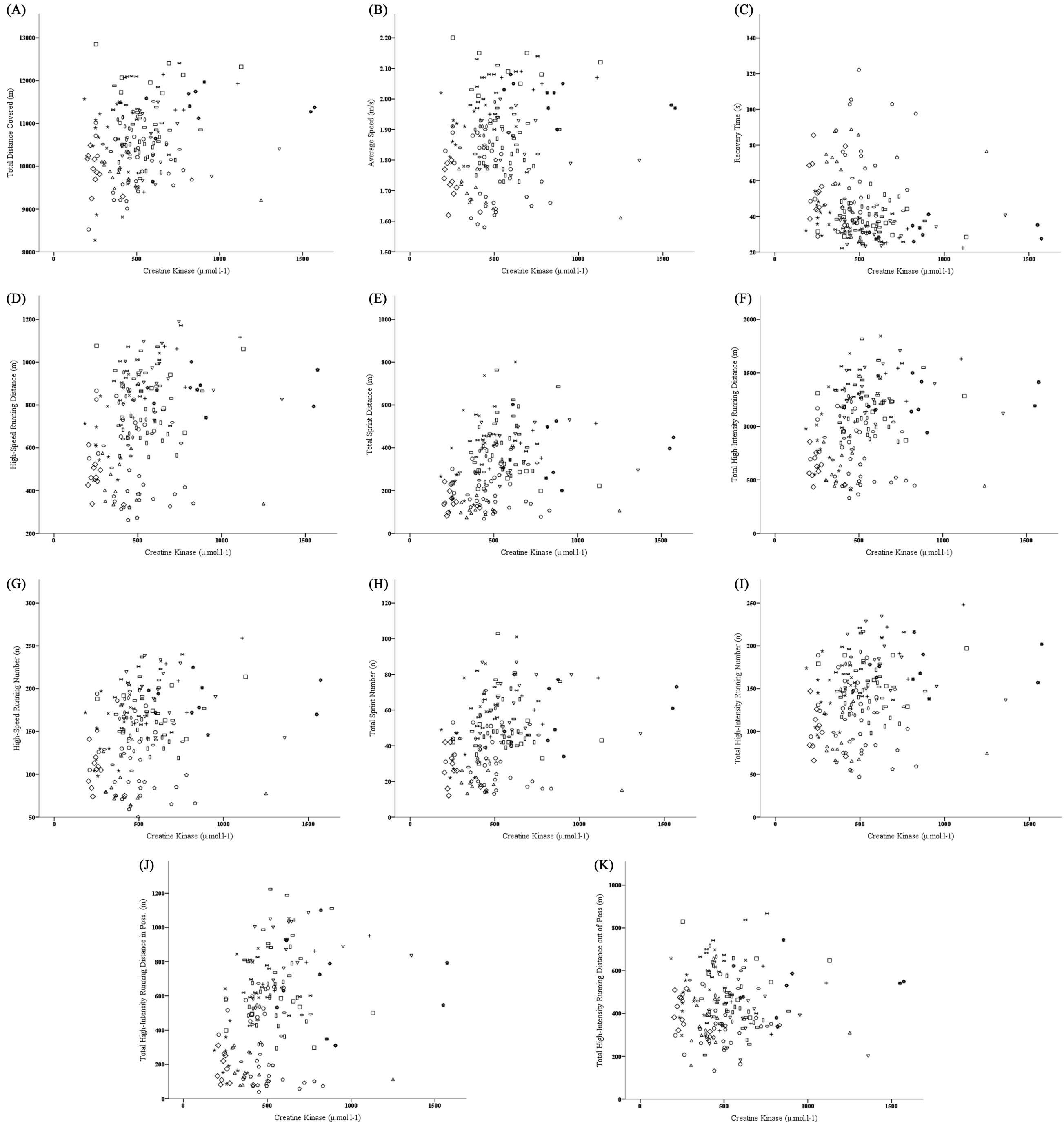


Figure 6.1. Elite soccer player's creatine kinase relationships compared to selected physical performance measures. A) Total Distance Covered; B) Average Speed (m/s); C) Recovery Time (sec); D) High-Speed Running Distance (m); E) Total Sprint Distance (m); F) Total High-Intensity Running Distance (m); G) High-Speed Running Number (n); H) Total Sprint Number (n); I) Total High-Intensity Running Number (n); J) Total High-Intensity Running Distance in Possession (m); K) Total High-Intensity Running Distance out of Possession (m).

6.4 Discussion

The aim of this investigation was to examine the relationships between blood CK and the physical match performance of a group of elite soccer players using information from a computerised semi-automatic tracking system (Prozone®). Our findings suggest that the activity completed within a match is not related to the CK concentrations that are observed 48 hrs post-match. This would suggest that CK might not be of value for practitioners to subtly track changes in the physical match performance potential of players during the competitive season. This is in contrast to previous research (Lazarim et al., 2009) that suggests that CK has the potential to be a useful marker for the early detection of muscle fatigue in soccer players. Based on our data, practitioners who are involved in the scientific support of players in elite soccer environments may therefore be advised to consider alternative physiological/biochemical markers within their monitoring programmes.

The application of the data in this investigation is partly dependent on the generalizability of the data to other populations of soccer players. The physical match performance metrics included in our study seem to be similar to those reported in a range of previously published literature (Di Salvo et al., 2009; Bradley et al., 2009; Krustrup et al., 2002; Mohr et al., 2003). This would seem to indicate that our sample is reflective of the physical demands that are associated with professional soccer at this competitive standard. The concentrations of CK that were observed 48hrs post-match also seem to be comparable to those in similar athlete populations (Hortobagyi & Denaham, 1989; Lazarim et al., 2009; Coelho et al., 2011; Nedelec et al., 2014). This would support the view within the literature that the completion of a professional soccer match leads to significant increases in CK for a number of days post-match. The physiological understanding of the reasons for increases in CK following exercise are not well understood (Andersson et al., 2008; Lazarim et al., 2009). It has been suggested that high CK levels are a function of the damage to muscle cell membranes during exercise (Hortobagyi & Denaham, 1989). Such damage may be related to the amount of eccentric activation of the muscle, as such actions result in a higher tension per cross sectional area (Thorpe & Sunderland, 2012). These actions are common during intense bouts of activity within a soccer match (Lazarim et al. 2009) and therefore are a potential explanation for the findings in this investigation. Our sample also displayed a large variation in the CK concentrations observed as noted previously within research on team sports players (Hortobagyi & Denaham, 1989; Lazarim et al., 2009; Coelho et al., 2011; Hunkin et al., 2013). Such variations are highly likely to be a result of the individual characteristics of players (McNeil & Khakee, 1992; Lazarim et al., 2009).

The individual variation that is observed in CK post-match provides the basis to examine the relationship between CK and physical match performance. While the physiological significance of increased CK on physical match performance remains unclear (Hunkin et al., 2013), the marked differences observed in CK within such populations may be partly due to the different amounts of intense exercise and/or specific match actions completed by soccer players (Lazarim et al. 2009) in different positions and tactical roles. The current investigation is the first that has examined the relationship between post-match CK and physical indicators of match performance in this elite population across multiple matches using highly accurate movement analysis techniques. Our data failed to demonstrate any significant relationships between any indicators of physical match performance and post-match CK values. Research from other team sports has in some ways supported this view by demonstrating that physical variables such as tackles and impacts are more clearly associated with CK than the movement patterns that soccer players complete (Johnston et al., 2013; Twist et al., 2012). When taken together this would suggest that CK may not accurately reflect changes in the activity profiles completed by soccer players during EPL matches and hence may not be useful in tracking the physiological stresses associated with elite competitive match-play across the season.

The failure to observe a link between the movement profile of EPL players and CK may also be a function of the experimental design employed within this investigation. Such issues may be related to the variables chosen for analysis and/or a consequence of the "real world" approach to this investigation. The variables chosen to explore the links between CK and movement profiles were based upon important match performance indicators in previous research (Mohr et al., 2003; Krustrup, 2006; Di Salvo et al., 2009). As such we are confident that our approach reflects an evidence-based evaluation of an individual's physical match performance. The semi-automatic computerised tracking system used to generate the data in this investigation has the potential to provide additional movement-related and technical variables. While the importance of these variables has not been systematically evaluated with respect to their impact on elite professional match-play, they have the potential to influence the CK response. For example, accelerations and decelerations that involve substantial eccentric components are frequently completed during matches and are regarded as contributing to elite performance (Bradley et al., 2013; Di Salvo et al., 2013). Future research should attempt to investigate the links between such non-traditional variables to see if these are more strongly related to post-match CK concentrations than more traditional indicators that are representative of the player's activity profiles.

“Real world” approaches to research provide data that is high in ecological validity yet which may be limited in terms of its degree of traditional experimental control. The data in this investigation was collected with a group of elite soccer players competing for a high-level team in a competitive season in the EPL. This approach influenced other potentially important aspects of the research design more specifically the timings of the collection of additional CK samples. The training schedule of the players prevented the collection of both pre-match and additional post-match CK samples. These restrictions clearly limit the potential to determine a detailed CK response to the preparation for and recovery from match-play or examine the relationships between CK and physical match performance at other time points post-exercise.

Understanding the relationships between match performance and indicators of the status of the muscular system in the elite soccer player who will compete in a large number of matches (> 60) during a domestic season would seem to be an important practical consideration. If the recovery time between matches is limited there is an increased risk of overload that can result in muscle damage and ultimately injury (Lazarim et al., 2009). While it has been suggested that CK provides a potential biochemical marker for use in elite team sports, our data indicates that changes in CK do not seem to be explained by the locomotor activity completed by soccer players during EPL matches. This would indicate that CK might not be of fundamental importance to the monitoring strategies used within elite soccer clubs to track performance. The “real world” approach to this study is however associated with limitations that does not permit a comprehensive recommendation on the application of CK analysis to athlete tracking to be made. As such this area requires further consideration especially with respect to an understanding of individual player characteristics and CK responses to acute and chronic exercise.

7.0 An Investigation into Elite Soccer Player's Physical Match Performance using Temporal Pattern Analysis

7.1 Introduction

Current methods for analysing physical performance in soccer have typically used semi-automatic computerised tracking systems (Bradley et al., 2009; Drust et al., 2007; Di Salvo et al., 2009). These approaches index performance into discrete motion modalities, which can then be classified according to type, intensity (or quality), duration (or distance), and frequency (Reilly, 1994). The findings from this research have provided valuable insights into the physiological requirements of the game and subsequently informed both further academic research and training practice (Drust et al., 2007). It is suggested within this research that soccer performance consists of a complex series of interrelationships between a wide variety of performance components that occur at both the level of the player and team (Gregson et al., 2010). As a consequence, simple frequency counts of activities may not necessarily capture the full complexity of a soccer performance (Johnsson et al, 2006). There is therefore, a need for research that uses data analysis methods and/or techniques that can generate more complete and, more complex quantitative representations of performance (Anguera & Jonsson, 2003). Establishing such "patterns" within the physical component of soccer performance would likely further develop coaching, physical conditioning practices and academic research (Bloomfield et al., 2005).

One aspect of analysis of performance that has received recent interest in the scientific literature is the analysis of temporal structures and the interrelationships between events within sport performances. This form of analysis is conducted using an observational software package called THÈME© (Magnusson, 1996, 2000) and uses a specifically developed algorithm to determine repeated temporal and sequential structures in real-time behaviour records (Borrie et al., 2002). The THÈME© software has been used to analyse tactical and technical performance in basketball (Fernandez et al., 2009), Judo (Gutierrez et al., 2011) and Karate (Lapresa et al., 2011). These findings suggest that insights into novel activity profiles (complex intra- and inter-individual patterns) can be derived using the behavioural patterns detected in combination with elementary statistics (Jonsson, 2003). Soccer specific research that has used T-pattern analysis is somewhat limited in comparison to other sports. The available investigations have primarily focused on the tactical and technical components of performance (i.e. the patterns associated to goal scoring opportunities in competitive matches). For example, Sarmento et al., (2010) used the analysis tool to identify attacking patterns of play in an elite Spanish soccer team while Borrie et al., (2002) identified both individual and team related patterns within English Premier League and International soccer teams. Both investigations indicated that temporal patterns do exist in technical performance in soccer. Previous work by Bloomfield et al., (2005) using T-pattern analysis successfully identified reoccurring patterns within the physical performance of an elite soccer. For example, Bloomfield et al., identified a pattern sequence for a player that began sprinting forwards sub-maximally, slowing down and shuffling at high-intensity, then slowing abruptly from a sprint. These successfully identified patterns of movement were, however, the consequence of the analysis of a single player case study for a very limited temporal period (15-min). This makes the generalizability of the data difficult to apply to new other research or investigations, but does confirm conclusions about the existence of patterns in the physical profile problematic.

The aim of this investigation is therefore, to analyse elite soccer player's physical match performance data using T-pattern analysis to determine the existence of patterns in physical performances. Furthermore, the study will look to provide insight into the structure and make-up of potential complex intra- and inter individual patterns that can occur within soccer match-play.

7.2 Methods

The following section of the methodology has been divided into three sub-sections in order to provide the reader with the necessary background and methodological information for the chapter. The first section describes what temporal patterns are and how the THÈME© algorithm searches data sets to discover temporal sequences. This provides important background information on the general approach to pattern analysis. The second section will then describe how the data set was collected via the Prozone® system and formatted for the THÈME© software in this current investigation. The final section will then provide information on how to interpret the pattern sequences from the THÈME© post analysis.

7.2.1 Description of Temporal Patterns and The THÈME© Algorithm

The THÈME© 5.0 software package (Magnusson, 1996, 2000) used in this investigation uses an approach based on the identification of a very general type of time pattern called a `T-pattern'. This particular pattern is one form of temporal pattern or configuration, which together with the corresponding detection algorithm, are the most readily used in areas of human and social behaviour (Magnusson, 2000). A T-pattern is essentially a combination of events in which the actions occur in the same order with the real-time differences between consecutive pattern components remaining relatively invariant (i.e. the time difference between A and B will be $x \pm y$)

(Borrie et al., 2002; Magnusson, 2000). The algorithm allows detection of repeated temporal and sequential structures that cannot be fully detected through unaided observation or with help of other statistical methods (Borrie et al., 2002).

The T-pattern analysis algorithm follows 2 stages when analysing the data for pattern sequences. At the first stage, the algorithm searches the data using a hierarchical structure (see figure 7.1 for example) that follows a bottom-up or level-by-level detection strategy. The algorithm starts by detecting simple pattern sequence (2 or 3) and then proceeds onto more complex pattern sequences of (4+). The algorithm performs the analysis in this order, as complex pattern sequences are derived from the simple pattern sequences, (see figure 7.1) (Magnusson et al., 2000). The first line of figure 7.1 provides a visual representation of the temporal structure of a sequence of movements in a soccer match (i.e. RUN, JOG, WALK, STAND STILL, and SPRINT) that appears in proportion to the time of their occurrence. Within the example line, a sequence of (AB) has occurred twice within a dataset that also contains other activity types (W, S, C and D).

The THÈME© algorithm searches for a tendency for A to be followed by at least one occurrence of B significantly more often than expected by chance within any time window or interval. If such an interval is found, it is then called a 'critical interval', and the relation between A and B is called a 'critical interval relationship'. For this calculation, THÈME© assumes as a zero hypothesis that A and B are both independently distributed and have the observed probability of occurrence per time unit, which is assumed to be constant throughout the continuous observation period.

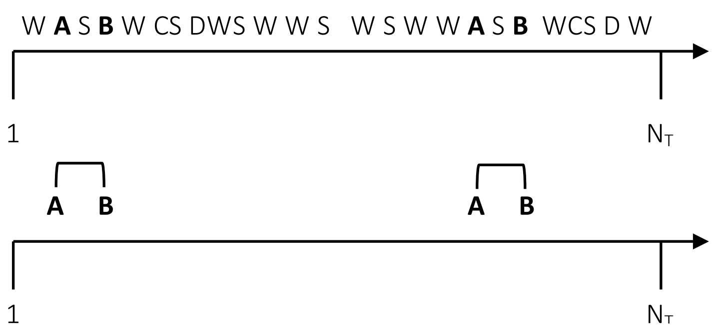


Figure 7.1. An example of the detection of a simple T-pattern sequence of 2 (A-B) within a larger data set of physical activity (W, S, C, D). The simple pattern (A-B) is shown to occur twice across the example time period (Borrie et al., 2002).

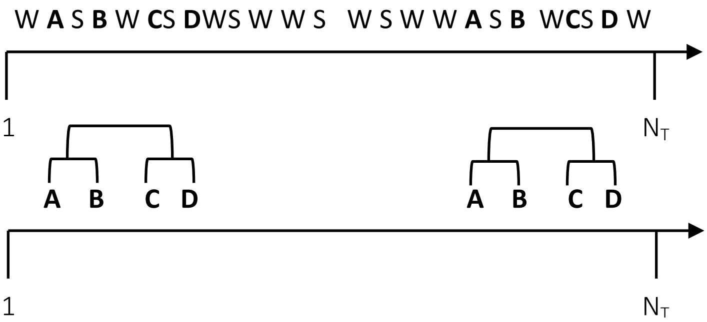


Figure 7.2. An example of how the THÈME© software detects a complex T-pattern sequence of 4 ((AB)(CD)) within a larger data set of physical activity (W, S). The complex pattern ((AB)(CD)) is shown to occur twice across the example time period (Borrie et al., 2002).

Real data will typically contain many more event types. Thus, in addition to the pattern (AB) being detected, others may also be found (i.e. (CD)). All occurrences of these simple patterns become events themselves, and are then added to the data and treated like the initial types of events in the next level of pattern detection. THÈME© repeats the above procedure, level-by-level, searching for more 'critical interval relationships' involving the detected patterns. A 'critical interval relationship' may be found between pattern (AB) and event type (S), giving rise to the pattern ((AB) S), or between the simple patterns (AB) and (CD), producing the more complex pattern ((AB)(CD)) (see figure 7.2). These may then become part of an even more complex pattern (see figure 7.3 for example). The total number of possible T-patterns, even in a moderate data set, can be very high. For example, when the potential number of event-types equals 100, the number of potential event patterns involving up to 10 event-types is many orders of magnitude greater than 100^{10}, if all possible time windows are also considered (Magnusson et al., 2000). To deal with such high frequencies of patterns, the algorithm performs a second stage of analysis that is called 'completeness competition'. At this stage, the analysis will eliminate detected patterns that are partial or redundant versions of other defected patterns. For example, pattern Q_X is considered less complete than pattern Q_Y if Q_X and Q_Y occur equally often and all events occur in Q_X also occur in Q_Y. If the reverse is also true, Q_X and Q_Y are considered equivalent and one is arbitrarily selected, and the other is dropped.

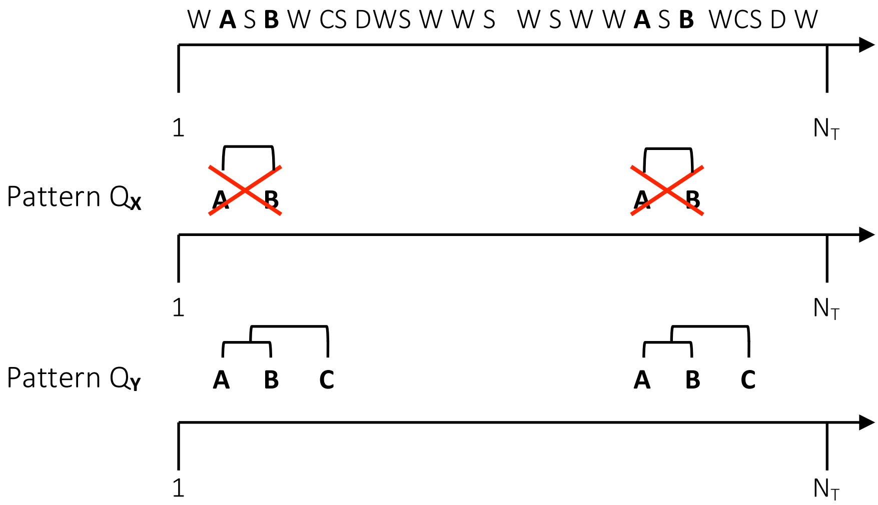


Figure 7.3. An example of a defected T-pattern sequence (Pattern Q_X) that has been considered less complete than Pattern Q_Y in the THEME completeness competition stage.

7.2.2 Methods for Current Investigation

7.2.3 Subjects and Match Data

Match performance data was produced using a computerised semi-automatic multi-camera image recognition system (Prozone®, Leeds, England). The collection of physical performance data for the current study used the same capturing process as previously highlighted in section 3.2.2. Physical competitive match data were collected from 5 soccer players who played for an elite professional soccer team competing in the English Premier League during the 2010-2011 domestic season. A total of 4 individual match observations were undertaken on each outfield player. Analysis was only undertaken on outfield players due to the specialised role of the goalkeeper. The reason for a reduced data sample was due to the sample being manually collected from the Prozone 3® system for each player and match. The study conformed to the ethical standards of the researcher's university ethics committee. The Head of the Sport Science and Medical Departments at the club in question granted informed consent on behalf of the players at the respective club.

The 5 selected players for analysis were assigned to the same playing positions as identified in previous literature (Di Salvo et al., 2009; Gregson et al., 2010). The specific breakdown of the positions were; 1 central defender; 1 wide defender; 1 central midfielder; 1 wide midfielder; and 1 attacker. Every player was analysed using data from the same 4 matches in an attempt to reduce the between game variability that has been found to occur with physical performance measures (Gregson et al., 2010, see chapter 3.0). Players' activities were coded into the following categories and speed thresholds: standing (0 m/s), walking (0.2-2 m/s), jogging (2-4 m/s), running (4-5.5 m/s), high-speed running (5.5-7 m/s), and sprinting (7+ m/s). The speed categories are the same as used in previous investigations using semi-automatic tracking systems (Di Salvo et al., 2009; Gregson et al., 2010; see chapter 3.0). For information on the reliability and validity of the Prozone® system please see section 3.2.3. The physical variable selected for analysis in this investigation was Average Speed. This measure was calculated by the Prozone® system as the total distance (m) divided by time (s). Metres per second (m/s) were used as the unit measure. The Prozone® system calculates average speed every 0.5 seconds, but due to the limitations in functionality of the Prozone 3® product, raw average speed data could not be exported from the software in time units smaller than 1-minute periods. Due to this, data points were instead collected manually every 10 seconds throughout each match by using the speed trace monitor provided through the Prozone 3® software (see section 3.2.2).

7.2.4 Data Collection for THÈME© Analysis

Due to the Prozone 3® product being unable to export time periods smaller than 1 minute a manual data collection process was required to collect smaller time period data. This required an observer to record the activity trace from the Prozone 3® product at every 10 second period in a pre-formatted Microsoft Excel® spreadsheet (Microsoft, Redmond, USA). The decision to collect data every 10 seconds was a function of limitations in the sensitivity of the speed trace to provide data (i.e. 10s being the smallest measurement unit available on the speed trace). For the temporal pattern algorithm to generate the most meaningful analyses, the raw data was time-coded, according to time of occurrence as well as event-type (Borrie et al., 2002; Bloomfield et al., 2005). At each 10 second time period the observer used the *x*-axis on the activity trace to locate the specific time point and then used the *y*-axis on the same trace to identify what speed the player had reached at that specific intersection (see figure 7.4 for example). Speed trace data was collected using whole speed values for all low-intensity efforts (i.e. 1.0 to 5.0 m/s). High-speed efforts were also collected at 0.5 (m/s) when the trace was above 5.5 (m/s) (i.e. 5.5, 6.0, 6.5, 7.0+ m/s). Speeds of 5.5 m/s were chosen as the intensity threshold, as this value was the Prozone® system threshold for high-speed running. Speeds between 6.5 and 6.9 (m/s) were only classified as high-intensity efforts as a sprint in the Prozone® system is defined as a speed of 7.0 (m/s) or greater. This characterisation required the speed trace to be rounded up or down to the nearest defined speed value. For example, if the speed trace line was 3.6m/s at the first 10-second period, it was categorised as 4m/s, whereas, a speed of 6.8m/s would be categorised as 6.5m/s, as it was not greater than 7.0m/s. After the collection process, the physical performance data recorded in the Microsoft Excel® spreadsheet was then divided into 15-minute time periods for analysis within the THÈME© software (i.e. 0-15, 30-15). These periods were selected as the previous investigation showed 15-minute time periods represented the lowest variability of all within-game time periods (see chapter 3.0 in thesis).

Once the data was divided into time periods it was then entered into the THÈME© software. The data input process into the THÈME© software required the user to enter the necessary criteria for the following areas to conduct the analysis; i) context of the game (1st or 2nd half); ii) numeric relationship (time period of action and categorisation of time period (i.e. 00:00:10 would be in the 0-15-minute time period)), and, iii) Prozone® physical activity category (i.e. a speed trace reading of 7.0 m/s would equal a sprint categorisation). The configuration of the software only permitted the user to continue to the following step once all relevant data fields have been entered. After completion of data entry, the THÈME© software commences the search using the unique algorithm for relationships between events within the data set.

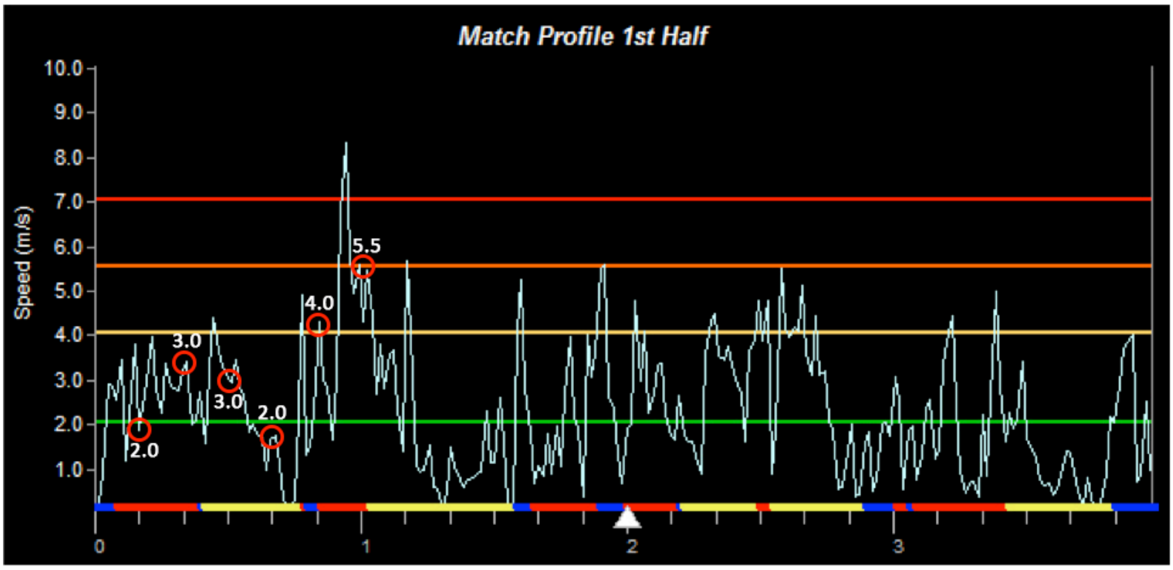


Figure 7.4. An example of the average speed trace taken from Prozone 3® application for a Central Defender in the first 3-minutes of a soccer match. The *x*-axis shows the 3 min time period in 10-second units and the *y*-axis shows the speed categories (m/s). The green line depicts the threshold for standing, walking and jogging (0-14.3 km/h^{-1}); the yellow line depicts the threshold for running (14.4-19.7 km/h^{-1}); the orange threshold line is high-speed running (19.8-25.1 km/h^{-1}); the red threshold line is sprinting (>25.1 km/h^{-1}). The red circles highlight the measurement value recorded for each of the opening 10-second periods.

7.2.5 Post THÈME© Pattern Analysis

After the analysis was completed, the software provided a visual representation of each temporal pattern that was discovered within the data set. Each of the patterns identified from the analysis could then be viewed within the software and subsequently exported. For the purposes of the current investigation only pattern sequences that included a high-intensity action were selected. This decision was based on previous research suggesting that high-intensity efforts are related to the actions that can result in winning or losing matches (Stolen et al., 2005) and are therefore considered a crucial element of soccer performance (Mohr et al., 2003). A total of 616 high-intensity patterns were identified across all 15-minute time periods (0-90 minutes). Due to such a large number of identified pattern sequences, the data was then filtered to refine the number of patterns for further analysis. The filter was performed on each different 15-minute time period with the 3 highest occurring patterns at each of the different pattern sequence lengths (i.e. 3 patterns from each of the simple pattern lengths of 2, 3 and also the complex sequences of 4, 5, 6) selected. This filter provided a refined total of 90 pattern sequences for further analysis (15 pattern sequences from each 15-minute time period). An example of a temporal pattern discovered in the current investigation can be seen in section 7.2.6.

7.2.6 An Example of a Temporal Pattern from THÈME©

The following section provides a detailed description of the visual outputs that the THÈME© 5.0 software provides once the algorithm search has been successfully completed. The description and detail included in this section is provided to help when interpreting the data included in this chapter.

Figure 7.5 shows an example of the data output from THÈME© 5.0 analysis software showing temporal and hierarchical representation of a T-pattern from the current analysis. The THÈME© software provides an individual temporal pattern output window for each of the pattern sequences identified in the analysis. Within each output window there are four descriptive boxes that relate to the single T-pattern that was discovered. The box in the top left corner of the screen (A) highlights what time period the pattern was discovered in. The example in the figure shows that the pattern occurred in the 0-15 min period (due to the grey highlighting around the time period). Box (B) shows the hierarchical construction of the pattern sequence using a dendrogram. The right-hand edge of the dendrogram details the physical action-taking place within the pattern whilst, the left-hand side details the structure of the pattern and describes how the individual actions combine to form a more complex pattern. The example pattern that can be seen in Figure 7.5 identifies a sequence that included a HIGH-SPEED RUN (5.5-7 m/s), RUN (4-5.5 m/s, JOG 2-4 (m/s), SPRINT (7+ m/s) AND WALK 0.2-2 m/s). The hierarchical construction of the pattern shows that the sequence includes 2 simpler pattern sequences of (RUN, JOG), (SPRINT, WALK) with the HIGH-SPEED RUN starting the complex pattern sequence. The total number of actions in a sequence also represents the pattern sequence length (i.e. 1 - HIGH-SPEED RUN, 2 - RUN, 3 - JOG, 4 - SPRINT and 5 - WALK = a pattern sequence length of 5). This can also be seen in box (B). The bottom box (C) shows the pattern, as a hierarchical structure, expressed in relation to the observation period of when it occurred during the match across time (i.e. where the pattern occurred within the selected

15min time period). The lines also display the connections between events and how much time passes between event occurrences and pattern occurrences. Only completed patterns are shown in this box. D) The upper right hand box displays the time of each event-type in the pattern and how the pattern connects through each event-type to make up the full sequence or ‘critical interval relationship’. The dots represent event occurrences and the zigzag lines that connect the dots represent pattern occurrences. The dots are aligned with the pattern descriptions in box (B) to help in identifying which pattern sequences link together. For example, in figure 7.5, there are 5 rows of dotted markers as the pattern has a sequence length of 5. It can be seen in the box (D) that there are a number of pattern sequences between the second row (RUN) and the third row (JOG). The zigzag lines that run from the top to the bottom dots illustrate how many completed pattern sequences occurred.

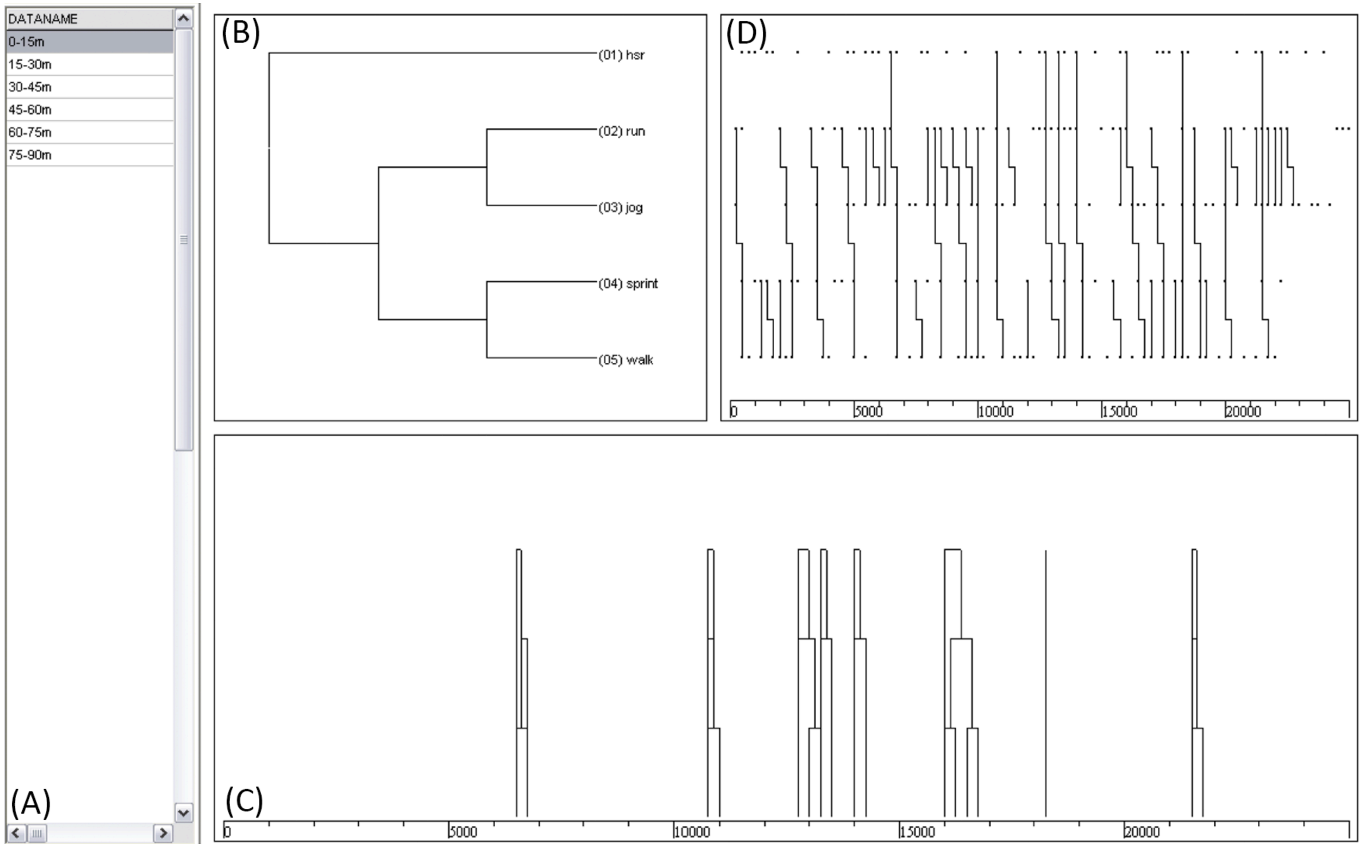
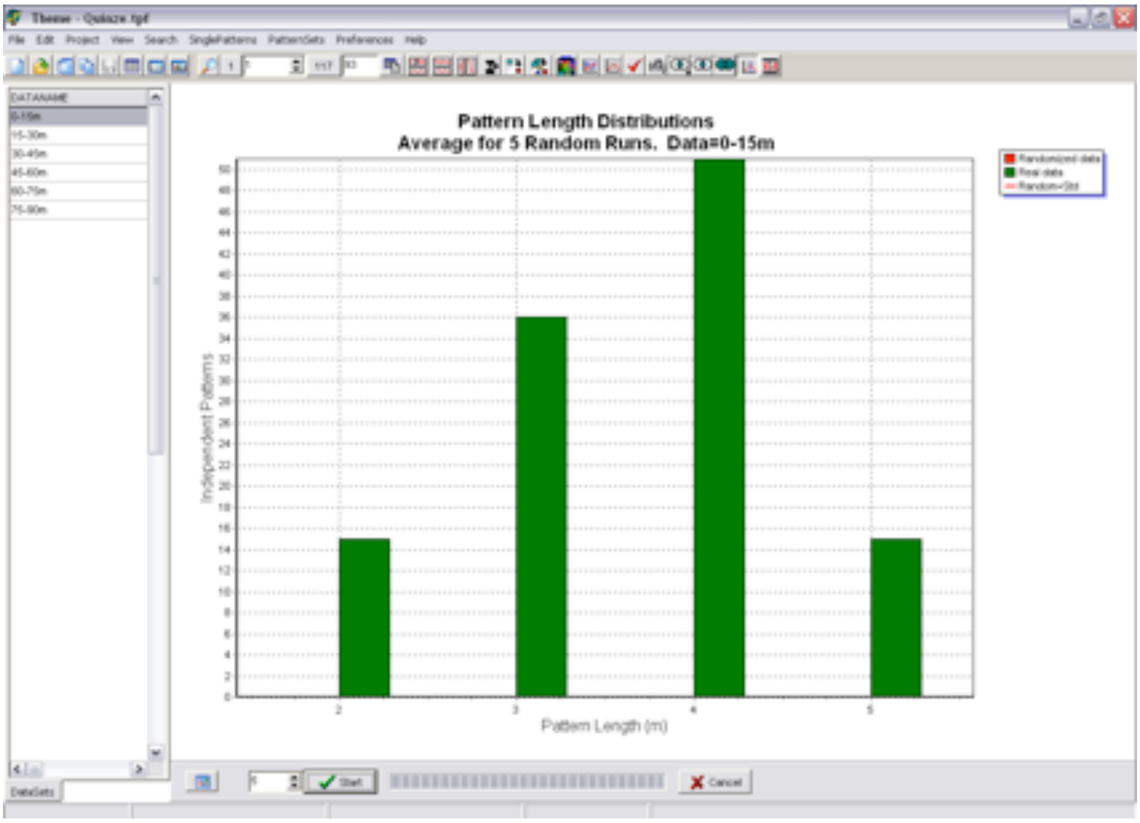


Figure 7.5. A data output from the THÈME© software detailing a temporal pattern of physical activity with a pattern sequence length of 5. The boxes within this figure should be read in order of A, B, C then D to successfully interpret each pattern. Box (A) highlights the time period that was selected for the analysis (i.e. 0-15min); (B) uses a dendrogram to illustrate the hierarchical construction of the pattern that was identified from the analysis. The dendrogram in box (B) shows the identification of a pattern that starts with a single HSR action and combines with 2 simple patterns (RUN, JOG) and (SPRINT, WALK) to make a complex sequence of 5 actions. Box (C) shows the hierarchical structure of the 5-sequence pattern expressed in relation to the observation period. The box shows that the time periods between each pattern differed due to the width of the structures. Only completed patterns are shown. Box (D) identifies how often the pattern sequence of 5 was found in the analysis. This box shows the critical interval relationships between each event type and how they formed to create a complete sequence. Each of the activity events is represented by dots and are organised in hierarchical rows. The lines between each dot represent a sequence links between events. This box helps identify how often the smaller patterns with the complex pattern were found within the analysis.

7.2.7 Statistical Analysis

The data were validated by randomising the data 5 times, and only accepting patterns in which the probability of the randomised data coinciding with the real results was less than or equal to 0. Also, the simulation filter provided in THÈME© version 5.0 was used. This filter performs randomisations for each critical interval relationship detected before accepting it as critical. The process replaces each occurrence series in the original data with a series containing the same number of random time points within the same observation interval, [1, N_T]. The temporal pattern detected would be accepted if the THÈME© programme found, among all the randomly generated ratios, critical interval relationships with internal intervals equal or smaller in size to those of the tested ratio (see figure 7.6). The level of significance for patterns to be found within the THÈME© program was set at 0.0001 and a minimum number of occurrences were set at 20. The smaller significance and occurrence level meant there would be a reduced likelihood of patterns occurring at random.

Figure 7.6. The THÈME© validity test using a randomized data sample for the 0-15-minute time period.



7.3 Results

7.3.1 The Existence of Temporal Patterns in Physical Soccer Performance

Figure 7.7 shows the number of different physical activity patterns that were found using the THEME© software during the match across all 15 min time periods. The figure highlights that temporal patterns do seem to exist in a soccer player's physical activities throughout all periods of the game. The THEME© software identified a greater number of different patterns in the second half compared to the first half of a match (252 v 364). The second half of the match was also found to contain the 15 min time period with the greatest number of different pattern occurrences (75-90 min = 182 different pattern sequences). The 30-45 min period was found to have the lowest frequency of different patterns (50).

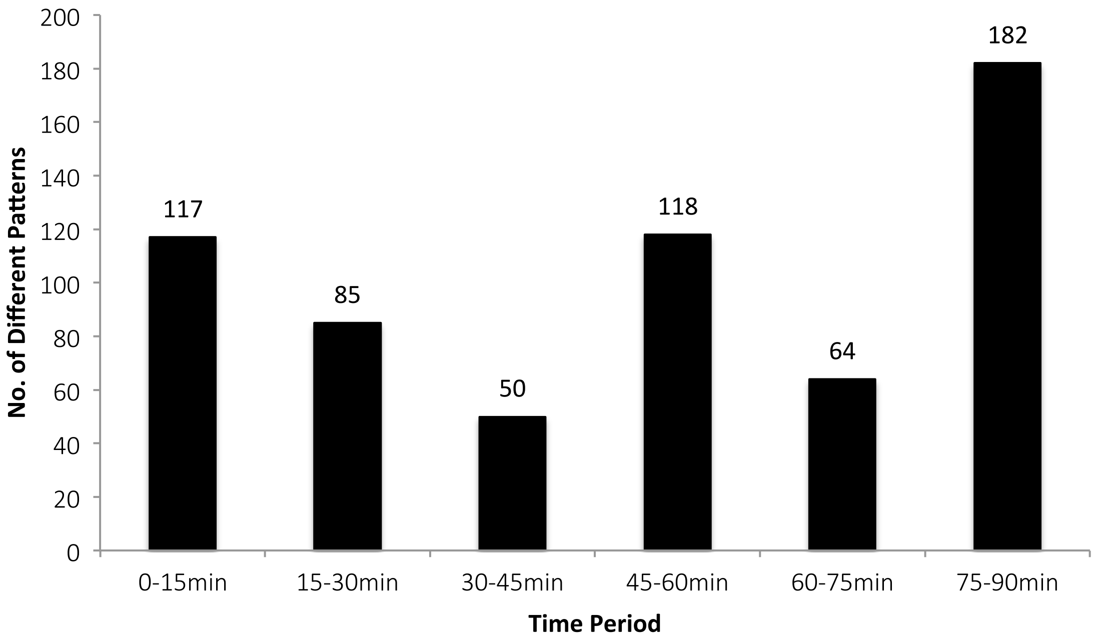


Figure 7.7. The number of different physical activity patterns that occurred within-game using 15 min time periods.

7.3.2 Temporal Patterns Changes Within-game

Table 7.1 shows the breakdown of the different pattern lengths that occurred within the game in each 15 min time periods. A total of 616 patterns that included a high-intensity activity were found during the sample of matches that were analysed for the investigation. The analysis software detected 5 different pattern sequence lengths (2,3,4,5 and 6) in the sample of physical data. Of those patterns detected, the patterns with a length of 4 were observed to occur the most within the game (242 occurrences), while the least common pattern was the more complex pattern sequence of 6 (3 occurrences). Simple pattern lengths of 2 were found to occur consistently in each time period (15-18 occurrences). It is also evident when examining Table 7.1 that the sequences of 4, 5 and 6 were most frequently observed during the opening 15-minute period (0-15min), the start of the second half (45-60min) and during final 15-minute period (75-90min) of the match.

Table 7.1. A breakdown of the different lengths of activity pattern found within-game using 15 min time periods, and the contribution the pattern length makes to the total number of patterns found in that period as a percentage (%).

Time Period	**Pattern Length**					**Total No. Of Patterns**
	2	**3**	**4**	**5**	**6**	
0-15 min	15 (*13%*)	36 (*31%*)	51 (*44%*)	15 (*13%*)	0 (*0%*)	117 (19%)
15-30 min	17 (*20%*)	35 (*41%*)	29 (*34%*)	4 (*5%*)	0 (*0%*)	85 (14%)
30-45 min	16 (*32%*)	24 (*48%*)	10 (*20%*)	0 (*0%*)	0 (*0%*)	50 (8%)
45-60 min	17 (*14%*)	39 (*33%*)	53 (*45%*)	8 (*7%*)	1 (*1%*)	118 (19%)
60-75 min	17 (*27%*)	31 (*48%*)	15 (*23%*)	1 (*2%*)	0 (*0%*)	64 (10%)
75-90 min	18 (*10%*)	59 (*32%*)	84 (*46%*)	19 (*10%*)	2 (*1%*)	182 (30%)
Total	**100 (16%)**	**224 (36%)**	**242 (39%)**	**47 (8%)**	**3 (1%)**	**616 (100%)**

The following section of the results provides information on the three time periods that had the highest total number of patterns sequences during the match (0-15min, 45-60min and 75-90min). Each time period is described separately and will provide information on i) the pattern sequences that were identified within the time period; ii) the structure and frequency of those selected pattern sequences; and iii) the visual outputs taken from the THÈME© software post analysis. The visual outputs are to provide the reader with the detail to understand the pattern structures and the occurrences across the different time periods.

7.3.3 Physical Activity Patterns in the Opening 0-15 Minute Period of the Game

THÈME© analysis the output windows as see in figure 7.8 will be used to highlight the sequence within the opening period of the match the THÈME© analysis identified 117 patterns. Of those 117 patterns, 44% of the sequences identified within this period were simple pattern sequences of 2 and 3. Figure 7.8 provides examples of the 2 highest occurring simple pattern sequence of 2 and 3 during this initial period of the game. This figure illustrates that the simple patterns of 2 and 3 occurred in a cyclical fashion throughout out the opening 15 min with sequences of 2 occurring 28 times and sequences of 3 - 20 times. In comparison, the complex patterns (4 and 5) identified in the analysis occurred less often during the opening period than compared to the simple patterns. Pattern sequences with a length of 4 occurred 18 times with sequences of 5 occurring 8 times during the opening 0-15 min period. It can also be seen in table 7.1 that the complex patterns (4 and 5) were made up of a variety of activity profile sequences (i.e. sequences of 4 had 51 variations and sequences of 6 had 15 variations). In comparison to the following period (15-30min), it can be seen that there is a considerable reduction in the structure of the pattern sequences and the number of patterns identified in the following time period (see figure 7.8). The figure also shows the considerably lower synchrony in pattern sequences in comparison to the opening period (0-15min).

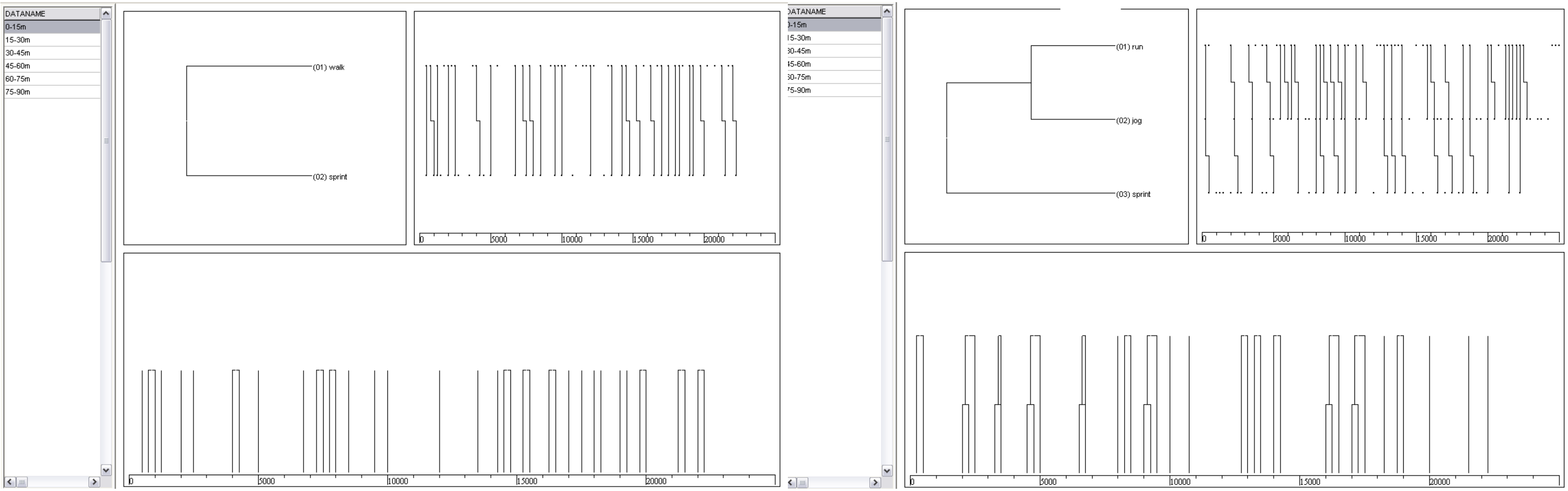


Figure 7.8. Temporal patterns with a sequence length of 2 and 3 that occur during the opening 15-minutes of the match (0-15min). The pattern sequence with a length of 2 shows a sequence of (WALK, SPRINT) and the sequence of 3 (RUN, JOG, SPRINT). Pattern sequence of 2 occurred 28 times across the 0-15 min time period and the sequence of 3 occurred 20 times.

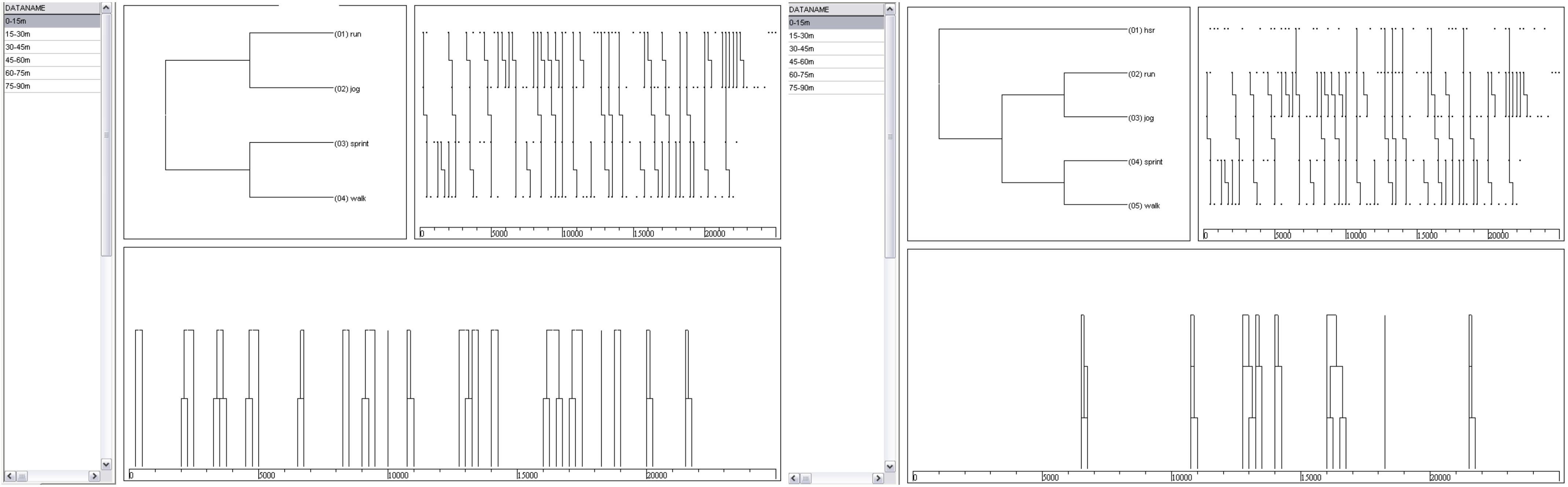


Figure 7.9. Temporal patterns with a sequence length of 4 and 5 that occur during the opening 15-minutes of the match (0-15min). The pattern sequence with a length of 4 shows a sequence of (RUN, JOG, SPRINT, WALK) and the sequence of 5 (HIGH-SPEED RUN, RUN, JOG, SPRINT, WALK). The pattern sequence of 4 occurred 18 times across the 0-15 min time period and the sequence of 5 occurred 8 times.

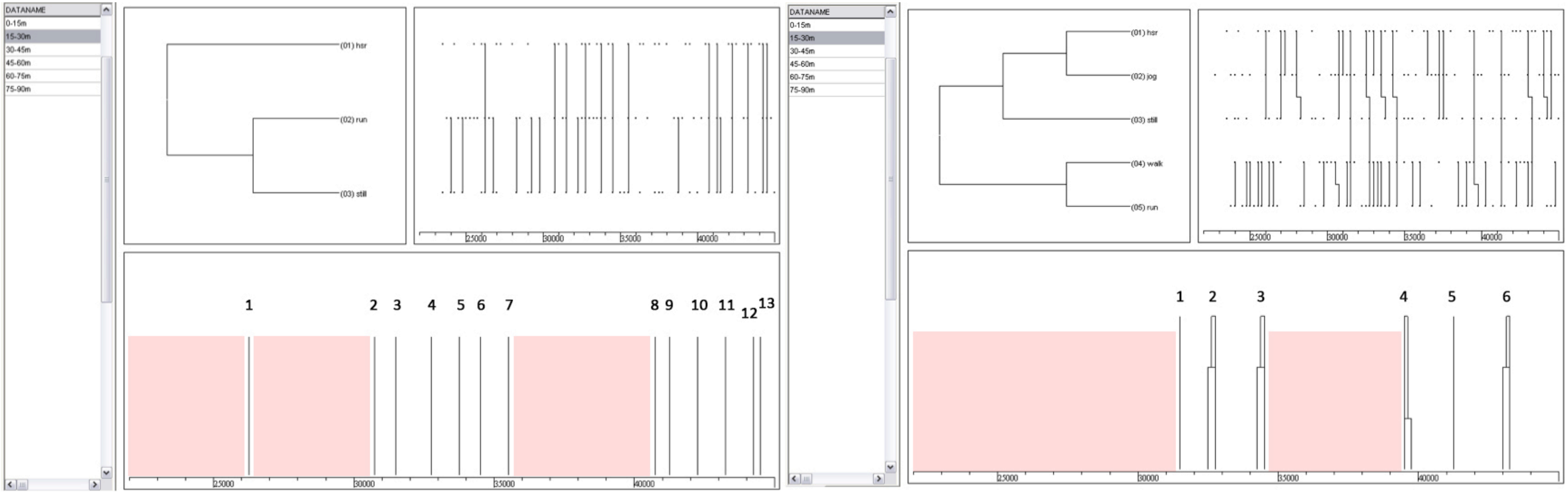


Figure 7.10. Temporal patterns with a sequence length of 3 and 5 that occur during the 15-30 minute period of the match. The pattern sequence with a length of 3 shows a sequence of (HIGH-SPEED RUN, RUN, STANDING STILL) and the sequence of 5 (HIGH-SPEED RUN, JOG, STILL, WALK, RUN). Pattern sequence of 3 occurred 15 times across the 15-30 min time period and the sequence of 5 occurred 5 times. The red shading highlights the time periods within the 15-30 minutes where there are no pattern occurrences. The red shading also highlights the longer time periods that occur between patterns in this time period. The numbering on both pattern sequences highlights the smaller number of pattern occurrences during the 15-30min period in comparison to the 0-15min period.

7.3.4 Physical Activity Patterns in the 45-60 Minute Period of the Game

At the start of the second half there was an increased number of pattern sequences identified from the analysis (118). Similar to the opening 0-15min period, the number of identified complex pattern sequences of 4 (53) and 5 (8) increased compared to the previous period in the match (30-45min). There was also evidence of the first pattern sequence of 6 occurring here. The simple pattern sequences of 2 (17 patterns) and 3 (39 patterns) showed similar values to the opening period of the match (1^{st} half - 15 and 36 patterns respectively). Complex pattern sequences of 4 made up around 45% of the total number of different patterns that were seen during this time period. Examples of pattern sequences of 3 and 6 actions show how variable the pattern sequences occur within the 45-60min period (see figure 7.11).

7.3.5 Physical Activity Patterns in the 75-90 Minute Period of the Game

The final period of the game (75-90min) showed a similar peak in the total number of pattern sequences identified to the opening period of the game 0-15min and the start of the second half (45-60min). The pattern sequences identified here were the highest in the match (182). This increase in this period seemed consistent for sequences of 4 (84), 5, (19) and 6 (2) (see table 7.1). The percentage distribution of the pattern sequences showed similar values to what was reported for 45-60min period (see table 7.1). Despite the 75-90min period reporting the highest number of identified patterns (182), the frequency of occurrences for each of the identified pattern were smaller than previously reported for the 0-15min and 45-60min periods. It can be seen in figure 7.11 that pattern sequences of 3 were slightly smaller in occurrence (17) as were sequences of 4 (10) than compared to 0-15min (3 = 36 and 4 = 51) and 45-60min periods (3 = 39 and 4 = 53). The highest values for the most complex sequences were found at this time point in the game with sequences of 5 occurring 8 times and sequences of 6 occurring 5 times. The final period of the match also reported 2 different complex pattern sequences of 6 indicating that this period had the most temporal structure in activity (see figure 7.12).

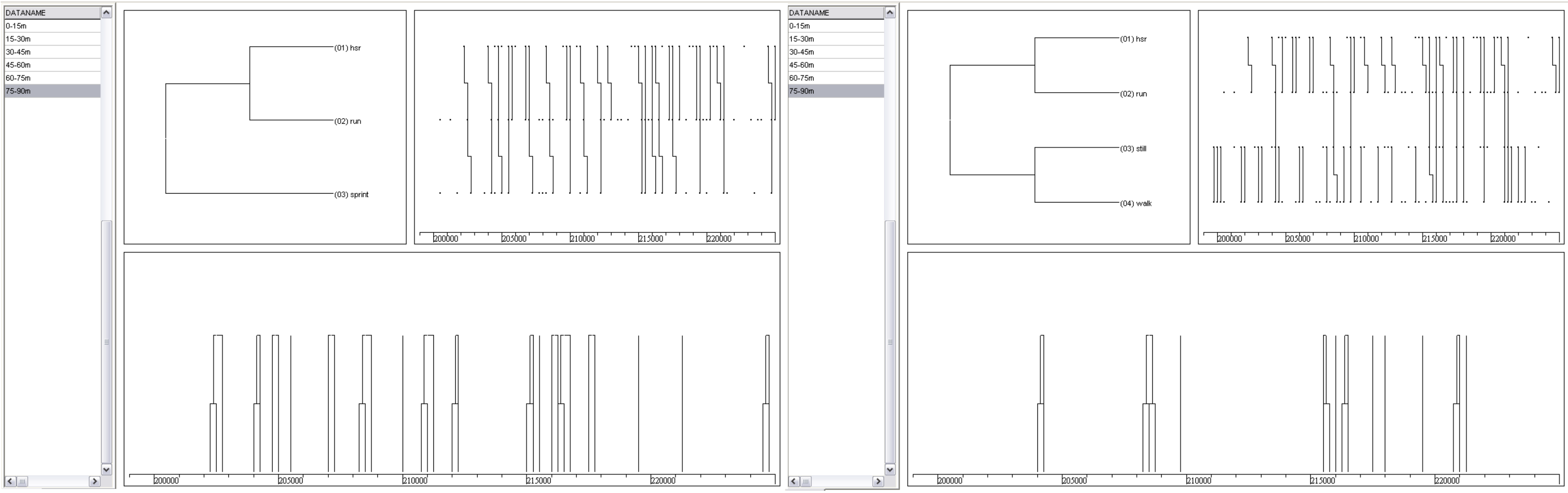


Figure 7.11. Temporal patterns with a sequence length of 3 and 4 that occur during the 75-90 minute period of the match. The pattern sequence with a length of 3 shows a sequence of (HIGH-SPEED RUN, RUN, SPRINT) and the sequence of 4 (HIGH-SPEED RUN, RUN, STILL, WALK). Pattern sequence of 3 occurred 18 times across the 75-90 min time period and the sequence of 4 occurred 11 times.

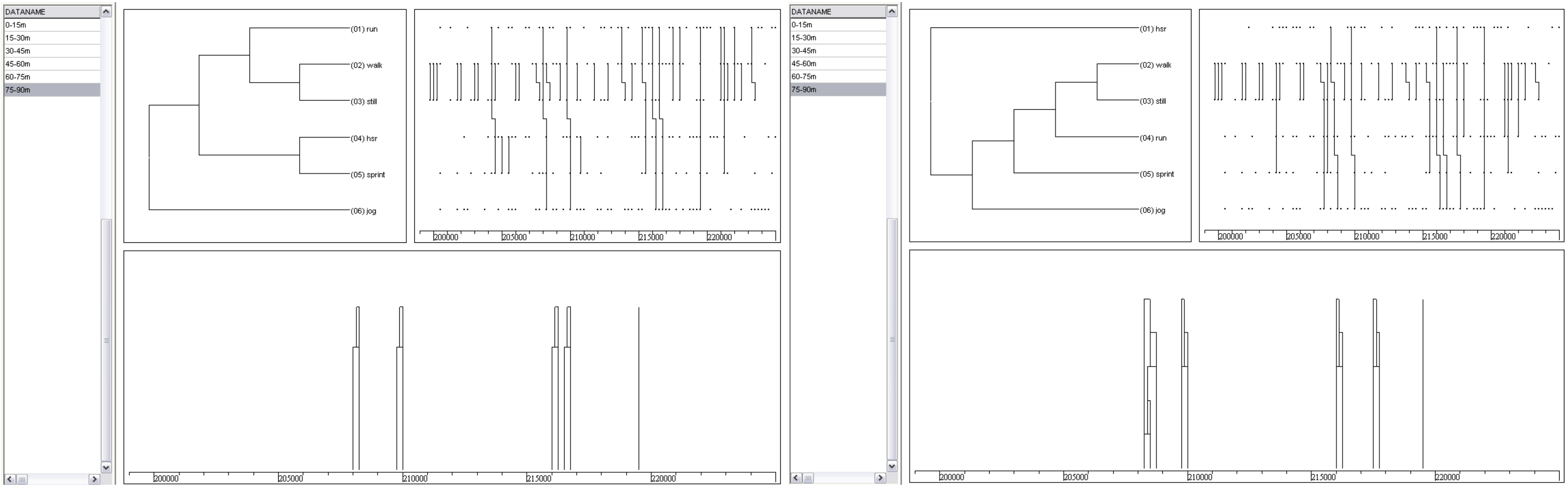


Figure 7.12. Temporal patterns with a sequence length of 6 that occur during the 75-90 minute period of the match. The pattern sequence on the left hand side with a length of 6 shows a sequence of (RUN, WALK, STANDING STILL, HIGH-SPEED RUN, SPRINT, JOG) and the sequence on the right (HIGH-SPEED RUN, WALK, STANDING STILL, RUN, SPRINT, JOG). Pattern sequence of 3 occurred 15 times across the 15-30 min time period and the sequence of 5 occurred 5 times.

7.4 Discussion

The main aim of the study was to investigate elite soccer player's physical match performance using temporal pattern analysis. The findings from our data show that temporal patterns do exist in the physical performances of soccer players and that these patterns are evident throughout all the time periods of the game that we identified. A total of 616 different temporal patterns that included high intensity activities were identified in the analysis. A greater number of these patterns were seen to occur in the second half of matches compared to the first half (252 v 364). Peaks in the occurrences of pattern sequences were observed between 0-15 min, 45-60 min and 75-90 min time periods. These frequencies may highlight temporally related changes in the nature of the game. These may reflect alterations in the demands and related changes in player and team approaches as a consequence of modifications in the certainty of the outcome of the result. The findings from the investigation therefore provide novel insights into the within-game characteristics and the temporal sequences that make up an elite soccer player's physical activity profile. This would suggest that this analytical approach has the potential to offer new perspectives in the study of physical performance and its practical application to training and match preparation.

The discovery of 616 temporal patterns that included a high-intensity action within the current data supports the existence of temporal patterns of activity within soccer and highlights the potential of this approach to illustrate new types of activity profiles in soccer performance (i.e. complex intra- and inter-individual patterns). Traditional frequency-based analysis, used to observe activity profiles in elite soccer players, have provided an important contribution to our understanding of the physical demands of the sport especially with respect to data such as the total number of high-intensity actions made by a player and the amount of high-intensity total distance covered in a match (Bangsbo et al., 2006; Bradley et al., 2013; Di Salvo et al., 2009). Such traditional approaches are limited by the provision of information on isolated activities rather than a representation of movements that are able to link consecutive discrete actions together. For example, a particular sequence found in the analysis was RUN, WALK, STANDING STILL, HIGH-SPEED RUN, SPRINT and JOG. This example pattern not only highlights the intermittent nature of an elite soccer player's activity profile, but also enables an understanding of the temporal make up of the pattern sequences. Understanding the combination of actions completed during games is important, as these patterns will ultimately determine the physiological response to exercise more so than any individual isolated activity. Such information provides new theoretical insights into how elite soccer players make up their activity bouts and how such activity may influence the physiological requirements needed to support this exercise. The findings of these investigations therefore have huge potential for the process of optimising training and physical conditioning.

The findings from the current study when compared to the within-game observations from study 3 of thesis highlight interesting similarities between the different forms of analysis. The opening period of the game (0-15 min) reported the third highest number of pattern sequence occurrences of 117. In comparison, study 3 showed a peak in average speed and total distance covered during the same period. This finding highlights that the number of pattern sequences are closely related to the distances and frequency counts of activity. This is further evidenced at the 60-75 min period that reported the second lowest number of pattern sequence occurrences (64) at the same period the largest drop in physical output was reported. In combination, these findings can suggest that the temporal information provided from the new method of analysis not only provides similar insights into physical performance in match-play that has previously been reported using frequency based profile, but also provides a deeper level of insight into physical performance. This new form of analysis allows researchers to look at physical activity in a broader context and move away from discrete events in isolation. These sequences when analysed in a wider context can develop our understanding of the physical loads placed on elite soccer players at different stages of match play. For example, a greater insight into the affects of temporal fatigue on physical performance could be reported through the identification of specific temporal pattern sequences that provide more insight to the mechanisms of fatigue in soccer match play than solely the frequency and distance covered.

Previous research investigating temporal patterns in soccer using THEME© software has focussed on identifying the existence of temporal patterns in tactical components of performance (Camerino et al., 2012; Sarmento et al., 2010; 2011; Jonsson et al., 2006; Lapresa et al., 2013). The current study is the first to investigate patterns in the physical activity profiles in soccer performance across multiple players and different matches. Previous work by Bloomfield et al., (2005) conducted a pilot study in this area using a novel analytical system, the Bloomfield Movement Classification (BMC), to look at physical activity. The time consuming nature of this analysis is limited to a single player during an isolated 15-minute period of a match. The outcome of the study was the identification of detailed and complex pattern sequences (10 and 15) that specifically related more closely to the player's actions (i.e. skips sideways left at low intensity, runs backwards at moderate intensity, turns 90° left). The current study has developed the earlier research of Bloomfield et al., (2005) by providing information on patterns that exist within a player's activity profile across larger periods of the game. The study also used a more conclusive data set that included a small sample of players from each of the key positional categories (fullback, central defender, central midfielder, wide midfielder and attacker) as used in previous literature (Di Salvo et al., 2006; 2009; Bradley et al., 2009; 2011). The data collection method also used an improved quality data source (i.e. Prozone®) to base the activity analysis; and has been found to be a proven measure of physical performance (Di Salvo et al., 2006). Incorporating a player from each of the key positional groups meant that the patterns identified were inclusive of the individual positional demands that have previously been found to occur in player's activity profiles (Bradley et al., 2011). Overall, the findings from both types of research show the huge potential of future investigations to develop our understanding of the physical movements performed in soccer and assist in the enhancement of physical conditioning to replicate match demands. It is therefore suggested that both types of research are further conducted to provide new information on patterns found in physical performance in soccer.

The current investigation is also the first to analyse temporal patterns within different time periods of the match. The current study identified the 0-15 min (117), 45-60 min (118) and 75-90 min (182) periods to have a higher number of pattern lengths and pattern complexities than the other time periods in the game. The higher occurrence of pattern sequences and complex patterns suggest that these periods of the match may be characterised by different requirements than other time periods. For example the initial parts of the first and second halves may be more chaotic in nature as the game attempts to find its natural rhythm. The identification of this reinforces previous research that highlights the infrequent and reactive nature of high-intensity actions in soccer match-play (Di Salvo et al., 2009). The high number of varying patterns lengths that were found to occur in peak periods of the game highlights a player's attempt to react to the match stimulus when requiring high-intensity activity involvements. This evidence conflicts with the notions suggested by Bradley et al., (2013) that elite level players are more selective about the high-intensity efforts they produce. Instead, it could be suggested that the high number of pattern sequences potentially shows that players are less selective, and more reactive to the changing game demands. A comprehensive interpretation of the patterns observed in our investigation is however difficult. This is due both to limitations in our approach (this was a preliminary investigation using a small sample size) and a lack of a pre-existing detailed theoretical framework with which to interpret the data. These findings do reflect the potential of this type of data to advance our understanding of performance in soccer. The application of such new approaches is in line with the ideas of Sarmento et al., (2010) where enhanced methods of collecting and analysing data must continue to be explored if insights are to be developed. A more comprehensive study is therefore required to investigate temporal patterns in the physical performance of soccer. Such a study should include the analysis of patterns for the different positions played in soccer as well as additional investigations of the occurrence of patterns in different time phases within a match. The larger data sets could mean the findings would be more representative of each of the sub-groups analysed (i.e. fullbacks, midfielders and strikers) and applicable to the applied setting to look at positional movements. However, at present, there are no estimated sample size requirements in the literature for physical measures when using temporal analysis. Despite the lack of clarity, it is recommended that future analysis incorporating temporal analysis should look to use a larger data set to increase the confidence of the findings.

In an attempt to provide a greater context to pattern occurrences within game, the time of goals scored and conceded were also used post analysis to see whether they related to critical moments in the game. The opening period of the match (0-15 min) that was considered 'chaotic' reported 0 goal occurrences (scored or conceded) with 117 pattern sequences occurring. Whereas, the start of the second half (45-60 min) showed that the respective club scored on 4 occasions (40% of total goals scored in sample of games) and conceded 0 during a period where a similar number of pattern sequences occurred (118). Furthermore, goals were conceded in the 60-75 min (2 - 25% of total goals conceded) and 75-90 min (3 - 38% of total goals conceded), which reported the second lowest (64) and highest periods (182) of pattern occurrences, respectively. These findings identify how the inclusion of critical moments (i.e. goals) into the current investigation is difficult to interpret any clear relationships with physical patterns. However, this extra level of analysis does highlight the importance of linking between temporal structure of physical and technical / tactical performances. It is suggested a more precise measure of goal occurrences would be required to analyse the impact of critical moments on physical performance. It could be suggested that future analysis would require the inclusion of the timing of the goals for the analysis to identify whether pattern sequences were affected when goals were scored or conceded. In addition, the inclusion of opposition pattern sequences could also help in understanding whether physical patterns altered for a team when scoring or conceding within the same match.

In summary, this was the first study to provide data on the patterns that exist with physical performances in soccer using a sample of elite soccer players. The data reported shows that patterns of different temporal lengths occur, varying from simple to complex patterns sequences, and that these occur cyclically throughout the game. The variation in pattern occurrences across the different periods of the game may suggest that player's activity is affected by the nature of the changing circumstances of the game. The peak periods (0-15min, 45-60min and 75-90min) that contain a high number of pattern sequences may represent "chaotic" phases of play that require players to be flexible in their movement patterns in order to meet the demands of the sport. This form of analysis would seem to have huge potential to develop our understanding of the physical movements performed in soccer and the physiological demands that are associated with them. A greater understanding of the movements patterns associated with elite soccer player's performances will enhance the quality of the training methodologies by better replicating the demands of matches.

8.0 Synthesis of Findings

The purpose of the following chapter is to provide an overview of the theoretical and methodological findings identified within the thesis to the broader research area of science and soccer. The first section of this chapter will look to evaluate the aims and objectives of the thesis; this will then be followed by a general discussion on the overarching findings from the thesis. The final section will then consider potential future research ideas based on this discussion.

8.1 Evaluation of Aims & Objectives of the Thesis

The proposed aim of this thesis was to investigate the potential for contemporary performance analysis to provide new insight into the physical and technical demands of elite level soccer. The aims and objectives stated in chapter 1 were fulfilled through the completion of the five investigations conducted in the thesis (chapters 3,4,5,6 and 7).

The variability associated with physical and technical performance variables used in elite soccer were quantified for both between game and within-game (using time periods of 1,5 and 15-min). Within-game time periods (1,5 and 15-min) were reported to have higher levels of variability when compared to between-game values for both physical and technical performance. The high levels of variation found in both between games and within-game for both physical and technical performance indicate the difficulty of interpreting performance changes during match-play. The lowest variation within-game for physical performance measures was found for 15 min periods with variables average speed and total distance covered reporting a variation of <10%. The lowest variation for technical performance measures was for 1-min periods (9-73%). Despite the lower variation in 1-min periods, the fewer number of measurement points included in 1-min data limit its use. The lowest levels of variability outside of 1-min data were reported in average time in possession (30% CV) and passing success rate (CV 29%) at the 15-min period. These findings provided performance measures for subsequent chapters (Aim 1).

The physical and technical measures that were identified as having the lowest coefficient of variation were then used to analyse data periods of 15-min to accomplish aim 2. The focus of aim 2 was to analyse within-game physical and technical demands in elite soccer using 15-minute time periods and to apply a new methodological approach to analysis. This study identified a drop in physical performance for the observed elite football team at the 60-75 min period and suggests either a fatiguing effect or highlighting the possibility of a player's ability to manage their physical activity during a game through an increased time in possession of the ball. It was also reported that the opening period of the match (0-15 min) represented a somewhat chaotic start with the highest distance covered and lowest average time in possession. These findings potentially challenge previous assumptions of within-game performance (i.e. accumulation of fatigue) and highlight new considerations to the interpretation of within-game performance. In addition, the use of new methodological approaches to analysing elite soccer performance within-game has shown the potential these findings can have in applied research. The novel approach identified meaningful performance changes in both the 0-15 min and 60-75 min time periods for both average speed and total distance. Average time in possession was identified as a meaningful performance change at the 0-15 min compared to the 75-90 min. The findings shows that the novel statistical analysis can aid in the interpretation of results for researchers who are interested in the impact of interventions or analysis for 'real world' practises. In addition, this form of analysis also provides an applied researcher with a greater statistical context to the data when interpreting performance changes that reduces the likelihood of misinterpreting data to factors such as high variability.

The relationship between blood CK and physical match performance in elite soccer players across a regular season period was examined to fulfil aim 3. The findings suggest that the activity completed within a match is not related to the CK concentrations that are observed 48 hrs post-match. While it has previously been suggested that CK provide a potential biochemical marker for use in elite team sports, the data collected in this study indicates that changes in CK do not seem to be explained by the locomotor activity completed by soccer players during EPL matches. This would indicate that CK might not be of fundamental importance to the monitoring strategies used within elite soccer clubs to track performance. It is suggested that practitioners who are involved in the scientific support of players in elite soccer environments may therefore be advised to consider alternative physiological/biochemical markers within their monitoring programmes. The "real world" approach to this study is however associated with limitations that do not permit a comprehensive recommendation on the application of CK analysis to athlete tracking to be made. This area requires further consideration especially with respect to an understanding of individual player characteristics and CK responses to acute and chronic exercise.

Elite soccer player's physical performance was analysed using T-pattern analysis to identify the structure and make-up of potentially complex intra- and inter individual patterns found in match-play. This research was completed in an attempt to fulfil aim 4. The findings from this chapter show that temporal patterns exist in physical performances of soccer players and that the patterns are evident throughout all the time periods of the game. The investigation identified a total of 616 different temporal patterns that included high-intensity activities and observed peaks in the occurrences of pattern sequences between 0-15min, 45-60min and 75-90min time periods. These peak periods were found to contain a high number of pattern sequences and may suggest "chaotic" phases of play that require players to be flexible in their movement patterns in order to meet the demands of the sport. This new analytical approach highlights the potential to offer new perspectives in the study of physical performance and its practical application to training and match preparation. The combination of findings from study 3 and study 5 together show that there is a huge potential for greater insight into within-game performance using both approaches in combination. The chaotic opening period of the match (0-15 min) and decline in physical performance (60-75 min) identified in study 3 could be further analysed using the pattern analysis. The identification of pattern sequences within those periods could provide greater understanding of the demands placed on elite players within-game.

8.2 General Discussion Of Findings

The purpose of the thesis was to provide new insights into the physical and technical demands of elite level soccer using contemporary performance analysis approaches. The investigative methods used in the thesis to provide such insights into performance followed a 'real world' or applied research approach. This meant that the approaches used in data analysis were high in ecological validity, yet somewhat limited in terms of the degree of traditional experimental control as highlighted in previous research (Drust et al., 2007). Taking this into consideration, each investigation attempted to apply robust methodological rigour to the data analysis to try and ensure that the outcomes and conclusions that could be drawn from the findings provided practical information that has relevance to the elite soccer population.

Overall, the findings from the thesis have highlighted the difficulty in contextualising elite soccer performance. The complex intermittent nature of soccer player's physical and technical performance has been shown to be inconsistent both between and within-game. This inconsistency has implications for the interpretation of physical and technical data in match-play and also the indication of meaningful performance indicators. The work conducted in studies 1, 2 and 3 aimed to emphasise the importance of measurement error, when analysing performance data in both a scientific and practical context. The findings of study 1 and study 2 reported that both physical and technical performance variables in soccer match-play are not stable properties and are subject to large within (player) and between-match variation (Atkinson, 2003; Gregson et al., 2010). The variation found across the within-game periods for physical and technical performance measures in study 1 and 2 ranged for 1-minute (7%-261%), 5-minute (16%-225%) and 15-minutes (9%-122%). The observation of such high variation has implications for the use of such data in research examining performance related interventions and attempting to interpret meaningful performance information. As an example, a performance measure that has a CV of 23% would mean that if an individual player improves this performance outcome by approximately 64% it could then be reasonably certain (95% probability) that this is a 'real' change and not attributable to 'normal' within-game variation (Gregson et al., 2010). The current thesis is in agreement with previous research that has recommended a larger sample size to overcome these limitations to accurately determine a performance change (Batterham & Atkinson, 2005). However, it is also important to acknowledge the difficulty of such a recommendation for applied researchers who are limited by the size of their population. Batterham & Atkinson (2005) reported that in order to detect a worthwhile change of 10% using a performance measure that had a coefficient of variation of 30%, it would require a sample size of approximately 200 soccer players. In the 'real world' environment such a sample is almost impossible to collect, due to the competitive nature of professional soccer there is a lack of accessible data or collaboration with other clubs to enhance sample size. It is therefore important to highlight the potential significance of using a sample that has a high number of repeated observations to enhance the statistical power of an investigation. The data from the study 1 and 2 of the thesis would seem to indicate that despite the small population used of 14 players, the findings would seem to be representative of larger and more diverse data sets, such as data samples of 400+ players to analyse variability for high-speed activities (Gregson et al., 2010). Study 1 and 2 used a high number of repeated observations of 7 games per player from one elite English soccer team for one full season and found variability values to be of similar size to Gregson et al., (2010) who used 2 or more games per player. The use of multiple observations for a small sample size is therefore encouraged to enhance the statistical power of an investigation and reduce the size of variation. These findings would seem to indicate that despite investigations that are limited to a smaller sample size, a higher repeated number of observations would seem to be representative of a larger and more diverse data sample and may increase the confidence of findings in performance data in applied research.

Selecting precise indicators of performance are also important to formulate applied research studies to examine the impact of interventions that could potentially affect the success of a player or team (Atkinson & Nevill, 2000). Previous research in soccer has primarily focused on the use of high-intensity activities to analyse performance due to the actions that can result in the winning or losing of matches, such as, movements to win the ball and actions with agility to go past defending players (Stolen et al., 2005). However, the evidence in this thesis highlights that the most explosive and demanding actions in soccer performance seem to be the least stable parameters within-game (39%-261% CV), and has implications for both the interpretation and also their use as an indicator of performance in applied research studies. This has been supported in other research on high-speed activities in soccer (Gregson et al., 2010; Rampinini et al., 2007). Obtaining a precise indicator of performance with low variability is important, as without the selection of an appropriate variable it is very difficult to formulate applied research studies to examine the impact of interventions that could potentially affect the success of a player or team (Bangsbo, 1994). Nevertheless, the important factor to consider in applied research is to ensure that the selected measure provides sufficient insight into elite soccer performance within-game. The within-game analysis that was conducted in the thesis identified average speed and total distance covered as the only performance measures that reported low variability (<10%). Both the selected measures were able to successfully identify changes in performance in study 3 at 0-15 minutes and 60-75 minutes using 15-minute periods. However, despite these important findings it can be agreed that a limitation to the use of total distance covered as a performance measure is that it only provides detail of the overall volume of load, and is limited in its ability to differentiate between small differences in specific activity patterns. The use of average speed however, encompasses elements of both the overall load, as well as the high-intensity actions, as the unit measures meters per second. At present, there is no variable that is accepted as the 'gold standard' when analysing soccer performance, but evidence from the thesis suggests that average speed could be considered an important measurement tool for future investigations. The sensitivity of the measure to changes in physical performance, as well as low variability within-game at 15-minutes reduces the likelihood of misinterpretation in data analysis. Further research is however required to provide evidence for such claims.

Study 1 and 2 also identified that the high levels of variability in within-game time periods (1, 5 and 15 min) can affect the interpretation of performance changes. The increased levels of variability reported within-game data implies that changes in performance are harder to detect, as there is an increased level of 'noise' surrounding the true change. For example, measures like total high-speed running distance were reported in the current thesis to have a CV of 102% using 5 min periods, and would therefore require a very large sample size based on the predicted sample of 200 required for a CV of 30% reported in study 1 (Batterham & Atkinson, 2005). Such findings highlight the potential misinterpretation of previous investigations that have explored the existence of temporal fatigue occurring in physical performance using total high-speed running distance and 5-minute data periods (Mohr et al., 2003; Bradley et al., 2009). It is therefore important for researchers to carefully select performance measures and time periods with low variability when analysing performance within-game. Furthermore, the variability reported from study 1 and 2 for 5 min (16%-225%) and 15 min (9%-122%) performance data also highlights important methodological and theoretical implications to future applied research. For instance, average speed reported a coefficient of variation of 16% at 5 min and 9% at 15 min. Methodologically, the higher variation reported in 5 min periods will require a greater sample size in comparison to the 15 min periods, as the 'noise' in the data is considerably greater than the signal. Whereas, the 15 min periods represents a more stable marker for analysis and does not require the same size of sample to analyse performance. On the basis of these findings it might seem appropriate for investigation to select time periods that represent the more stable time period. However, from a theoretical perspective, it is also important to identify which time period is better suited for the requirements of the investigation. For example, investigations looking to measure temporal fatigue in performance within-game would require more discrete time periods to identify such changes in performance (i.e. 5 min). Whereas, the use of 15 min periods for analysis would provide a more generalised context to the within-game periods, and would potentially overlook subtle changes in performance. This information therefore highlights the importance for future applied research to factor in these considerations before designing studies to analyse performance changes using within-game time periods.

The chaotic nature of the opening period (0-15 minutes) of the match found in study 3 of the thesis highlights an important consideration for future theoretical approaches attempting to analyse within-game data. Traditional match analysis has typically used the opening 15-minute period of the match as a benchmark for comparative analysis in physical and technical measures (Bradley et al., 2009; Carling & Dupont, 2010). However, the findings from the current study and Lovell et al., (2013) using physical performance measures, suggest an alternative interpretation that match-play during this period is possibly attempting to find its natural rhythm, and assumes that this period might perhaps be an unrealistic baseline. It is suggested that the work-rate of an elite professional soccer match represents a positive pacing strategy during each half, wherein the proportion of high-speed running performed in the first 15-min of each half is often the greatest (Lovell et al., 2013). These findings in combination challenge traditional theorem on within-game performance, and highlights the need for a truer representation of the physical and technical demands in match-play, such as the use of averaged data or a more generalised based line measurement (Lovell et al., 2013). Due to the analytical approaches conducted in the thesis, such inferences are beyond the scope of the current thesis and highlight an area of research for future applied research.

The approaches used in research typically index performance into discrete motion modalities, which can then be classified according to type, intensity (or quality), duration (or distance), and frequency (Reilly, 1994). Such approaches have been found to limited by the provision of information on isolated activities rather than a representation of movements that are able to link consecutive discrete actions together. As a consequence, the thesis looked to explore physical performance data using temporal pattern analysis to generate more complete and more complex quantitative representations of performance (Anguera & Jonsson, 2003). The findings from the explorative investigation provided novel insights into the within-game characteristics and the temporal sequences that make up an elite soccer player's physical activity profile. For example, the analysis was also able to identify pattern sequences that not only highlight the intermittent nature of an elite soccer player's activity profile, but also an understanding of the temporal make up of the pattern sequences. Understanding such combinations of actions are important, as these patterns will ultimately determine the physiological response to exercise more so than any individual isolated activity. Overall, these findings highlight the potential this contemporary approach can have on the process of optimising training and physical conditioning. It is therefore recommended that this form of analysis be implemented in future investigations exploring physical performance within-game. Additionally, due to the discrete nature of this analysis it can also recommended that the pattern analysis approach be used in combination with within-game analysis to provide greater insight into periods of the match. As highlighted in the above paragraph, periods such as the 0-15 min period that show significant increases in physical output within a game could be further analysed to identify whether specific temporal pattern sequences occur in a player's activity profile. Thus providing a greater context to the demands of elite soccer players within-games. Unlike the other studies, the recommendation to apply a greater data set to this approach might not enhance the findings of physical performance. Instead, this form of analysis might be more informative in it's ability to analyse performance using smaller data samples. It is acknowledged that a greater data sample could be more representative of each of the positional sub-groups (i.e. fullbacks, midfielders and strikers) and could be more applicable to the applied setting to look at positional movements. However, the greater sample could effect the interpretation of the data as the pattern sequences become more generalizable and potentially distort the unique information that can be provided from such an approach.

Novel approaches to analysing performance data were also explored using physical performance measures and biological markers within this thesis. The thesis was the first to examine the relationship between post-match CK and physical indicators of match performance in an elite population across multiple matches. Study 4 failed to demonstrate any significant relationships between any indicators of physical match performance and post-match CK values. This finding suggests that CK may not accurately reflect changes in the activity profiles completed by soccer players during EPL matches. However, the failure to observe a link between the movement profile of EPL players and CK may also be a function of the applied research approach employed within this investigation, as well as within the thesis. Possible reasons for this could be related to the selected performance measures. The variables chosen to explore the links between CK and movement profiles were based upon important match performance indicators in previous research (i.e. high-speed running distance). From the findings in the methodological studies 1 and 2, it could be suggested that the high variability associated to these 'match winning' actions could be a factor as to why no relationships between CK and performance were found. Another possible factor as to why the study failed to identify any significant relationships could be a function of the experimental design employed within this investigation. Due to applied nature of the investigations within the thesis, studies had to adhere to the club's respective training schedule for the players, which prevented the collection of both pre-match and additional post-match data samples (i.e. CK collection). These restrictions clearly limit the potential to determine a detailed biological response to the preparation for and recovery after match-play, or examine the relationships between biological markers and physical match performance at other time points post-exercise. This finding further highlights the difficulty in design of "real world" approaches to research that look to provide data that are high in ecological validity, yet limited in terms of its degree of traditional experimental control. Suggestions to improve the data collection process are difficult in such applied environments, as the researchers are limited in there access to players and are affected by rest days, away matches, club schedules and player commitments pre or post training. Though this does not suggest that data collection for biological measures are not possible in elite soccer. Instead, it highlights the need for testing to be conducted in applied environments that have greater control, or the development in blood collection techniques that reduce the required time frame to collect and analyse blood.

The performance data that was collected for the purposes of the thesis used a computerised semi-automatic multi-camera image recognition system (Prozone®, Leeds, England). The method of data analysis has been widely used in previous research that has attempted to analyse performance data between games (Di Salvo et al., 2006; Bradley et al., 2009) and now within-game (see chapters 3.0 and 4.0). This form of analysis is associated with significant costs and prohibits these techniques to be employed by an individual research scientist. A limitation of using the 3rd party commercial system was that Prozone® collected the data and then systematically analysed it using proprietary software to provide an interactive coaching and analysis tool. This meant that the data collection process was completed by Prozone® and was not under the control of the researcher. A further limitation to the use of this method was the inability to analyse the validity and reliability of the measurement tool for the purposes of the thesis. Instead, the thesis relied on previous investigations testing the Prozone® system, which found the system to be reliable for measuring match activity in soccer (Di Salvo et al., 2006). The third limitation to using the Prozone® system was the data was only available in the post-production format that reports data at a minimum unit of 0.5 seconds. These smaller time periods of 0.5 seconds were also unavailable for export from the software, as raw data and were limited to exports of 1-minute data periods. This prevented even smaller within-game time periods being analysed. The use of smaller time period (i.e. 0.5 seconds) could have provided an even deeper insight into the interactions within-game, particularly using novel approaches such as temporal pattern analysis.

8.3 Conclusions

The aims of the thesis were to investigate the potential for contemporary performance analysis to provide new insight into the physical and technical demands of elite level soccer. These aims were fulfilled through the completion of the five investigations found in chapters 3 to 7. The findings from the thesis show that there is large variability associated to physical and technical performance measures within-game. The size of the variability has important implications in the interpretation of such data. It is therefore recommended that appropriate analysis be performed to identify the variability within data sets before attempting to investigate performance. The identification of average speed and total distance to report <10% variability identifies the potential of new measures to identify changes in soccer performance. The analysis of within-game performance using both these measures identified key periods within the game that challenge current theoretical understanding of within-game performance. In addition, novel analytical approaches were also found to provide new insights into the complexity of performance within-game. This thesis was the first to use temporal pattern analysis with physical performance measures and has provided new information on the existence of temporal patterns within-game. Whereas, physical performance measures were unable to demonstrate a significant relationships with post-match CK values. In conclusion, this thesis identifies the difficulty in measuring the complexity of physical and technical performance in elite soccer using current methods of analysis. It is therefore suggested that novel approaches are used in applied research to ascertain greater insights into physical and technical elite soccer performance.

8.4 Recommendations For Future Research

The five investigations completed within this thesis have provided novel information on the physical and technical demands of elite soccer performance. These findings have encouraged the development of new theoretical approaches for future research. The following sections looks to detail those key aspects for each chapter of the thesis.

Suggestions arising from Chapter 1 and Chapter 2:

1. The evidence from studies 1 and 2 identified that greater data sample sizes using a longitudinal approach have the potential to improve the statistical power of research investigating performance changes within-game. It is therefore suggested that future research should analyse a larger data set of physical and technical performance data across multiple seasons in order to identify positional difference, seasonal changes and performance measure changes using within-game time periods.

Suggestions arising from Chapter 3:

2. Physical and technical performance measures used in the current analysis were found to change within-game across 15-minute time periods. In particular, the 0-15 min and 60-75 min periods were found to represent meaningful changes in performance. It is therefore suggested that a future investigation should continue to examine these periods using smaller timer periods for analysis (i.e. 5 min) and also in combination with the novel pattern analysis approach. This would look to provide further understanding to the changes observed in elite soccer within-game performance. It is also important not to discredit the inclusion of high-intensity measures from future analysis despite the high variability.

Suggestions arising from Chapter 4:

3. The data from this study showed that there was no correlation between the biological marker Creatine Kinase (CK) and soccer performance measures. However, the approach highlighted the importance to conduct future analysis using new biological markers and performance data. It is therefore suggested that a future investigation should analyse new biological markers such as C-Reactive Protein (CRP), which has been suggested to be a more sensitive biological measure than CK, with a wider selection of performance measures to help ascertain the impact match-play has on elite soccer players,

Suggestions arising from Chapter 5:

4. The findings from the exploratory investigation provided novel insights into the within-game characteristics and the temporal sequences that make up an elite soccer player's physical activity profile. It is therefore suggested that a future investigation performs a comprehensive investigation

using this analytical approach to offer new perspectives in the study of physical performance and its practical application to training and match preparation.

8.5 Practical Implications for Practitioners in the Field

The following section looks to provide an overview of the findings and how they can be related to practical implications within a professional soccer club**.**

The research findings from the thesis can be utilised by a number of practitioners who are a part of the support team at a professional football club. The findings from study 1, 2 and 3 provide particular insights for sport science and fitness practitioners who are responsible for match and training data. The studies highlight the difficulties in the interpretation and measurement of performance data. Study 1 and 2 in particular hopes to raise a greater awareness for researchers / practitioners of the variability associated to physical and technical measures when looking at within-game performance, and also provide recommendations on how to interpret such information.

Studies 1-3 also aimed to raise a greater awareness in the delivery of information to fellow practitioners and coaching staff. The development in technology now allows access to a huge selection of player and team's physical and technical data, which can be used by practitioner to assist in the quantification of performance when reviewing previous matches, team selection or player acquisition. It is therefore vital the information being provided by the practitioners to coaches, managers or stakeholders in their respective clubs is appropriately selected and considers the variability surrounding performance data, as well as the importance of data sample size when providing reports or presentations.

The following points aim to highlight the key practical recommendations for interpreting data as an applied practitioner:

- Due to the limited access to greater data sample sizes in professional or elite clubs it is encouraged that practitioners attempt to use multiple observations when analysing a relatively small sample to enhance the statistical power of an investigation and reduce the size of variation.

- Due to the potential for high levels of variability for many physical and technical measures used in elite soccer clubs, it is recommended that practitioners establish and report CV's for their data sets when performing any form of investigative analysis.

- The large degree of between and within-game variability, particularly for high-intensity activity, has important implications for interpreting physical performance during competition play. The findings within the thesis identify that both high-intensity activities are not consistent between or within-games. As a result, single match observations do not provide reliable representations of physical activity profiles, and it is recommended that multiple observations obtained from many matches are necessary to accurately represent high-speed activity performance profiles.

- It would be suggested to consider the precision of your selected performance measures and whether alternative measures can be used in investigations. For example, the use of average speed as an alternative measure to HI activity measurements.

- Be aware of the variability associated to within-game time periods and how the size of the variability for performance measures can increase / reduce dependant on the selected time period.

The findings from study 3 could also be used to help educate coaching staff who may not necessarily be used to interpreting physical or technical data post training or matches. The ability to contextualise the findings on within-game performance alongside the coach's own objective analysis could aid in their decision-making for future matches (i.e. player selection or substitutions). Providing data without context has the potential to lead to poor decision-making, whereas, coaches who have a greater interpretation of within-game performance trends that have been reported in this thesis and other research (i.e. physical peaks in activity in the opening 15-minutes of each half) could help in critical moments of the game.

The findings from study 5 of the thesis that investigated patterns of activity within elite soccer player's physical performances could also be utilised by the fitness conditioning and medical practitioners within football clubs. The ability to design and implement training practices that replicate movement patterns and activity bouts from competitive matches for individual playing positions (i.e. for a fullback or striker) could help enhance conditioning programmes and the physical preparation of players. This area of research if developed further could also have an impact on the rehabilitation and injury prevention of players. Tailored training programmes that are designed specifically to each position based on the demands of the game have the potential to enhance a player’s physical resilience to repetitive movements that occur during competitive matches, thus reducing the risks of potential injury. Additionally, the rehabilitation of a player could also be enhanced as physiotherapists and conditioners are able to design rehabilitation programmes to better prepare a player when returning to training and matches.

8.5 Personal Reflections from a Research-Practitioner

As a part of my thesis I felt it was important to provide an insight into the practitioner-researcher journey that I've followed to the completion of my PhD. When considering these potentially conflicting areas, I've attempted to capture the key challenges and frustrations as a practitioner-researcher that will hopefully provide useful information to fellow researchers and practitioners who are either embarking on a similar journey or considering such a role.

Background

To provide a context, the reason why I started the PhD was very simple. Since the age of 16 I knew I wanted to work in professional football. The exact professional role within the football industry was not clear to me, or even after graduating from my undergraduate degree. The role was not a primary concern of mine thanks to the positive experiences of working in both sport science and performance analysis roles at 2 Premier League football academies, which were a part of my university placements. After graduating from Liverpool John Moores University studying Science & Football, I was interested in continuing my academic journey and undertaking a Masters course in the hope that the higher level of education would open more doors to a more rewarding job in a football club. It was at this point that I was given the opportunity to work with a Premier League football club on a 3-year full-time PhD internship working with both the sport science and performance analysis departments thanks to a newly developed partnership between the club and the university.

The Internship Role

The major part of my role as an intern was working with the performance analysis department. The responsibilities of this role included set piece analysis for future opponents, creating pre match documents and post-match clipping. Alongside these duties I also worked 1-day a week within the sport science department assisting with the collection of heart rate and GPS tracking data during training and analysis of physical match performance data. The design of my research attempted to harness the experiences and knowledge that I was developing from my multi-disciplinary role at the club and decided to focus my thesis around the investigation of elite players physical and technical performance in match-play.

Cultural Challenges

One of the biggest cultural challenges that I've experienced since the start of my internship was the volatility of employment in professional football. Even before the start of my internship I'd learnt second hand about the volatility of the elite industry from fellow practitioners at guest lectures where they shared their experiences of how new management often brought new backroom staff, which could inevitably result in a loss of employment. Entering into the professional football world for the first time this was something I had learnt to accept as a part of the high-pressured elite team culture. When reflecting on my own personal experiences throughout the 5 years it has taken me to complete my thesis, I've worked for a football club and latterly a senior international team. During this time, I've experienced first-hand a club change ownership, 3 changes of manager, 6 changes of coaching staff, >50 different playing staff, 2 changes to the heads of departments that I've worked under, and as I write this, my international senior football team has just announced wholesale re-structuring which will directly effect many colleagues and have implications for my own future. It is interesting to reflect on these experiences as I've grown to accept that change is inevitable in a result-driven business. Though some of these changes in staffing have not appeared to directly affect me, I have realised with hindsight, that they did affect me. The biggest impact this has had on me with regards to the PhD was inevitably my research became secondary to my desire to succeed at my role so to remain in football. Whether a new head of department, or drawing closer to the end of a short-term contract, certain watershed situations drove me to focus more on my day-to-day work and meet the new demands and expectations of my line manager rather than devote the quality time and energy to focus on my research. This was a difficult and frustrating situation to be confronted with as a practitioner and as a researcher, and on reflection I think it is important to highlight why the job had to come first. Whether this pathway was the best decision to allow for me to complete my research could be questioned, but arguably the pathway I did choose allowed me to experience football at both club and international level.

Reality of being a practitioner-researcher

Despite the initial efforts to combine my work and research, it became apparent very quickly in my first year at the club that my role and responsibilities as a performance analyst were not aligned with my initial expectations to be a research-practitioner, and instead would run as two separate entities until the completion of my PhD. The day-to-day role as a performance analyst required a very different skill-set than the academic proficiencies I had hoped to bring to the role through my thesis. The creation of pre-match dossiers, coding and clipping of set plays and player events were very different to the research papers I was trying to read on technical performance measures used to investigate match performance. Upon reflection, the nature of my role made the journey certainly more problematic and challenging than what I initially anticipated and hoped for. The workload as a performance analyst was a constant wave of pre and post match analysis, particularly working for an ambitious club that had involvements in European, domestic league and cup competitions with an excess of 50 matches per season. My attention to my research was very much dependant on the fixture periods at the football club. For example, during intense periods from December to January I would put my thesis on hold as the games rolled in on average every 4 days for an entire month. As a result, my focus and energy to my research was as intermittent as the player activity profiles I was trying to investigate. The demands of the role as a practitioner-researcher brought out sometimes-strong feelings of conflict that lead to frustration - partly from the lack of time to focus on my research, but also from mental exhaustion of trying to do 2 full-time jobs at the same time, and mechanically working through my reading and completion of tasks. If I were able to change anything through my PhD experience it would have been to strike a better balance between my commitments as a performance analyst and as a researcher.

Conclusion

My initial passion for the subject of my thesis remains strong. However, working in the competitive and demanding environment of football has taken its toll on my thesis. The pursuit of excellence is engrained in me and I've been forced to question what else I could have done to produce an excellent thesis of which I am proud and also function to the best of my ability in a high demanding job role. The answer is that I've had to compromise. Whilst the job role has been rewarding and I feel I have carried out my duties to a high level there remains an acknowledgment that by my own high standards my thesis has not developed my thinking to the highest extent to which I initially had hoped for. However, as a body of work I feel that it is informative and well researched with some interesting areas for further investigation. I feel I need to highlight to the reader the heights of the frustrations that you might face when innocently or naively embarking on your own research-practitioner journey. Good luck.

9.0 References

Andersson, H.A., et al., 2008. Neuromuscular fatigue and recovery in elite female soccer: Effects of active recovery. *Medicine and Science in Sport and Exercise.* 40(2), pp. 372-380.

Anguera, M.T., & Jonsson, G.K., 2003. Detection of real-time patterns in sport: Interactions in soccer. *International Journal of Computer Science in Sport*. 2(2), pp.118–121.

Anguera, M.T., 2005. Microanalysis of T-pattern: Analysis of Symmetry/asymmetry in social interaction. In: Anolli, L., Duncan, S., Magnusson, M., & Riva, G., *The hidden structure of social interaction: From genomics to culture patterns.* Amsterdam: IOS Press, pp.51-70.

Apple, F.S., and Rhodes, M., 1985. Enzymatic estimation of skeletal muscle damage by analysis of changes in serum creatine kinase. *Journal of Applied Physiology*. 65(6), pp.2598–600.

Ascensao, A., et al., 2008. Biochemical impact of a soccer match-analysis of oxidative stress and muscle damage markers throughout recovery. *Clinical Biochemistry*. 41(10-11), pp.841-851.

Ascensao, A., et al., 2012. Effects of cold water immersion on the recovery of physical performance and muscle damage following a one off soccer match. *Journal of Sports Sciences.* 29(3), pp.217-225.

Atkinson, G., & A.M, Nevill., 2001. Selected issues in the design and analysis of sports performance research. *Journal of Sports Sciences.* 19(10), pp.811-825.

Atkinson, G., 2003. What is this thing called measurement error? In: Reilly T, Marfell-Jones M. *Kinanthropometry VIII: proceedings of the 8th International Conference of the International Society for the Advancement of Kinanthropometry (ISAK)*. London: Taylor and Francis, pp.3-14

Baird, M.F., et al., 2012. Creatine kinase and exercised related muscle damage implications for muscle performance and recovery. *Journal of Nutrition and Metabolism.* 13, pp.1-13, Article ID 960363, doi:10.1155/2012/960363.

Bangsbo, J., 1994. The physiology of soccer – with special reference to intense intermittent exercise. *Acta Physiologica Scandinavica*, 151(suppl. 619), pp.1-155.

Bangsbo, J., et al., 2006. Physical and metabolic demands of training and match-play in the elite football player. *Journal of Sports Sciences.* 24(7), pp.665-674.

Bangsbo, J., et al., 2007. Metabolic response and fatigue in soccer. *International Journal of Sports Physiology and Performance.* 2(2), pp.111-127.

Barnes, C., et al., 2014. The evolution of physical and technical performance parameters in the English Premier League. *International Journal of Sports Medicine.* 35(13), pp.1095-1100.

Batterham, A.M., & W.G. Hopkins., 2006. Making meaningful inferences about magnitudes. *International Journal of Sports Physiology and Performance.* 1(1), pp.50-57.

Batterham. A.M., & G. Atkinson., 2005. How big does my sample need to be? A primer on the murky world of sample size estimation. *Physical Therapy in Sport.* 6(3), pp. 153-163.

Bishop, P.A., et al. 2008. Recovery from training: a brief review. *Journal of Strength and Conditioning Research.* 22 (3), pp.1015-1024.

Bland, J.M., and Altman, D.G., 1995. Calculating correlation coefficients with repeated observations: Part 1-correlation within subjects. *British Journal of Sports Medicine*. 310(6977), pp.446.

Bland, J.M., and Altman, D.G., Calculating correlation coefficients with repeated observations: Part 2-correlation between subjects. *British Journal of Sports Medicine.* 310(6980), pp.633.

Bloomfield, J., et al., 2005. Temporal pattern analysis and its applicability in soccer. *Journal of Sports Sciences.* 20(10), pp.1-15.

Bloomfield, J., et al., 2007. Physical demands of different positions in FA Premier League soccer. Journal of Sports Science and Medicine. 6(1), pp.63–70.

Borrie, A., et al., 2002. Temporal pattern analysis and its applicability in sport: an explanation and exemplar data. *Journal of Sports Sciences.* 20(10), pp.845-852.

Bradley, P., et al., 2007. The reliability of Prozone MatchViewer: a Video-based technical performance analysis system. *International Journal of Sports Performance Analysis.* 7(3), pp.117-129.

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

Bradley, P.S., et al., 2009. High-Intensity running in English FA Premier League Soccer Matches. *Journal of Sports Sciences.* 27(2), pp. 159-168.

Bradley, P.S., et al., 2009. High-Intensity running in English FA Premier League Soccer Matches. *Journal of Sports Sciences.* 27(2), pp. 159-168.

Bradley, P.S., et al., 2010. High-Intensity activity profiles of elite soccer players at different performance levels. *Journal of Strength and Conditioning Research.* 24(9), pp. 2343-2351.

Bradley, P.S., et al., 2011. Sub-maximal and maximal Yo-Yo intermittent endurance test level 2: heart rate response, reproducibility and applicant to elite soccer. *European Journal of Applied Physiology.* 111(6), pp.969-978.

Bradley, P.S., et al., 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), pp.821-830.

Bradley, P.S., et al., 2013. Gender differences in match performance characteristics of soccer players competing in the UEFA Champions League. *Human Movement Science.* 33(1), pp. 159-171.

Bradley, P.S., et al., 2013. Match performance and physical capacity of players in the top three competitive standards of English professional soccer. *Human Movement Science.* 32(4), pp. 808-821.

Bradley, P.S., et al., 2013. The effect of high and low percentage ball possession on physical and technical profiles in English FA Premier League soccer matches. *Journal of Sports Sciences.* 31(12), pp. 1261-1270.

Bradley, P.S., et al., 2013. The effect of high and low percentage ball possession on physical and technical profiles in English FA Premier League soccer matches. *Journal of Sports Sciences.* 31(12), pp. 1261-1270 .

Brancaccio, B., et al., 2010. Biochemical markers of muscular fatigue. *Clinical Chemistry and Laboratory Medicine.* 48(6), pp. 757-767.

Brancaccio, P., Maffuli, N., & Limongelli, FM., 2007. Creatine kinase monitoring in sports medicine. *British Medical Bulletin,* 81-82, pp. 209–230.

Bryne, C., & Eston, R., 2002. The effect of exercise-induced muscle damage on isometric and dynamic knee extensor strength and vertical jump performance. *Journal of Sports Sciences.* 20(5), 417-425.

Camerino, O.F., et al., 2012. Dynamics of the game in soccer: Detection of T-patterns. *European Journal of Sports Science.* 12(3), pp. 216-224.

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 Science*. 29(1), pp.63–71..

Carling, C., 2010. Analysis of physical activity profiles when running with the ball in a professional soccer team. *Journal of Sports Sciences.* 28(3), pp. 319-326.

Carling, C., and Dupont, G., 2011. Are declines in physical performance associated with a reduction in skill-related performance during profession soccer match-play? *Journal of Sports Sciences.* 29(1), pp.63-71.

Carling, C., et al., 2008. The role of motion analysis in elite soccer. *Sports Medicine.* 30(10), pp.839-862.

Carling, C., et al., 2012. Analysis of repeated high intensity running performance in professional soccer. *Journal of Sports Sciences.* 30(4), pp.325-336.

Castellano, J., et al., 2011. Reliability and accuracy of 10Hz GPS devices for short-distance exercise. *Journal of Sports Science and Medicine*. 10(1), pp.233–234.

Chevion, S., et al., 2003. Plasma antioxidant status and cell injury after sever physical exercise. *Proceedings of the National Academy of Sciences of the United States of America.* 100(9), pp.5119-5123.

Coelho, D.B., et al., 2011. Creatine kinase kinetics in professional soccer players during a competitive season. *Revista Brasileira De Cineantropometria & Desempenho Humano.* 13(3), pp.189-194.

Dellal, A., et al., 2010. Physical and technical performance in European soccer match-play: FA Premier League and La Liga. *European Journal of Sports Sciences*.;11(1), pp.51–59.

Dellal, A., et al., 2011. Variation of activity demands in small sided soccer games. *International Journal of Sports Medicine.* 35(5), pp. 370-375.

Dellal, A., et al., 2012. Technical and physical demands of small vs. Large sided games in relation to playing position in elite soccer. *Human Movement Science.* 31(4), pp.957-969.

Dellal, A., et al., 2013. The effect of a congested fixture period on physical performance, technical activity and injury rate during matches in a professional soccer team. *British Journal of Sports Medicine.* 49(6), pp.390-394.

Di Mascio, M., & Bradley, P.S., 2013. Evaluation of the most intense high-intensity running period in English Premier League Soccer Matches. *Journal of Strength and Conditioning Research.* 27(4), pp.909-915.

Di Salvo, V., et al., 2006. Validation of Prozone ®: A new video-based performance analysis system. *International Journal of Performance Analysis in Sport.* 6(1), pp.108-119.

Di Salvo, V., et al., 2007. Performance characteristics according to playing position in professional soccer. *International Journal of Sports Medicine.* 28(3), pp.222–227.

Di Salvo, V., et al., 2009. Analysis of high intensity activity in premier league soccer. *International Journal of Sports Medicine.* 30, pp.205.212.

Di Salvo, V., et al., 2013. Match performance comparison in top English soccer leagues. *International Journal of Sports Medicine.* 34(6), pp.526-532.

Drust, B., et al., 1998. Analysis of work-rate in soccer. *Sports Exercise and Injury.* 4 (4), pp.151-155.

Drust, B., et al., 2007. Future perspectives in the evaluation of the physiological demands of soccer. *Sports Medicine.* 37(9), pp.783-805.

Edwards, R.H., 1983. Biochemical bases of fatigue in exercise performance: Catastrophe theory of muscular fatigue. In: Knuttgen, H.G, Vogel, J.A., Poortmans, J. *Biochemistry of exercise.* Champaign: Human Kinetics, pp. 2 – 28.

Ehles, G.G., et al., 2002. Creatine kinase levels are elevated during a 2-a-day practices in collegiate football players. *Journal of Athletic Training.* 38(2), pp.151-156.

Ekblom, B., 1986. Applied physiology of soccer. *Sports Medicine*. 3(1), pp.50—60.

Ekblom, B., 1970. Effect of physical training on circulation during prolonged severe exercise. *Acta Physiologica Scandinaviaca.* 78(2), pp.145-158.

Ekblom, B., et al., 1971. Temperature regulation during continuous and intermit- tent exercise in man. *Acta Physiologica Scandinaviaca*. 81(1), pp.1–10.

Fernandez, J., et al., 2009. Identifying and analysing the construction and effectiveness of offensive plays in basketball by using systematic observation. *Behavior Research Methods.* 41(3), pp.719-730.

Field, A., 2005. *Discovering statistics using IBM SPSS Statistics: and sex and drugs and rock 'n' roll (2nd edition).* Sage, London.

Gregson, W., et al., 2010. Match-to-Match variability of high-speed activities in Premier League Soccer. *International Journal of Sports Medicine.* 31(4), pp.237-242.

Gutierrez-Santiago, A., et al., 2011. The temporal structure of judo bouts in visually impaired men and women. *Journal of Sports Sciences.* 29(12), pp.1443-1451.

Güzel, N.A., et al., 2007. Effects of different resistance exercise protocols on nitric oxide, lipid peroxidation and creatine kinase activity in sedentary males. *Journal of Sports Science and Medicine.* 6(4), pp.417–422.

Hopkins, W.G., & Hewson, D.J., 2001. Variability of competitive performance of distance runners. *Medicine and Science in Sport in Exercise.* 33(9), pp.1588.1592.

Hopkins, WG. 2004. How to interpret changes in an athletic performance test. *Available from: Sportscience 8, 1-7, 2004 (sportsci.org/jour/04/wghtests.htm).*

Hortobágyi, T., and Denahan, T., 1989. Variability in creatine kinase: methodological, exercise, and clinically related factors. *International Journal of Sports Medicine.* 10(2), pp.69–80.

Howatson, G., et al., 2009. The influence of cold water immersions on adaptation following a single bout of damaging exercise. *European Journal of Applied Physiology*. 105(4), pp.1–7.

Hughes, M. D., & Bartlett, R.M., 2002. The use of performance indicators in performance analysis. *Journal of Sports Sciences*. 20(10), pp. 739-754.

Hukin, S.L., et al., 2013. Creatine kinase and its relationship with match performance in elite Australian Rules football. *Journal of Science and Medicine in Sport.* 17(3), pp.332-336.

Impellizzeri, F.M., et al., 2005. Physiological assessment of aerobic training in soccer. *Journal of Sports Sciences.* 23(6), pp.583-592.

Ispirlidis, I., et al., 2008. Time-course of changes in inflammatory and performance responses following a soccer game. *Clinical Journal of Sport Medicine*, 18(5), pp.423–431.

James, N., et al., 2002. Analysis of strategies in soccer as a function of European and domestic competition. *International Journal of Sports Performance Analysis.* 2(1), pp.85-119.

Johnston, R.D., et al., 2013. Influence of physical contact on neuromuscular fatigue and markers of muscle damage following small-sided games. *Journal of Science and Medicine in Sport* 15/03/2013, doi: 10.1016/j.jsams.2013.07.018.

Johnstone, R.D., et al., 2013. Influence of an intensified competition on fatigue and match performance in junior rugby league players. *Journal of Science and Medicine in Sport.* 16(5), pp.460-465.

Jones, H., et al 2013. Within-subject correlations between evening-related changes in body temperature and melatonin in the spinal cord injured. *Chronobiology International.* 31(2), pp.157-165, 2013.

Jonsson, G.K., 1997. Self-esteem, friendship and verbal and nonverbal interaction. In: Atzwanger, K., Grammer, K., & Schafer, K., *New aspects of human ethology.* New York: Plenum, pp.206.

Jonsson, G.K., 2006. Hidden patterns of play interaction in soccer using SOF-CODER. *Behaviour Research Methods.* 38(3), pp.372-381.

Kempton, T., et al., 2013. Between match variation in professional rugby league competition. *Journal of Science and Medicine in Sport.* 17(4), pp.404-407.

Kempton, T., et al., 2013. Match-related fatigue reduces physical and technical performance during elite rugby league match-play: a case study. *Journal of Sports Sciences.* 30(16), pp. 1770-1780.

Kempton, T., et al., 2014. Match-to-Match variation in physical activity and technical skill measures in professional Australian Football. *Journal of Science and Medicine in Sport.* 18(1), 109-113.

Kempton, T., et al., 2015 An integrated analysis of match related fatigue in professional rugby league. *Journal of Sports Sciences.* 33(1), pp.39-47.

Kraemer, W.J., et al., 2013. Changes in creatine kinase and cortisol in national collegiate athletic association division I American football players during a season. *Journal of Strength and Conditioning Research.* 27(2), pp. 434-441.

Krustrup, P., et al., 2002. Activity profile and physiological demands of top-class soccer assistant refereeing in relation to training results. *Journal of Sports Sciences.* 20(11), pp. 861-871.

Krustrup, P., et al., 2005. Physical demands during an elite female soccer game: Importance of training status. *Medicine and Science in Sport and Exercise.* 37(7), pp.1242-1248.

Krustrup, P., et al., 2006. The Yo-Yo IR2 Test: Physiological response, reliability, and application to elite soccer. *Medicine and Science in Sport and Exercise.* 38(9), pp. 1666-1673.

Krustrup.P., et al., 2006. Muscle and Blood Metabolites during a Soccer Game: Implications for sprint performance. *Medicine and Science in Sport and Exercise.* 38(6), pp.1165-1174.

Lago, C & Martin, R., 2007. Determinants of possession of the ball in soccer. *Journal of Sports Sciences.* 25(9), pp.969–974.

Lago, C., & Dellal, A., 2010 Ball possession strategies in elite soccer according to the evolution of the match-score: The influence of situational variables. *Journal of Human Kinetics.* 25, pp.93–100.

Lapressa, D., et al., 2011. Spatial and temporal analysis of karate kumite moves; comparative study of the senior and 12-13 year old groups. *International Journal of Performance Analysis in Sport.* 11(1), pp.57-70.

Lapressa, D., et al., 2013. Comparative analysis of sequentiality using SDIS-GSEQ and THEME: A concrete example in soccer. *Journal of Sports Sciences.* 31(15), pp.1687-1695.

Lazarim, FL., et al., 2009. The upper values of plasma creatine kinase of professional soccer players during the Brazilian National Championship. *Journal of Science and Medicine in Sport.* 12(1), pp.85-90.

Louro, H., et al., 2010. Stability of patterns of behaviour in the butterfly technique of the elite swimmers. *Journal of Sports Sciences and Medicine.* 9(1), pp.36-50.

Magalhaes, J., et al., 2010. Impact of Loughborough intermittent shuttle test versus soccer match on physiological, biochemical and neuromuscular parameters. *European Journal of Applied Physiology*. 108(1), pp.39–48.

Magnusson, M.S., 1996. Hidden real-time patterns in intra- and inter-individual behavior: Description and detection. *European Journal of Psychological Assessment*. 12, pp.112–123.

Magnusson, M.S., 2000. Discovering hidden time patterns in behaviour; T-patterns and their detection. *Behaviour Research Methods.* 32(1), pp. -93-110.

McLellan, C.P., et al., 2010. Creatine kinase and endocrine responses of elite players pre, during and post rugby league matches. *Journal of Strength and Conditioning Research.* 24(11), pp.2908-2919.

McNeil PL., & Khakee R., 1992. Disruptions of muscle fiber plasma membranes. Role in exercise-induced damage. *The American Journal of Pathology.* 140(5), pp.1097-109.

Mohr, M., et al., 2003. Match performance of high-standard soccer players with special reference to development fatigue. *Journal of Sports Sciences.* 21(7), pp.519-528.

Mohr, M., et al., 2005. Fatigue in Soccer: A Brief Review. *Journal of Sports Sciences.* 23(6), pp.593-599.

Mohr, M., et al., 2008. Match activities of elite women soccer players at different performance levels. *Journal of Strength and Conditioning Research*, 22(2), pp.341–349.

Mohr, M., et al., 2010. Examination of Fatigue development in elite soccer in a hot environment: A Multi-Experimental Approach. *Scandinavian Journals of Medicine and Science in Sport.* 20(3), pp.125-132.

Nedelec, M., et al., 2012. Recovery in Soccer Part I – Post-Match Fatigue and Time Course of Recovery. *Sports Medicine.* 42(12), pp.997-1015.

Nedelec, M., et al., 2013. Recovery in Soccer Part II—Recovery Strategies. *Sports Medicine.* 43(1), pp.9-22.

Nedelec, M., et al., 2014. The influence of soccer playing actions on the recovery kinetics after a soccer match. *Journal of Strength and Conditioning Research.* 28(6), pp.1517-1523.

Nicholas, C.W., et al., 2000. The Loughborough intermittent shuttle test: A field test that simulates the activity pattern of soccer. *Journal of Sports Sciences.* 18(2), pp.97-104.

Odetoyinbo, K., et al., 2009. The effect of a succession of matches on the activity profiles of professional soccer players. *In*: T.Reilly, F.Korkusuz*. Science and Football VI.* London UK: Routledge, pp.105-110.

Paton, C.D., & Hopkins W.G., 2006. Variation in performance of elite cyclists from race to race. *European Journal of Sport Science*. 6(1), pp. 25-31.

Prieto, I., et al., 2014. Knowledge of errors in the teaching-learning process of judo-techniques: Osoto-Guruma as a case study. *Journal of Human Kinetics.* 41(1), pp.253-263.

Raastad, T., et al., 2002. Neuromuscular fatigue and recovery after soccer matches in elite soccer players. In: *7th Annual congress of the European college of sports science*. Athens, Greece: Pashalidis Medical Publisher, pp.825.

Rampinini, E., et al., 2007. Variation in top level soccer match performance. *International Journal of Sports Medicine.* 28(12), pp.1018-1024.

Rampinini, E., et al., 2009. Repeated-sprint ability in professional and amateur soccer players. *Applied Physiology, Nutrition and Metabolism.* 34(6), pp. 1048-1054.

Rampinini, E., et al., 2009. Technical performance during soccer matches of the Italian Sera A league: Effect of fatigue and competitive level. *Journal of Science and Medicine in Sport.* 12(1), pp.227-233.

Reilly, T. (2003). Motion analysis and physiological demands. In: Reilly, T., Williams, A.M. *Science and soccer*. London, UK: Routledge, pp. 59-72.

Reilly, T., & Thomas, V., 1976. A motion analysis of work-rate in different positional roles in professional football match-play. *Journal of Human Movement Studies*. 2, pp.87-97.

Reilly, T., 2003. Environmental stress. In: Reilly T, Williams AM. *Science and soccer.* London: Routledge, pp.65-84.

Reilly, T., 2003. Motion analysis and physiological demands. In: Reilly, T., Williams, A.M. *Science and soccer*. London: Routledge, pp.59-72.

Reilly, T., 2006. *Training for football: a scientific approach to fitness*. London: Routledge.

Reilly, T., 2007. *Science of Athletic Training Soccer: A Scientific Basis for Developing Strength, Skills and Endurance*. London, UK: Routledge.

Reilly, T., et al., 2008. Muscle Fatigue during football match-play. *Sports Medicine.* 38(5), pp. 357-367.

Rienzi, E., et al. 1999. Investigation of anthropometric and work-rate profiles of Rugby Sevens players. *Journal of Sports Medicine of Physical Fitness* 39(2), pp.160–164.

Rienzi, E., et al., 1998. Investigation of anthropometric and work-rate profiles of elite South American international soccer players. *Journal of Sports Medicine and Physical Fitness*. 40(2), pp.162 – 169.

Rienzi, E., et al., 2000. Investigation of anthropometric and work-rate profiles of elite South American international soccer players. *Journal of Sports Medicine and Physical Fitness.* 40(2), pp.162-169.

Ruiz-Ruiz, C., et al., 2013. Analysis of entries into the penalty area as a performance indicator in soccer. *European Journal of Sports Science.* 13(3), pp. 241-248.

Russell, M., & Kingsley, M., 2011. Influence of exercise on skill proficiency in soccer. *Sports Medicine.* 41(7), pp.523-539.

Russell, M., et al., 2012. Technical demands of soccer match-play in the English championship. *Journal of Strength and Conditioning Research.* 27(10), pp.2869-2873.

Sarmento, H., et al., 2010. Development and validation of a notational system to study the offensive process in football. *Medicina (Kaunas).* 46(6), pp.401-407.

Sarmento, HM., et al., 2011. T-patterns detection in the counter-attack of the F.C. Barcelona. *British Journal of Sports Medicine.* 45(15), pp.1-5.

Schutz, R.W., & Gessaroli, M., 1987. The analysis of repeated measures designs involving multiple dependent variables. *Research Quarterly for Exercise and Sport*. 58(2), pp.132–149.

Silva, J.R., et al., 2013. Biochemical impact of soccer: an analysis of hormonal, muscle damage, and redox markers during the season. *Applied Physiology, Nutrition and Metabolism.* 39(4), pp.432-438.

Silva, J.R., et al., 2013. Neuromuscular function, hormonal and redox status and muscle damage of professional soccer players after a high level competitive match. *European Journal of Applied Physiology.* 113(9), pp.2193-2201.

Smart, D.J., et al., 2007. The relationship between changes in interstitial creatine kinase and game related impacts in rugby union. *British Journal of Sports Medicine.* 42(3), pp.198-201.

Smith, L.L., 2000. Cytokine hypothesis of overtraining: a physiological adaptation to excessive stress? *Medicine & Science in Sports & Exercise*, 32(2), pp.317-331.

Stewart, A.M., & Hopkins, W.G., 2000. Consistency of swimming performance within and between competitions. *Medicine and Science in Sport and Exercise.* 32(5), pp.997-1001.

Stolen, T., et al., 2005. Physiology of soccer: an update. *Sports Medicine*. 35(6), pp.501-536.

Taylor, J.B., et al., 2008. The influence of match performance location, quality of opposition, and match status on technical performance in professional association football. *Journal of Sports Sciences.* 26(9), pp.885-895.

Thorpe, R., & Sunderland, C., 2012. Muscle damage, endocrine, and immune marker response to a soccer match. *Journal of Strength and Conditioning Research.* 26(10), pp.2783-2790.

Twist, C., et al., 2012. Neuromuscular, biochemical and perceptual post-match fatigue in professional rugby league forwards and backs. *Journal of Sports Sciences.* 30(4), pp.359-367.

Weston, M., et al., 2011. Variability of Soccer Referees' Match Performances. *International Journal of Sports Medicine.* 32(3), pp.190-194.

Williams, A.M., Reilly, T., 2000. Talent identification and development in soccer. *Journal of Sports Science.* 18(9), pp.657–667.

Winter, E.M., and Maughan, R.J., 2009. Requirements for ethical approval. *Journal of Sports Sciences.* 27(10), pp.985.