Effects of situational variables on the physical activity profiles of elite soccer players in different score line states.

Athalie J. Redwood-Brown[1], Peter G. O'Donoghue[2], Alan M. Nevill[3] Chris Saward[1] Nicholas Dyer[4] and Caroline Sunderland[1]

[1]Sport, Health and Performance Enhancement Research Centre, Department of Sports Science, Nottingham Trent University, UK. [2]Cardiff Metropolitan University, UK, [3]Wolverhampton University, UK, [4]Teqnick Ltd, UK,

Correspondence concerning this article should be addressed to Athalie.Redwoodbrown@ntu.ac.uk

ABSTRACT

The aims of this study were to investigate the effects of playing position, pitch location, team ability and opposition ability on the physical activity profiles of English premier league soccer players in difference score line states. A validated automatic tracking system (Venatrack Ltd.) was used to track players in real time (at 25Hz) for total distance covered, high speed running distance and sprint distance. This is the first study to include every team from an entire season in the English premier league, resulting in 376 games, 570 players and 35’000 rows of data from the 2011-12 season being analysed using multi-level modelling. Multi-level regression revealed an inverted “u” shaped association between total distance covered and goal difference (GD), with greater distances covered when GD was zero and reduced distances when GD was either positive or negative. A similar “u” shaped association was found with high speed distance covered at home. In addition distance covered (both at home and away) were predicted by playing position. All activity profiles (with the exception of sprint distance at home) were predicted by pitch location and time scored. Lastly, distance away from home and high speed running at home were predicted by opposition ability. Score line appears to effect player activity profiles across a number of temporal factors and thus should be considered by managers when preparing and selecting teams in order to maximise performance. The current study also highlighted the need for more sensitive score line definitions in which to consider score line effects.

Key Words: Multi-level modelling, Playing position, Pitch location, Opposition ability, Team ability. Goal difference.

1. INTRODUCTION

Determining what constitutes successful performance (defined as winning) has been one of the main points of focus for football performance research in order to provide objective performance evaluations, comparisons and predictions[1,2,3]. A large portion of football game research has investigated situational variables related to successful performance, such as game location (i.e. home or away) or quality of opposition (defined as either finishing position in the league table or progress in knock out competition) as well as key performance indicators (e.g. action related variables such as high speed distance completed or accuracy of passing)[2,4,5,6,7,8,9]. Advancements in technology (such as computerised tracking systems) have enabled researchers to analyse match performance in a more detailed manner helping professionals to identify these key attributes of success more readily[8,10,11,12,13,14].

In order to win a match, the successful team must score more goals than their opponent. Commonly, comparisons between successful and unsuccessful teams are made through the investigation of playing patterns and success of performance variables such as shots on goal, crosses, corners, ball possession etc. [12]. Although some studies[11,13] have investigated the activity profiles of various playing positions of elite soccer players, only a few to date have considered how successful and unsuccessful teams differ when in different score lines states (e.g. 1-0, 2-0, 1-1 etc.). Those that have investigated specific score line effects[11,13] have generally excluded key temporal factors (opposition ability, team ability, score lines and match location), which have been shown to effect player performance[5,6,7,8].

The main methodological criticism of previous research has been the failure to consider normal performance, e.g. how teams perform when no goals are scored and the standard of the opposition (e.g. whether the team were considered top, middle or bottom of the league). For example, much of the difference in work rate observed between different score line states may be due to the opposition's ability or simply fatigue rather than score line. Although studies have shown that the percentage of time spent performing high intensity activity is lower during the second half of soccer matches than during the first half[15] it is possible that differences in the percentage of time spent performing high intensity activity may result from score line effects rather than fatigue. Especially as more recent research has suggested that teams pace themselves injecting periods of sub-maximal or maximal bursts late on in matches[5,16] therefore dismissing the previous thoughts that teams fatigue towards the latter stages of a match. Redwood-Brown et al.[17] recently highlighted the impact of psychological factors on the performance of players during a match, suggesting players reduce their effort if the outcome of a match becomes obvious during the second half (e.g., the opposition are of a higher standard)[18]. Although fatigue and normalised performance has been considered in recent studies[5,8,16] the sample size and subjective nature of the data collection methods has limited the application of the findings.

A secondary issue has been the technological barriers in data collection methods that have limited the ability to generalise findings for both physical and technical performance investigated. Categorising players by position (defenders, midfielders, attackers) in relation to score line effects has been considered for activity profiles but only using very small data sets[5,19] or single clubs[20] using overall match status (winning, drawing, losing) rather than by how much the team were winning or losing by. There is however, a need to investigate score line effects on performance using a greater volume of data as well as objective and reliable methods. Semi-automatic player tracking systems are a useful tool providing large volumes of objective and reliable movement data to professional soccer clubs[15,21]. The volume of player movement data available from semi-automatic player tracking would allow further investigation of how different playing positions react to score line changes. Access to data can also be problematic leading to many studies using a case study approach, with only one team analysed limiting the application of findings to wider populations.

The third issue with previous studies into score line is the lack of a gold standard for defining activity profiles that occur during the match (such as high speed running and sprinting). The use of computerised systems have been more apparent when investigating player movement, although with a number of different definitions, this has led to a difficulty in comparing findings. It has also been suggested that using a running speed as a high intensity value does not consider the energy cost of moving at a full range of speeds, for example, when a player is in possession of the ball[22] or moving in backwards and sideways directions at much lower speeds. In 2012 Redwood-Brown et al.[23] validated the first fully automated tracking system (measuring at 25Hz) which was found to have good validity over a range of soccer specific movements and speeds. In addition this system is highlighted in its ability to produce and store data on a much larger scale and to a greater accuracy than seen in previous studies. The aim of the present study was to investigate the interaction of a number of situational factors (playing position, pitch location, opposition ability, team ability) which have independently been found to impact on player performance, specifically activity profiles in different score line states. The use of the automated tracking system validated by Redwood-Brown et al.[25] can also allow the aggregated data of several teams to be analysed rather than a single team, thus creating more normative data to improve team performance in a collective way. We hypothesise that performance, specifically HSR and SD will be highest when the score is close. We also hypothesise that performance will differ between different playing position and pitch location in different GD's.

2. MATERIALS AND METHODS

2.1 Data Set

In total 376 of the 380 games played during the 2011-2012 English Premier League season were used in the current study which included 570 independent players and 35’000 rows of data. The omission of four games was due to a number of technological incidents outside of the operators’ control, which disabled the system and resulted in the tracking data becoming unusable. This resulted in 20 teams who played against each other at both their own ground and that of their opponent’s, with the exception of the teams affected by the excluded games. The ability of each team and their respective opponents was calculated using their final league position (ranked 1-20, i.e., 1st in the league to 20th in the league) at the end of the season once all games had been played. This was in line with previous research[24] which has highlighted the need for greater sensitively when using ability as a situational factor relating to team performance. For accuracy, player position (striker, midfielder, defender) was determined at the start of each game using the official team’s sheets provided to the press association. This ensured players who may change positional role depending on the tactical strategy adopted by the team were accurately defined for each game. In line with previous research[25] the pitch was split evenly into three sections (attacking third, middle third and defensive third) using a theodolite and calibrated pitch dimensions (specific to each individual stadium). Consent to use the data for research purposes was given by both Venatrack Ltd and the English Premier League. Ethical approval was granted by the University’s Ethics Committee.

2.2 Data Gathering

Visual-AI (Venatrack Ltd, UK) technology was used to track the players in the current study. This allowed players to be monitored in real time (at 25 Hz) providing identification through recognition algorithms (based on x,y,z coordinates for hands, feet, head and the pelvis & shoulder lines; Venatrack Ltd, UK). The video capture system used 28 HD colour cameras positioned at specific locations around the respective soccer stadium. Twenty Eight HD cameras were used to ensure maximum positional accuracy (visual acuity) was provided to the computer algorithm. By using a greater number of cameras, a greater number of pixels with which to quantify the pitch area and thus provide a greater accuracy for measuring each point was achieved. The estimated visual acuity for the current system was in the range 5 – 25mm compared to previous systems, which have been estimated at between 500mm – 1500m depending on the region of the pitch. The cameras position, orientation and field of vision were determined and fixed using a Theodolite (Nikon NPL 362, Japan) during installation. The cameras were positioned to give a full view of the pitch using the systems unique configuration co-ordinates (unique to each ground), which allowed each position on the pitch to be covered by at least five cameras at any one time (Venatrack Ltd, UK). Calibration of the automatic tracking system was completed by a team of technical experts who had collectively over eighteen years of experience of visual AI technology, such as that used by the system in question. The system was also found to be valid and reliable for tracking player movement at both high speed and sprinting distances[23]

.

2.3 Performance Indicators (Activity Profiles)

For each player, the total playing time was used to calculate how much relative time the player spent in each activity zone. Initially the zones were presented as incremental categories from 0-1 $m \cdot s^{-1}$, 1-2 $m \cdot s^{-1}$ etc. and then further categorised into high speed running and sprinting based on previous literature [5,7]. High speed running was defined as *"the total distance spent moving at 4* $m \cdot s^{-1}$ *or faster"* (to include movements such as shuffling, running backwards etc. which have been shown to increase work rate but are not included when higher speeds are used) [22]. Sprinting was defined as *"the total distance spent* moving at 8 $m \cdot s^{-1}$ or *faster"*. This resulted in three values for each player; total distance covered, total distance covered in the high speed zone ($\leq$ 4 $m \cdot s^{-1}$) and total distance covered in sprinting zone ($\leq$ 8 $m \cdot s^{-1}$).

2.4 Data Analysis

Firstly, due to the hierarchical structure of the data, multi-level modelling was used to predict the activity profiles across goal differences with each of the match related and performance related variables using MLwiN software package (v 2.22, Bristol University, Bristol, UK). For each variable, a two-level hierarchical structure was defined with repeated measures (level 1) grouped with match ID (level 2). The benefit of this hierarchical structure means that, unlike traditional longitudinal data analysis techniques such as repeated measures ANOVA, the same number of measurement points per individual are not required. Therefore, due to the variation that occurs between matches in the current data set, this statistical technique is well suited to the current data structure. A multi-level model of this nature is also able to describe the underlying trends of a particular component in the population (the fixed part of the model), as well as modelling the unexplained variation around the mean trend for that component due to individual differences (the random part of the model) [26] or in this case differences both within (repeated measures) and between matches (match ID).

The first stage in this multi-level modelling statistical analysis approach was to create a model that explained changes in distance covered, high speed distance covered and sprint distance covered. Each activity profile (total distance covered, high speed distance covered, sprint distance covered) performance characteristic was modelled in turn. Firstly, to investigate the variance between players the intercept was allowed to vary randomly between players. The effect of score line defined by GD (centered at 0 goals) on each of the three activity profiles of players was modelled. GD was introduced to the model as a quadratic term to establish whether the data would be better explained by a curve. Subsequently, the effect of playing position, the zone on the pitch the activity took place; the time the goal was scored; the opposition's ability and the team's ability were added to the model (fixed components). These fixed components were accepted or rejected on the basis of firstly, changes in the model fit; as indicated by a difference in log likelihood between models, and the effect of the variable on the activity profiles of players, indicated by z-scores. Following each analysis, the assumption that variations in intercepts were normally distributed with an average of zero was assessed visually using normality probability plots[26]. Statistical significance was accepted at the 95% confidence level ($P < 0.05$). Mean ± SD were used to describe the average and variability of the activity profile data.

3. RESULTS

A total of 570 players across 376 games were analysed, with the maximum number of appearances from one player being 38 games and the minimum 1 game. Table 1 presents the activity profiles for each of the teams included in the analysis across the three match statuses (winning, drawing, losing). The average distance covered per player per game (Mean ± SD) was 10020.2m ± 141.7m, with players covering on average 395.6 ± 33.9m of high speed running per game and 107.0 ± 21.3m sprinting distance (a full break down of each teams activity profiles can be seen in the supplementary Table 1).

Tables 2 and 3 present the final multi-level models for the development of the match-running performance characteristics of total distance covered, high speed distance covered and sprint distance covered for players of different playing positions, in different pitch zones, across different abilities and against different standards of opposition of players in the 376 English Premier League games analysed. The random part of the multi-level models predicted that the fit of all models was improved when the intercept was allowed to vary randomly ($P < 0.05$), as indicated by the between game standard error displayed in Tables 2 and 3. Only variables that were significant when added to the model are presented in the tables.

3.1 Distance Covered

Modelling indicated that the distances covered at both home and away in relation to GD were non-linear and best described with a quadratic term. The estimated models of distance cover for home and away teams that included GD as an independent factor can also be seen in Table 2. The table shows that for distance covered at home; GD, GD^2, playing position, time scored and pitch zone significantly improved the model fit. For distance covered away from home, the same was true, with the addition of opposition ability. It is possible to calculate the performance of players, playing either, at home or away using the coefficients from Table 2. For example, the prediction equation for distance covered at home for a midfielder in the middle 3rd of the pitch, who are in a +2 GD at half time (45 minutes) is: Constant + (β_1 * GD centered at 0) + (β_2 * GD centered at 0^2) + (β_3 * midfielder) + (β_4 * middle 3rd) + (β_5 * time scored) which is: 118.53+ (-0.601 * 2) + (-0.462 * 2^2) + (7.275) + (-12.082) + (-0.069 * 45) = 107.6 $m \cdot min^{-1}$ (9681.1m per 90 min. game).

3.2 High Speed Running

Modelling indicated that high speed running distance covered away from home in relation to GD was non-linear and best described with a quadratic term. Goal difference was not found to significantly influence distance covered whilst playing at home. The estimated models of high speed distance covered for home and away teams can be seen in Table 3. The table shows that for high speed distance covered at home, pitch zone, opposition ability and time scored significantly improved the model fit. For high speed running distance covered away from home, GD, GD^2, the time goals were scored and pitch zone significantly improved the model. The prediction equation for high speed distance covered away from home for all players in the middle 3rd of the pitch, who are in a +2 GD at half time (45 minutes) is: Constant + (β_1 * GD centered at 0) + (β_2 * GD centered at 0^2) + (β_3 * middle 3rd) + (β_4 * time scored) which is: = 7.376 + (0.21 * 2) + (-0.112 * 2^2) + (-4.904) + (0.001 * 45) = 2.9 $m \cdot min^{-1}$ (260.5m per 90 min. game).

3.3 Sprint Distance

Modelling indicated that sprint distance covered at both home and away was not affected by GD. In fact the only parameter that was found to explain this activity was pitch zone and only when playing away from home. The prediction equation for sprint distance covered away from home for all players in the middle 3rd of the pitch, who score at half time (45 minutes) is: Constant + (β_3 * middle 3rd) + (β_4 * time scored) which is: 2.742 + (-2.002) + (0.015 * 45) = 1.42 $m \cdot min^{-1}$ (127.4m per 90 min. game).

3.4 Goal Difference Effects

Figures 1-3 display the predicted goal difference related changes in significant activity (per player per 90 minutes) for each playing position, pitch zone and opposition ability (ranked 1st, 10th and 20th) respectively. Supplementary Tables S2, S3, S4 and S5 display the mean ± SD of match-running performance for each of the categories (playing position, pitch location, team ability rank and opposition ability rank).

Models predicted that for all playing positions and across all pitch zones, the total distance covered both at home and away from home was greatest when GD was close (-1 to +1) decreasing towards the extremes of GD (+5 or -5). Players also tended to decrease their activity more when losing heavily as opposed to winning, this was more prominent when playing away from home. Goal difference was only found to predict high speed running when playing away from home showing a similar pattern to total distance covered. Teams covered less distance (both total distance covered away and high speed distance at home) when playing lower ranked teams (e.g. rank 20), whereas in comparison a team's own ability was not found to predict any physical performance across GDs. Although time scored appeared in the majority of predictive models, its impact was small. Across all performance parameters (except sprint distance at home) models predicted that the later into the game a goal was scored the less total distance, high speed distance and sprint distance away from home that was covered.

4. DISCUSSION

The aim of the present study was to investigate the effect of playing position, pitch location, team ability and opposition ability on the activity profiles of English premier league players across various goal differences (GD). The multi-level model suggested that activity profiles changed with changes in GD in a non-linear manner and there was significant variation between matches, specifically teams covered more distance and more high speed distance (at home) when the score was close (e.g., +/- 2 goals). Modelling also suggested that activity profiles were influenced by playing position, pitch location and opposition ability, as well as the time at which goals were scored.

4.1 Goal Difference/Score line

In general, predictive modelling suggested that distance covered decreased as GD increased either positively (scoring team) or negatively (conceding team), across all playing positions and all pitch locations. Playing away from home this decrease was greater when teams conceded goals than when teams scored (e.g. less distance was covered at -3 compared to +3 GD), whereas at home the decrease was even for both the scoring and conceding teams. Research [3,6,27] suggests that teams who are winning may relax their work rate, potentially allowing opponents back in the game. Alternatively, although losing teams may initially increase their work rate[4,28] to get back in the game, they may quickly lose motivation to maintain a sufficient work rate which maybe especially true when teams play away from home as shown in the findings here. From a psychological perspective, it has been suggested[29] that teams move through a period of building momentum as they work towards scoring through positive play to cruising (where teams try and economise effort). This often results in a decrease in effort[27, 29 30] once the goal has been achieved as shown in the current study. The reverse maybe true when teams are losing and experiencing negative momentum, i.e., although an initial surge in effort is sometimes seen to overcome this deficit (as teams search for a goal to get back in the game), if the negative momentum persists, teams tend to abandon the activity and reduce their effort dramatically[29,30] as seen when teams conceded more goals in the current study. The current findings further support the misconception that physical activity profiles are related to purely fatigue, rather than the psychological effects of the score line. This is especially pertinent as recent research[5,16] has found little support for decreases in physical activity as a function of fatigue.

High speed running also decreased as GD increased either positively (scoring team) or negatively (conceding team). Away from home, this decrease was more rapid for the conceding team, whereas when playing at home the decrease was similar for both conceding and scoring teams. As previous research considering GD as opposed to match status has been limited, it is difficult to compare results from this current study, however in general, high speed running was at its highest when the GD was small (e.g. -1-+1) supporting previous studies which have shown that players spend a greater percentage of time performing high speed activity when level, than when behind or ahead[18,29]. In support of previous research[18] the current findings suggest that players may maintain their efforts to overcome negative momentum (e.g., losing or conceding) whilst they perceive the goal to still be in reach (e.g., conceding only 1-2 goals). However, once this goal is perceived out of reach (e.g., -3 and beyond in the current study) findings suggest teams decrease their effort, especially when playing away from home. This therefore suggests that although GD is a major factor in influencing player activity, the ‘size’ of the GD and the environment (playing at home or away) may also play a role in predicting player movement activity and thus should be considered by managers and coaches.

4.2 Playing Position

According to the predictive models, playing position influenced total distance covered both at home and away from home across all GD's. Midfielders covered more meters per minute when playing both at home and away from home than either strikers (1.1 $m \cdot min^{-1}$ less at home and 0.43 $m \cdot min^{-1}$ less away from home than midfielders) or defenders (7.3 $m \cdot min^{-1}$ less at home and 6.8 $m \cdot min^{-1}$ less away from home than midfielders). This was consistent across all GD's. No significant differences were found between playing positions for either high speed running or sprint distance. Indeed, it is commonplace for midfielders to cover more distance due to their interlinking role between attack and defence within a team[15]. Strikers, on the other hand have generally been found to cover more high speed running and sprint distance than defenders and in some cases midfielders in an attempt to capitalise on goal scoring opportunities[31]. The lack of significant differences between players in the current study is most likely related to the higher frequency of the automated tracking system used ensuring more accurate estimates of both high speed running and sprint distance, which has previously been problematic.

In relation to score line Redwood-Brown et al.[8] found midfielders covered more high speed running when level, defenders more when losing and attackers more when winning. A similar pattern was reported by Bradley and Noakes[11] who found central defenders covered 17% less and attackers 15% more high speed running during matches that were heavily won versus heavily lost (score differential ≥3 goals). The lack of sensitivity to the playing positions maybe the reason for no significant effect of high speed running or sprint distance in the current study. Thus suggesting that individual player comparisons maybe more relevant when investigating the effect of score line in relation to physical activity profiles.

4.3 Pitch Zone

All playing positions were found to cover more distance per minute in the attacking 3rd both at home and away from home than either the middle 3rd (12.1 $m \cdot min^{-1}$ less at home and 14.1

m·min^{-1} less away from home than attacking 3^{rd}) or defending 3^{rd} (7.9 m·min^{-1} less at home and 11.4 m·min^{-1} less away from home) across all GDs. High speed running followed a similar pattern with more covered in the attacking 3^{rd} both at home and away than either the middle 3^{rd} (4.0 m·min^{-1} less at home and 4.9 m·min^{-1} less away from home than attacking 3^{rd}) or defending 3^{rd} (2.0 m·min^{-1} less at home and 3.2 m·min^{-1} less away from home) across all GDs. No significant differences were found between pitch location for sprint distance covered at home, however when playing away from home, more distance was covered in the attacking 3^{rd} than either the middle 3^{rd} (2.0m less away from home than attacking 3^{rd}) or defending 3^{rd} (2.01m less away from home than attacking 3^{rd}) across all GDs.

Although research considering the interactional effect of pitch position and score line is scarce, Lago[6] did find when teams were behind they spent more time in the attacking third than when in the lead potentially in search of a consolation goal if the opportunity arises. Similarly, García-Rubio et al. [32] found that when teams are winning they tend to play less risky options, and with a more structured defence strategy placing more players between the ball and their own goal thus reducing the amount of time, and thus distance covered in the defending and middle thirds. This supports the idea that winning teams are more likely to adopt a counterattack style of play[6,10] and therefore helps to explain why the middle 3^{rd} had the lowest values for distance covered in the current study as the majority of games end with one dominant team.

The strategy (e.g., time spent in each pitch location) teams employ when either winning or losing maybe somewhat determined by the ability of that team. For example, winning teams have been found to maintain 'control' of the game by keeping possession especially if higher in ability[2,9], which contradicts the idea that teams adopt a direct style of play when winning[2,9]. This therefore suggests that there is a need to investigate activity profiles and technical performance together especially, when considering the pitch location during different score line states as higher ability teams may be able to maintain their style of play despite other variables (e.g., match location or evolving score) [28].

4.4 Team Ability

Models predicted that the ability of the team did not predict activity profiles of players across GDs. Even though research has found teams higher in ability covered more distance than lower ranked teams, especially in higher speed zones[19]. A possible explanation for this maybe that teams are more capable than previously thought at adapting their strategy based on the evolving score. A more plausible explanation is that there may not be much difference between the top and bottom ranked teams in the English Premier League in terms of physical activity profiles and 'ability' is better explained by a team's technical performance[33] This provides additional support for the need to investigate both physical and technical performance together in line with individual teams, playing formations and strategies in order for managers and coaches to maximum team performance.

4.5 Opposition Ability

Models predicted that when playing away from home, teams covered 0.09m per minute, less total distance and when playing at home 0.04m less high speed distance for every decrease in rank position of their opposition. For example when playing against opposition who finished second in the league, teams would cover 0.09m total distance and 0.04m high speed distance per minute less than when playing the top ranked team. Whereas when playing opposition ranked 10th in the league teams covered 0.81m total distance and 0.36m high speed distance less per minute. This was in support of previous research[5,19] which has found players cover more ground when their opposing team is higher in ability compared to medium or bottom ranked teams[4]. No significant differences were found for total distance covered at home, high speed running away from home or sprint distance either home or away. Lago and Dellal[9] suggested when playing against higher or lower ranked opposition, teams may bunch together at either end of the pitch reducing the total distance covered, but increasing sub-maximal and maximal activity profiles. Lago-Penas and Lago-Ballesteros[34] suggested that match location and quality of opposition have equal importance, for example if a lower rank teams plays at home against higher ranked opposition the influence of both these variables maybe compromised accounting for the small effect shown in the current findings.

Teams consistently reported the highest distance covered and high speed distance when the game was close (e.g., -1 to +1). Although it is not always the case that these games will end in a close final score, previous research has found teams cover more high speed running when they play opposition of similar ability compared to lower ranked or higher ranked teams[5]. These findings also support the idea that the technical performance of a team maybe more indicative of their overall ability (final league position) than how far they run during a match[4,33,35]. This is especially true, as recent research has shown teams are able to inject sub-maximal and maximal runs towards the end of the match, showing no signs of physical fatigue[9].

4.6 Limitations

Although the current study included playing position in the multi-level modelling, unlike more recent studies only 3 categories were used. Splitting these categories further (e.g., into wide and central midfielder) would further highlight any variation between playing position. It would however, be interesting to investigate the extent that individual differences contribute to the overall team, or in this case, the overall mean of their playing position given the amount of research[20,36] that suggests variability between players with regards performance accomplishments and success and failure. Another consideration/limitation of the current study was the definition used for score line, although the current study used a more sensitive score line definition to the traditional win, loss, draw it did not give an indication to the actual evolving score line; e.g. 2-0 could be perceived by players differently to 4-2 but would have the same GD. This should therefore be investigated in future research.

4.7 Perspectives and Future Directions

Goal difference was found to have a large and varied impact on the activity profiles of premier league soccer players where total distance both at home and away and high speed distance covered at home were greatest when the goal difference was close. Pitch zone was found to have the biggest effect on activity profiles across GD being present in all but one model, this was followed by playing position. Opposition ability was found to effect teams but on a much smaller scale – supporting the findings that the difference in ability maybe negated when teams are on their own territory[37]. The absence of team ability in all models suggests that the physical movement of players is less of a predictor of overall team performance than technical performance and thus both aspects should be considered when modelling player and team performance.

One area that should be considered in future research is the impact of individual player performance. The current study was not able to present individual players data with regards to the impact of score line however previous work using a case study approach of one team has found that players differ in their approach to different score line states[20]. In order to achieve maximum success, it may therefore be more appropriate, that in order to maximise team performance, the starting eleven should be picked based on the external factors highlighted to influence player performance, for example, if playing against top opposition it may be more appropriate to select players who perform better against higher abilities, or in a negative score line states. Similarly, if some players prefer to defend a lead it may be more appropriate to sub them on, once a lead has been established. In summary players' individual perceptions of the score line have been shown to alter players' motivation, confidence and effort[17] and thus the effect they have on their physical activity profiles. Due to the variety of results found in the current study, future research should consider adopting a case study approach in order to maximise player and ultimately team performance in relation to temporal factors.

4.8 Acknowledgments

We gratefully acknowledge Venatrack Ltd. for allowing access to their database and for granting permission to use the data for the purposes of this research. The authors declare no conflict of interest. The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation and do not constitute endorsement by the American College of Sports Medicine.

References

1. Clemente FM, Couceiro MS, Martins FM, Mendes RS. Using network metrics in soccer: A macro-analysis. J Hum Kinet. 2015;45(1):123-34.
2. Jones PD, James N, Mellalieu SD. Possession as a performance indicator in soccer. Int J Perform Anal Sport. 2004;4(1):98-102.
3. Paul DJ, Bradley PS, Nassis GP. Factors affecting match running performance of elite soccer players: Shedding some light on the complexity. Int J Sports Physiol Perform. 2015;10(4):516-9.
4. Castellano J, Blanco-Villaseñor A, Alvarez D. Contextual variables and time-motion analysis in soccer. Int J Sports Med. 2011;32(06):415-21.
5. Hewitt A, Norton K, Lyons K. Movement profiles of elite women soccer players during international matches and the effect of opposition's team ranking. J Sports Sci. 2014;32(20):1874-80.
6. Lago C. The influence of match location, quality of opposition, and match status on possession strategies in professional association football. J Sports Sci. 2009;27(13):1463-9.
7. O'Donoghue P, Robinson G. Score-line effect on work-rate in English FA Premier League soccer. Int J Perform Anal Sport. 2016;16(3):910-23.
8. Redwood-Brown A, O'Donoghue P, Robinson G, Neilson P. The effect of score-line on work-rate in English FA Premier League soccer. Int J Perform Anal Sport. 2012;12(2):258-71.
9. Taylor BJ, Mellalieu DS, James N. A comparison of individual and unit tactical behaviour and team strategy in professional soccer. Int J Perform Anal Sport. 2005;5(2):87-101.

10. Andrzejewski M, Konefał M, Chmura P, Kowalczuk E, Chmura J. Match outcome and distances covered at various speeds in match play by elite German soccer players. Int J Perform Anal Sport. 2016;16(3):817-28.
11. Bradley PS, Noakes TD. Match running performance fluctuations in elite soccer: indicative of fatigue, pacing or situational influences?. J Sports Sci. 2013;31(15):1627-38.
12. Lago-Peñas C, Rey E, Lago-Ballesteros J. The influence of effective playing time on physical demands of elite soccer players. Open Sports Sci J. 2012;5:188-92.
13. Lago-Peñas C, Gómez-López M. How important is it to score a goal? The influence of the scoreline on match performance in elite soccer. Percept Mot Skills. 2014;119(3):774-84.
14. O'Donoghue P, Robinson G. Validity of the Prozone3 R Player Tracking System: A Preliminary Report. Int J Comput Sci Sport. 2009;8(1):37-53.
15. Di Salvo V, Gregson W, Atkinson G, Tordoff P, Drust B. Analysis of high intensity activity in Premier League soccer. Int J Perform Anal Sport. 2009;30(03):205-12.
16. Sparks M, Coetzee B, Gabbett JT. Variations in high-intensity running and fatigue during semi-professional soccer matches. Int J Perform Anal Sport. 2016;16(1):122-32.
17. Redwood-Brown AJ, Sunderland CA, Minniti AM, O'Donoghue PG. Perceptions of psychological momentum of elite soccer players. Int J Sport Exerc Psychol. 2017;13:1-7.
18. Shaw J, O'Donoghue PG. The effect of scoreline on work rate in amateur soccer. In O'Donoghue, PG and Hughes, MD, editors. Notational analysis of sport VI. Cardiff: CPA Press, UWIC; 2004:84-91.

19. Andersen LJ, Randers MB, Westh K., et al. Football as a treatment for hypertension in untrained 30–55-year-old men: a prospective randomized study. Scand J Med Sci Sports. 2010;20(s1):98-102.
20. Redwood-Brown A, Bussell C, Singh Bharaj HA. The impact of different standards of opponents on observed player performance in the English Premier League. J. Hum. Sports Exerc. 2012;7(2).
21. Carling C, Bloomfield J, Nelsen L, Reilly T. The role of motion analysis in elite soccer. Sports Med. 2008;38(10):839-62.
22. Bloomfield J, Polman R, O'Donoghue P. The 'Bloomfield Movement Classification': motion analysis of individual players in dynamic movement sports. Int J Perform Anal Sport. 2004;4(2):20-31.
23. Redwood-Brown A, Cranton W, Sunderland C. Validation of a real-time video analysis system for soccer. Int J Sports Med. 2012;33(08):635-40.
24. Taylor JB, Mellalieu SD, James N, Shearer DA. The influence of match location, quality of opposition, and match status on technical performance in professional association football. J Sports Sci. 2008;26(9):885-95.
25. Ridgewell A. Passing patterns before and after scoring in the 2010 FIFA World Cup. Int J Perform Anal Sport. 2011;11(3):562-74.
26. Twisk JW. Applied longitudinal data analysis for epidemiology: a practical guide. Cambridge University Press; 2013. 336 p.
27. O'Donoghue P, Tenga A. The effect of score-line on work rate in elite soccer. J Sports Sci. 2001;19(1):25-6.
28. Lago-Peñas C, Dellal A. Ball possession strategies in elite soccer according to the evolution of the match-score: the influence of situational variables. J Hum Kinet. 2010;25:93-100.

29. Briki W, Den Hartigh RJ, Gernigon C. Psychological momentum in sport: towards a complex and dynamic perspective. French Psych. 2016;61(4):291-302.

30. Carver C. Pleasure as a sign you can attend to something else: Placing positive feelings within a general model of affect. Cogn Emot. 2003;17(2):241-61.

31. Faude O, Koch T, Meyer T. Straight sprinting is the most frequent action in goal situations in professional football. J Sports Sci. 2012;30(7):625-31.

32. García-Rubio J, Gómez MÁ, Lago-Peñas C, Ibáñez JS. Effect of match venue, scoring first and quality of opposition on match outcome in the UEFA Champions League. Int J Perform Anal Sport. 2015;15(2):527-39.

33. Rampinini E, Impellizzeri FM, Castagna C, Azzalin A, Ferrari BD, Wisløff UL. Effect of match-related fatigue on short-passing ability in young soccer players. Med. Sci. Sports Exerc. 2008;40(5):934-42.

34. Lago-Peñas C, Lago-Ballesteros J. Game location and team quality effects on performance profiles in professional soccer. J Sports Sci Med. 2011 Sep;10(3):465.

35. Bush M, Barnes C, Archer DT, Hogg B, Bradley PS. Evolution of match performance parameters for various playing positions in the English Premier League. Hum Mov Sci. 2015;39:1-1.

36. Iso-Ahola SE, Dotson CO. Psychological momentum: Why success breeds success. Rev. Gen. Psych. 2014;18(1):19.

37. Pollard R, Gómez MA. Home advantage in football in South-West Europe: Long-term trends, regional variation, and team differences. Eur J Sport Sci. 2009;9(6):341-52.

TABLE 1. Mean activity profiles per player for each club included in the analysis in a winning, drawing and losing score line state.

			WINNING			DRAWING			LOSING		
Team	Number Games Played	Number of Players Included	Total DC (m)	Total HSR (m)	Total Sprint Dist. (m)	Total DC (m)	Total HSR (m)	Total Sprint Dist. (m)	Total DC (m)	Total HSR (m)	Total Sprint Dist. (m)
1	38	32	9885	422	169	10332	397	97	9896	372	118
2	38	27	9822	403	135	10294	386	87	9827	386	126
3	38	31	9776	423	137	10077	371	114	9889	468	161
4	38	30	9600	439	156	10153	402	114	9685	387	147
5	35	29	9801	395	94	10338	396	77	9693	430	90
6	38	30	10265	439	126	10539	399	93	10007	416	124
7	37	29	9796	381	84	10217	355	85	9929	371	91
8	37	25	9555	379	120	10198	404	99	9927	403	139
9	38	26	9919	354	97	10425	316	92	9684	335	109
10	38	32	10073	423	143	10385	383	78	10238	429	168
11	37	27	9806	324	100	10530	569	105	9981	369	118
12	38	28	10056	382	106	10504	435	106	10198	444	94
13	38	36	9796	412	130	10005	346	68	9807	370	134
14	38	23	9887	348	74	10365	338	69	9905	307	74
15	38	28	9690	393	102	10339	449	184	9869	541	150
16	38	25	9929	413	105	10179	386	102	10118	428	147
17	38	31	9790	321	103	10187	434	59	9646	339	65
18	37	25	9652	361	112	10266	399	77	9892	399	101
19	38	24	9854	377	80	9966	317	63	9729	342	84
20	37	32	10109	350	79	10482	404	87	10077	452	134
TOTAL	**376**	**570**	**9853.5**	**387.6**	**117.2**	**10289.6**	**394.9**	**98.6**	**9900.2**	**399.8**	**123.7**
SD		3	174.7	35.6	32.6	166.8	54.9	36.8	169.6	54.2	36.9

TABLE 2. Estimated Models for Total Distance Covered per minute both Home and Away

Distance Covered – Home		
Fixed Effects	Coefficient	SE
Constant	118.527	0.646
Goal Difference	0.601	0.189
Goal Difference^2	-0.462	0.072
Midfielder	7.275	0.554
Striker	1.116	0.557
Time Scored	-0.069	0.01
Defending 3rd	-7.884	0.558
Middle 3rd	-12.082	0.553
Random Effects	Variance	SE
Between Game (Repeat)	349.365	6.146
Within Game (Match ID)	27.199	3.589

Distance Covered – Away		
Fixed Effects	Coefficient	SE
Constant	123.625	1.088
Goal Difference	1.388	0.217
Goal Difference^2	-0.362	0.083
Midfielder	6.75	0.601
Striker	0.433	0.605
Time Scored	-0.087	0.011
Defending 3rd	-11.436	0.606
Middle 3rd	-14.081	0.602
Opposition Ability	-0.204	0.078
Random Effects	Variance	SE
Between Game (Repeat)	407.802	7.215
Within Game (Match ID)	44.289	5.217

Notes. Independent intercepts estimates (at Goal Difference 0) for each playing position (reference defender), pitch location (reference attacking 3rd), team ability (rank 1), opposition ability (rank 1) and time scored (minute 1).

TABLE 3. Estimated Models for Total High Speed Distance Covered per minute both Home and Away.

High Speed Running – Home		
Fixed Effects	Coefficient	SE
Constant	6.654	0.238
Defending 3rd	-1.971	0.174
Middle 3rd	-4.011	0.168
Opposition Ability	-0.035	0.017
Time Scored	0.011	0.003
Random Effects	Variance	SE
Between Game (Repeat)	29.707	0.554
Within Game (Match ID)	1.279	0.232

High Speed Running – Away		
Fixed Effects	Coefficient	SE
Constant	7.376	0.289
Goal Difference	0.21	0.103
Goal Difference^2	-0.112	0.042
Defending 3rd	-3.221	0.302
Middle 3rd	-4.904	0.294
Time Scored	0.01	0.005
Random Effects	Variance	SE
Between Game (Repeat)	88.651	1.664
Within Game (Match ID)	6.298	0.904

Notes. Independent intercepts estimates (at Goal Difference 0) for each playing position (reference defender), pitch location (reference attacking 3rd), team ability (rank 1), opposition ability (rank 1) and time scored (minute 1).

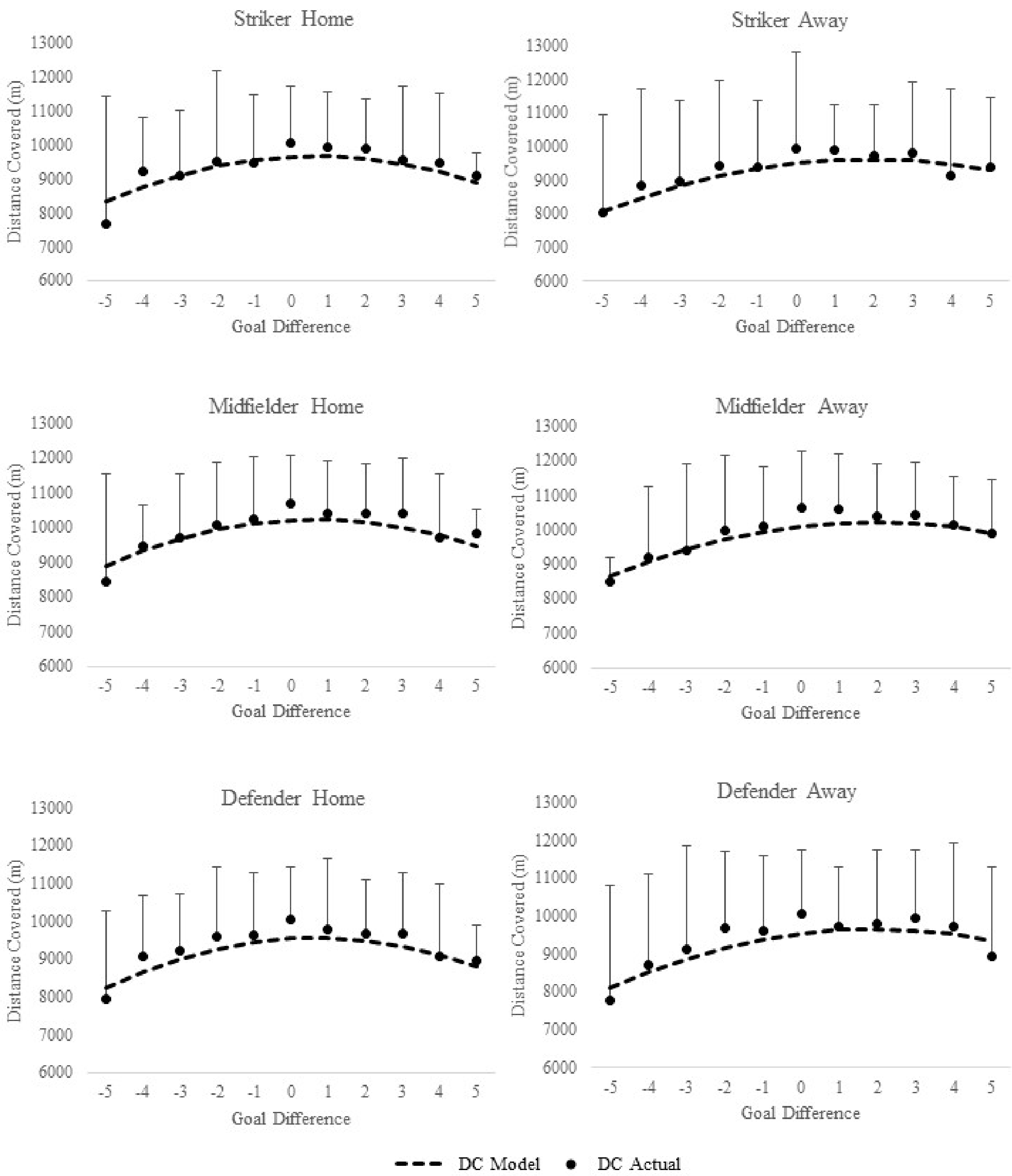

Figure 1: Total distance covered(m) during match-play in English Premier League across difference goal differences. Curves are based on predicted distances covered from multi-level models of longitudinal data. Points are based on the 'raw' distance covered data (mean ± SD). Data are presented by playing position both at home and away during match-play.

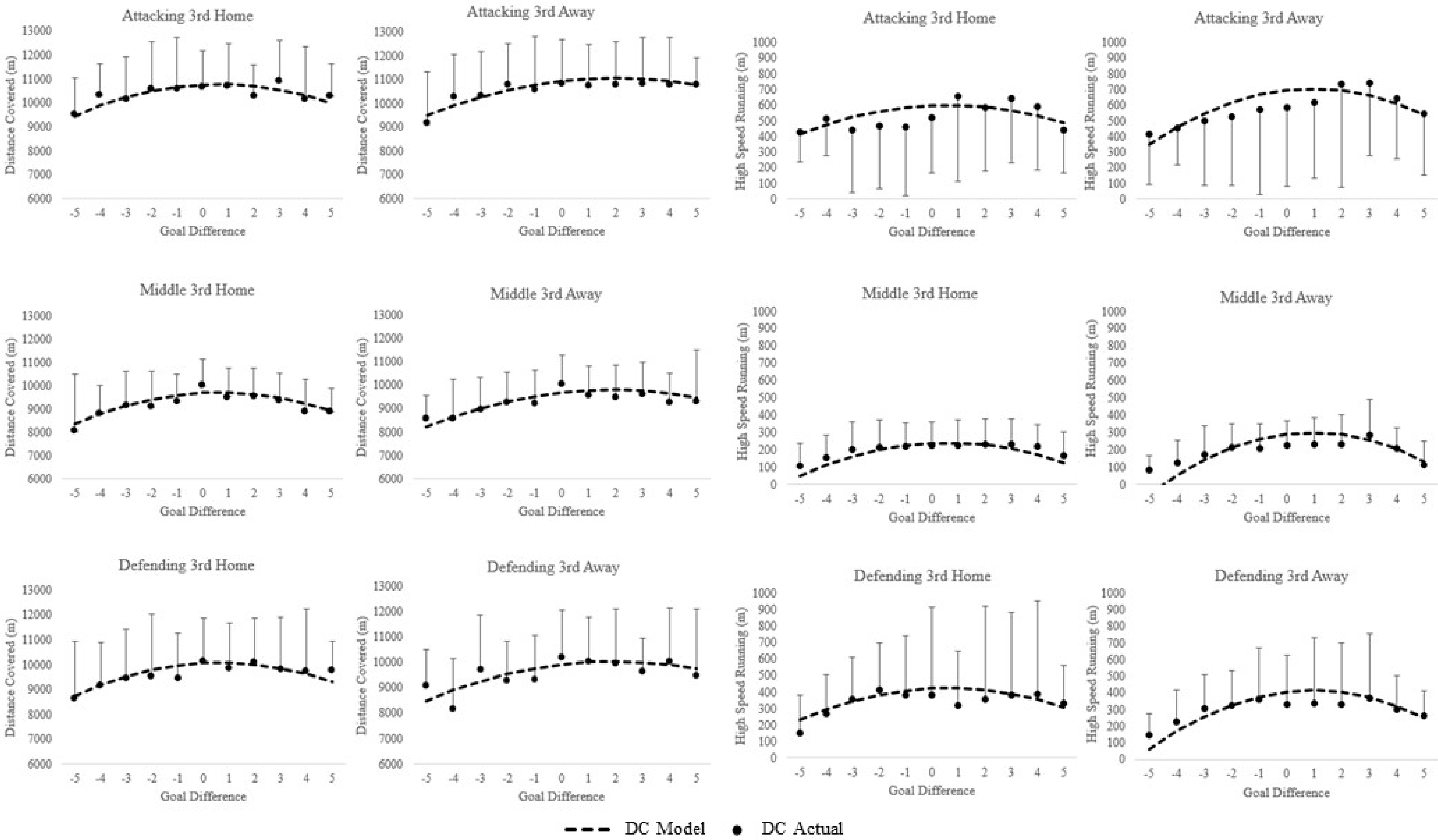

Figure 2: Total distance covered (m) and total high speed distance covered (m) during match-play in English Premier League across difference goal differences. Curves are based on predicted distances covered from multi-level models of longitudinal data. Points are based on the 'raw' distance covered data (mean ± SD). Data are presented by pitch location during match-play.

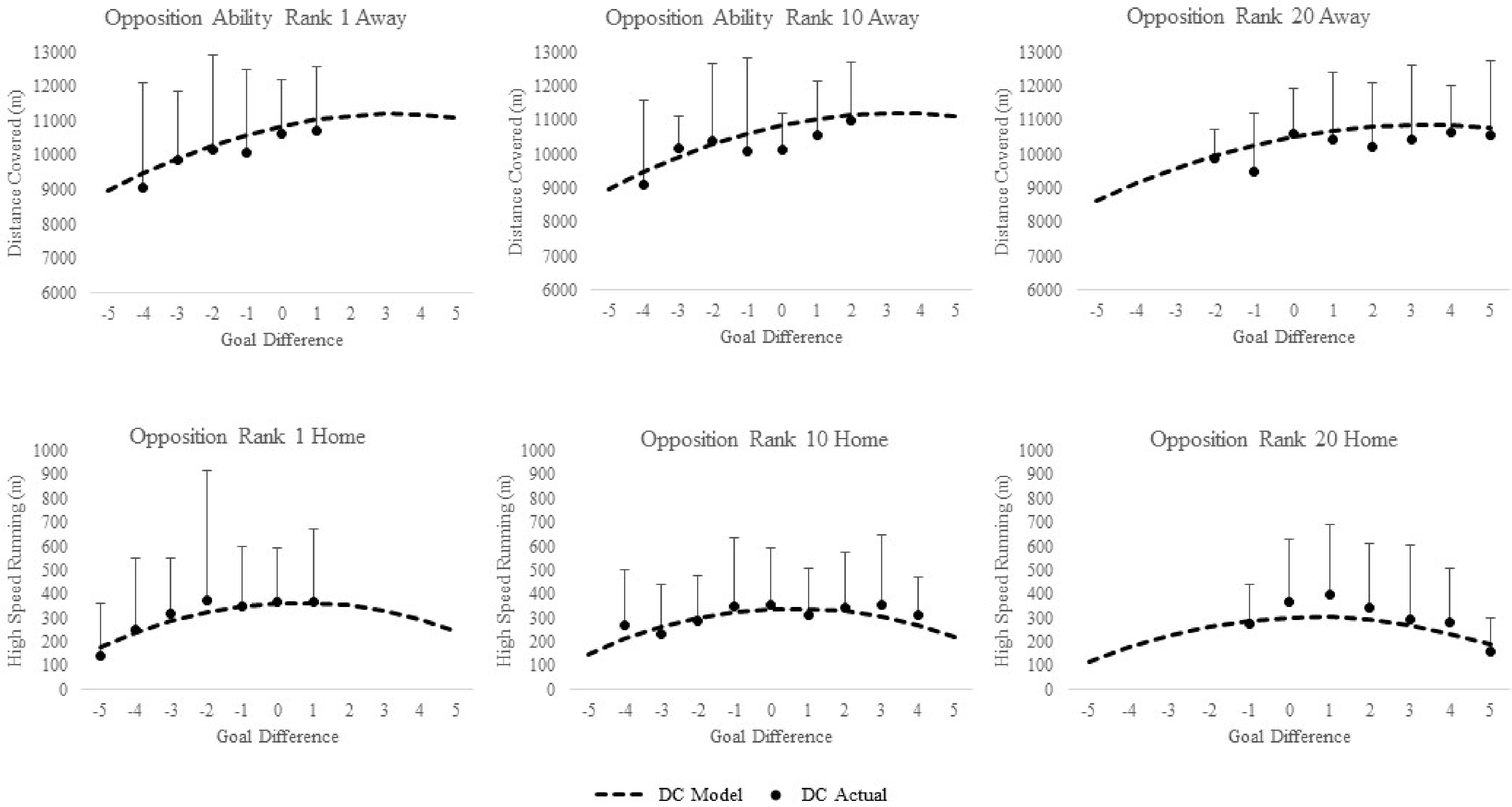

Figure 3: Total distance covered (m) during match-play in English Premier League across difference goal differences. Curves are based on predicted distances covered from multi-level models of longitudinal data. Points are based on the 'raw' distance covered data (mean ± SD). Data are presented for opposition ability rank that were significant predictors of performance variables during match play within the model.