ORIGINAL ARTICLE

Technical performance in the English Premier League: The influence of team quality and match location

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ABSTRACT

The purpose of this study was to compare the technical performance metrics of top- and bottom-tier English Premier League teams, examine the effect of match location on these metrics, and identify the statistically significant factors of winning. A total of 266 match observations were analysed via Mann–Whitney U tests and binary logistic regression. Top-tier teams had higher numbers in Shot, Shot on Target, Successful Take-On, Tackle Attacking 3rd, Pass Completed, Through Ball, Long Pass Completed, and Cross. Bottom-tier teams, on the other hand, recorded more Shot on Target Against, Clearance, Blocked Shot, Tackle Defensive 3rd, Yellow Card, Long Pass Completed %, and Aerial Duel Won. Generally, teams had increased offensive outputs in home games, while playing away primarily influenced defensive actions. For top-tier teams, each additional Aerial Duel Won and Shot on Target increased winning odds by 35% and 65%, respectively. Cross, Tackle Attacking 3rd, and Shot on Target Against decreased these odds by 30%, 43%, and 45%, respectively. Among bottom-tier teams, each event of Clearance increased odds of winning by 13%, while Shot on Target Against decreased them by 37%. These findings can be useful to coaches and performance analysts for evaluating and improving team performance.

Keywords: Performance analysis, Association football, Match analysis, Technical performance metrics, Match location.

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INTRODUCTION

Match analysis in association football, or simply "*football*," involves the objective recording of team activities and behavioural events in games, which aids in evaluating and providing feedback on both team and individual performance (Carling et al., 2005; O'Donoghue, 2009). This process allows teams to refine their strengths and address areas that need improvement. Likewise, by analysing an opponent's performance, coaches can devise strategies that neutralize that opponent's strengths and exploit their weaknesses (Carling et al., 2008).

A central element of such analyses is performance indicators: a set of selected variables that define some aspect of performance, establish an ideal profile necessary for athletic success, and contribute to the prediction of future outcomes in sport (Hughes & Bartlett, 2002; Jones et al., 2004). Hence, researchers have emphasized the importance of developing and utilizing these indicators (Carling et al., 2005; Carling et al., 2008; Hughes & Bartlett, 2002), and many studies have explored their relationships with match, seasonal, or tournament success (Andrzejewski et al., 2022; Bilek & Ulas, 2019; Castellano et al., 2012; Delgado Bordonau et al., 2013; Kubayi & Larkin, 2020; Lago-Ballesteros & Lago-Peñas, 2010; Lago-Peñas et al., 2010; Liu et al., 2015a; Liu et al., 2015b; Liu et al., 2015c; Liu et al., 2016; Mao et al., 2016; Stafylidis et al., 2024; Souza et al., 2019; Yue et al., 2014).

Within this field of research, performance metrics generally fall under two categories: physical and technical. Of the two, technical parameters (e.g., shots, passes, crosses) are widely regarded as more robust indicators of performance compared to pure physical activities, such as total distance covered, average speed, and average acceleration (Bush et al., 2015; Castellano et al., 2012; Lago-Peñas et al., 2010; Liu et al., 2015b; Nassis et al., 2015; Rampinini et al., 2009). Moreover, technical performance profiles can be improved when contextualized by team quality (Liu et al., 2015b; Rampinini et al., 2009). However, there is still a lack of studies comparing the technical performance of teams of differing quality. Consequently, the present study investigates which technical metrics differ between higher- and lower-ranked teams and identifies the indicators most strongly associated with match success in both groups.

Situational variables like the quality of opposition, match status, and match location have also been shown to influence team performance (Lago, 2009; Taylor et al., 2008). While all three have been extensively studied, match location can be further explored. According to Tucker et al. (2005), match location can affect primary, secondary, and tertiary measures. "*Primary measures consisted of fundamental skill execution (i.e., batting average, free throw percentage, penalties per game). Secondary measures usually reflected the scoring necessary to win a contest (e.g., points or goals scored), while tertiary measures indicated the final match outcome (win/loss, point's difference etc.)*" (p. 23). Most studies regarding match location have evaluated its impact through tertiary measures (e.g., Allen & Jones, 2012; Almeida & Volossovitch, 2017; Goumas, 2014; Leite, 2017; Liu et al., 2016; Peeters & van Ours, 2021; Schwartz & Barsky, 1977), consistently reporting higher success rates at home compared to away, a phenomenon known as "*home advantage*."

A limited number of studies have examined the impact of match location on primary measures, in the form of technical performance metrics (e.g., Carmichael & Thomas, 2005; Liu et al., 2015c; Lago-Peñas & Lago-Ballesteros, 2011; Taylor et al., 2008; Tucker et al., 2005), and even fewer have accounted for team quality in this context (Lago-Peñas & Lago-Ballesteros, 2011; Liu et al., 2015c). Lago-Peñas & Lago-Ballesteros (2011) and Liu et al. (2015c) suggest that stronger and weaker teams do not experience the same home

advantage. Thus, it seems important to examine how match location affects technical performance, while considering how team quality may moderate these effects.

A range of technical performance metrics were selected according to existing literature (Castellano et al., 2012; Lago-Ballesteros & Lago-Peñas, 2010; Lago-Peñas et al., 2010; Lago-Peñas & Lago-Ballesteros, 2011; Liu et al., 2015a; Liu et al., 2016; Mao et al., 2016). A key contribution of this study is the introduction of four metrics that have been largely unexplored in similar analyses: Tackle Defensive 3rd, Tackle Attacking 3rd, Long Pass Completed % and Shot Distance. While tackles themselves have been incorporated in previous analyses (Almeida et al., 2014; Kubayi & Larkin, 2020; Liu et al., 2015a; Liu et al., 2015b; Liu et al., 2015c; Liu et al., 2016; Mao et al., 2016; Stafylidis et al., 2024; Tucker et al., 2005), no attention has been paid to their location on the pitch. By differentiating tackles in the defensive and attacking thirds of the pitch, this study offers a more nuanced look at their tactical significance. Long Pass Completed % can indicate a "*direct*" playing style driven by frequent long passes (Fernández-Navarro et al., 2018; González-Rodenas et al., 2020a), while Shot Distance provides insights into shot quality, given the role of shooting distance in scoring likelihood (González-Rodenas et al., 2020b; Pollard et al., 2004).

Previous studies have classified teams based on final league rankings, often without applying a rigorous statistical framework (Lago-Ballesteros & Lago-Peñas, 2010; Liu et al., 2015b; Rampini et al., 2009). To address this gap, this study employs k-means clustering to objectively categorize the 20 teams at the end of the season, focusing on the top and bottom clusters for subsequent analysis.

Accordingly, the present study aims to: (1) compare technical performance metrics between top- and bottom-tier English Premier League teams; (2) identify which technical metrics are affected by match location; and (3) determine the key performance indicators most strongly associated with winning.

MATERIAL AND METHODS

Data

The sample contained 18 technical performance metrics of teams in the 2023–24 English Premier League season. Match statistics were collected from the publicly available Sports Reference's FBref (FBref.com, 2024), which is powered by Opta Sports, a data collection company considered to be the gold standard (Sapp et al., 2017).

Initially, k-means clustering was applied to divide the 20 teams into four clusters (see Section 2.2 for more details). Teams that finished 1st to 3rd were assigned to the "*top*" tier, while those ranked 17th to 20th formed the "*bottom*" tier. This selection resulted in 114 match observations in the top group, and 152 observations in the bottom group.

Of the 18 metrics, 16 were directly obtained from FBref (Fbref.com, 2024) and checked for multicollinearity ($r > 0.8$). The remaining two metrics were derived from the existing metrics: Long Pass Completed %, calculated as $\frac{\text{Long Pass Completed}}{\text{Pass Completed}} \times 100$, and Shooting Accuracy %, calculated as $\frac{\text{Shot on Target}}{\text{Shot}} \times 100$. Operational definitions for all metrics (Table 1) are based on FBref (FBref.com, 2024) and other sources (Liu et al., 2013; Liu et al., 2015a).

Statistical analysis

K-means clustering was applied to group the 20 teams according to final league points in the 2023–24 Premier League season. The elbow method, as shown in Figure 1, indicated that the optimal number of clusters was four, after which the top cluster (1st–3rd) and bottom cluster (17th–20th) were selected for further analysis.

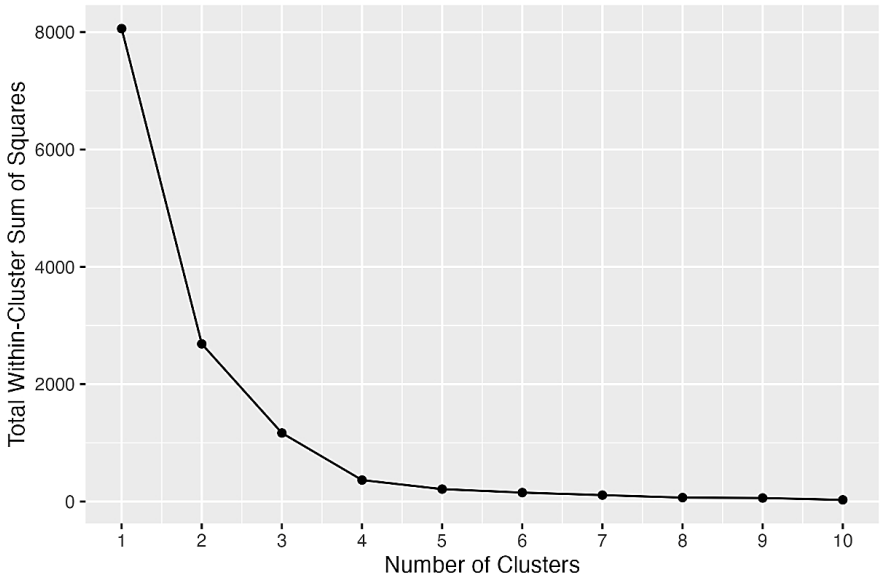

Figure 1. Elbow method for determining the optimal number of clusters.

Descriptive data of the metrics were presented using means (M) and standard deviations (SD) according to tier (top-tier and bottom-tier) and match location (home and away). The assumptions of normality of residuals was assessed through Shapiro–Wilk's test and homogeneity of variances was evaluated using Levene's test. As most of the metrics did not satisfy these assumptions, Mann–Whitney U tests, which are statistically equivalent to the Wilcoxon Rank–Sum test, were performed instead of Student's t-tests. First, a Mann–Whitney U test was carried out to analyse the differences in technical metrics between top- and bottom-tier teams. Then, the same test was implemented again to find the differences in metrics between home and away matches in both tiers. Rank-based effect sizes (ES) were calculated for each Mann–Whitney U test and interpreted as small (ES = 0.1), medium (ES = 0.3), or large (ES = 0.5) (Cohen, 1988).

Following this, binary logistic regression was conducted for both tiers to identify the statistically significant performance indicators associated with winning. Match outcome was the dependent variable (1 = wins and 0 = draws and losses), while the values of the performance indicators were the independent variables, which were modelled to calculate the logarithm of odds of winning a match (Peng et al., 2002). Long Pass Completed % and Shooting Accuracy % were excluded in the regression due to issues with multicollinearity ($r > 0.8$). Although the dataset was unbalanced, as top-tier teams had a higher proportion of wins and bottom-tier teams had a higher proportion of draws and losses, no under sampling or oversampling methods were utilized. Crone and Finlay (2012) argue that such balancing does not improve logistic models and that retaining all data yields better results. Model fit was evaluated using the Hosmer–Lemeshow goodness-of-fit test, and Nagelkerke R^2 was calculated to measure the model's explanatory strength. All statistical analyses were carried out using the statistical software R (R Core Team, 2024), with $p < .05$ considered statistically significant.

Table 1. Operational definitions of the technical performance metrics.

Offensive Metrics	
Shot	An attempt to score a goal, made with any (legal) part of the body, either on or off target.
Shot on Target	An attempt to goal which required intervention to stop it going in or resulted in a goal/shot which would go in without being diverted.
Shooting Accuracy %	Shot on Target as a proportion of Shot.
Shot Distance	Average distance, in yards, from goal of all shots taken. Only players with a minimum of 0.395 shots per squad game are included in this statistic. Penalty kicks are excluded.
Successful Take-On	An attempt by a player to beat an opponent when they have possession of the ball. A successful take-on means the player beats the defender while retaining possession.
Defensive Metrics	
Shot on Target Against	A conceded attempt on goal which required intervention to stop it going in or resulted in a goal/shot which would go in without being diverted.
Tackle Defensive 3rd	The act of gaining possession from an opposition player, when he is in possession of the ball in the defensive third of the pitch.
Tackle Attacking 3rd	The act of gaining possession from an opposition player, when he is in possession of the ball in the attacking third of the pitch.
Blocked Shot	A defensive block, blocking a shot going on target. This must be awarded to the player who blocks the shot.
Clearance	Players attempt to get the ball out of the danger zone, when there is pressure behind them, or there is pressure on the player to clear the ball from the danger zone.
Yellow Card	Where a player was shown a yellow card by the referee for reasons of foul, persistent infringement, hand ball, dangerous play, time wasting, etc.
Passing & Organizing Metrics	
Pass Completed	An intentional ball from one player to another.
Long Passes Completed	A completed pass longer than 30 yards.
Through Ball	A completed pass sent between defenders back into open space.
Cross	Any ball sent into the opposition team's area from a wide position.
Offside	Being caught in an offside position resulting in a free kick to the opposing team.
Aerial Duel Won	Two players competing for a ball in the air, for it to be an aerial both players must jump and challenge each other in the air and have both feet off the ground. The player who wins the duel gets the Aerial Won.
Long Pass Completed %	Long Pass Completed as a proportion of Pass Completed.

RESULTS

Table 2 presents the results of the Mann–Whitney U test comparing the technical performance of top- and bottom-tier teams. For offensive metrics, top-tier teams recorded significantly more total shots (p = .00, ES = 0.53, large effect), on-target shots (p = .00, ES = 0.47, moderate effect) and successful take-ons (p = .03, ES = 0.13, small effect). By contrast, shooting accuracy (p = .07, ES = 0.11, small effect) and average shot distance (p = .10, ES = 0.10, small effect) did not reach statistical significance at the $p < .05$ level.

Regarding defensive metrics, bottom-tier teams conceded a higher number of on-target shots (p = .00, ES = 0.52, large effect) and recorded more clearances (p = .00, ES = 0.54, large effect) and blocked shots (p = .00, ES = 0.39, moderate effect). They also made more tackles in the defensive third of the pitch (p = .00, ES = 0.39, moderate effect) and received more yellow cards (p = .00, ES = 0.19, small effect). In contrast, top-tier teams attempted more tackles in the attacking third of the pitch (p = .00, ES = 0.22, small effect).

For passing and organizing metrics, top-tier teams completed more passes (p = .00, ES = 0.74, large effect), through balls (p = .00, ES = 0.48, moderate effect), long passes (p = .00, ES = 0.29, small effect), and crosses (p = .00, ES = 0.19, small effect). Bottom-tier teams, on the other hand, relied more heavily on long passes relative to their total passes (p = .00, ES = 0.62, large effect) and won more aerial duels (p = .00, ES = 0.27, small effect). No significant differences were found concerning the number of offsides per match (p = .62, ES = 0.03).

Table 2. Comparison of technical performance metrics between top- and bottom-tier teams.

Metric	Top-Tier Teams (M ± SD)	Bottom-Tier Teams (M ± SD)	Z	*p*	Effect Size (ES)
Metrics Relating to Offense					
Shot	18.52 ± 7.11	10.97 ± 4.61	8.60	.00*	0.53
Shot on Target	6.46 ± 3.23	3.49 ± 2.09	7.69	.00*	0.47
Successful Take-On	8.69 ± 3.49	7.76 ± 3.72	2.19	.03*	0.13
Shooting Accuracy %	36.00 ± 15.00	32.00 ± 16.00	1.82	.07	0.11
Shot Distance	16.61 ± 2.07	17.24 ± 3.64	-1.65	.10	0.10
Metrics Relating to Defence					
Shot on Target Against	2.97 ± 1.94	5.88 ± 2.90	-8.44	.00*	0.52
Clearance	13.64 ± 6.44	24.76 ± 10.37	-8.78	.00*	0.54
Blocked Shot	2.54 ± 2.10	4.61 ± 2.75	-6.41	.00*	0.39
Tackle Defensive 3rd	6.26 ± 3.36	9.37 ± 4.09	-6.29	.00*	0.39
Tackle Attacking 3rd	2.92 ± 1.83	2.13 ± 1.77	3.58	.00*	0.22
Yellow Card	1.63 ± 1.33	2.18 ± 1.48	-3.08	.00*	0.19
Metrics Relating to Passing and Organizing					
Pass Completed	562.16 ± 132.16	305.12 ± 105.26	12.07	.00*	0.74
Long Pass Completed %	7.20 ± 2.20	11.30 ± 3.36	-10.12	.00*	0.62
Through Ball	2.55 ± 1.74	0.98 ± 1.18	7.81	.00*	0.48
Long Pass Completed	39.18 ± 11.82	32.36 ± 8.85	4.81	.00*	0.29
Aerial Duel Won	12.38 ± 6.38	15.55 ± 6.17	-4.35	.00*	0.27
Cross	19.18 ± 8.63	15.88 ± 8.21	3.14	.00*	0.19
Offside	2.01 ± 1.72	1.87 ± 1.63	0.00	.62	0.03

Note. * = Significant at $p < .05$

Table 3. Differences in technical performance metrics for top-tier teams by match location.

Metric	Home (M ± SD)	Away (M ± SD)	Z	*p*	Effect Size (ES)
Metrics Relating to Offense					
Shot	20.88 ± 7.10	16.16 ± 6.33	-3.51	.00*	0.33
Shot on Target	7.12 ± 3.11	5.79 ± 3.23	-2.11	.03*	0.20
Shooting Accuracy %	35 ± 12	36 ± 17	0.72	.47	0.07
Successful Take-On	8.95 ± 3.77	8.44 ± 3.20	0.00	.66	0.04
Shot Distance	16.67 ± 2.00	16.55 ± 2.15	0.00	.95	0.01
Metrics Relating to Defence					
Clearance	11.40 ± 5.42	15.88 ± 6.63	3.73	.00*	0.35
Blocked Shot	1.88 ± 1.60	3.19 ± 2.33	3.16	.00*	0.30
Tackle Defensive 3rd	5.44 ± 3.15	7.09 ± 3.39	2.68	.01*	0.25
Tackle Attacking 3rd	3.23 ± 1.93	2.61 ± 1.69	-1.67	.09	0.16
Yellow Card	1.47 ± 1.36	1.79 ± 1.29	1.58	.11	0.15
Shot on Target Against	2.67 ± 1.50	3.28 ± 2.27	0.00	.29	0.10
Metrics Relating to Passing and Organizing					
Cross	21.02 ± 9.32	17.35 ± 7.52	-2.13	.03*	0.20
Offside	2.21 ± 1.71	1.81 ± 1.73	-1.58	.11	0.15
Pass Completed	583.54 ± 124.95	540.77 ± 136.76	-1.56	.12	0.15
Long Pass Completed %	7.01 ± 2.19	7.38 ± 2.22	1.09	.27	0.10
Aerial Duel Won	12.75 ± 5.75	12.00 ± 6.98	-1.04	.30	0.10
Long Pass Completed	40.02 ± 12.46	38.35 ± 11.18	-0.64	.52	0.06
Through Ball	2.63 ± 1.80	2.47 ± 1.68	0.00	.68	0.04

Note. * = Significant at $p < .05$

As shown in Table 3, when playing at home, top-tier teams took significantly more total (p = .00, ES = 0.33, moderate effect) and on-target (p = .03, ES = 0.20, small effect) shots, along with more crosses (p = .03, ES = 0.20, small effect). In away matches, these teams made more clearances (p = .00, ES = 0.35, moderate effect) and blocked shots (p = .00, ES = 0.30, moderate effect). They also made more tackles in the defensive third (p = .01, ES = 0.25, small effect).

Table 4. Differences in technical performance metrics for bottom-tier teams by match location.

Metric	Home (M ± SD)	Away (M ± SD)	Z	*p*	Effect Size (ES)
Metrics Relating to Offense					
Shot	12.75 ± 4.83	9.18 ± 3.62	-4.52	.00*	0.37
Successful Take-On	8.26 ± 3.63	7.25 ± 3.76	-2.16	.03*	0.18
Shooting Accuracy %	30.00 ± 15.00	35.00 ± 17.00	2.15	.03*	0.17
Shot on Target	3.74 ± 2.26	3.25 ± 1.89	-1.35	.18	0.11
Shot Distance	17.19 ± 3.02	17.29 ± 4.19	0.00	.95	0.01
Metrics Relating to Defence					
Blocked Shot	3.87 ± 2.64	5.34 ± 2.68	3.42	.00*	0.28
Tackle Attacking 3rd	2.59 ± 1.83	1.67 ± 1.59	-3.37	.00*	0.27
Clearance	22.66 ± 10.92	26.86 ± 9.41	2.56	.01*	0.21
Tackle Defensive 3rd	8.82 ± 4.17	9.92 ± 3.96	1.73	.08	0.14
Yellow Card	1.97 ± 1.35	2.38 ± 1.59	0.00	.10	0.13
Shot on Target Against	5.54 ± 2.84	6.21 ± 2.94	1.55	.12	0.13
Metrics Relating to Passing and Organizing					
Cross	18.75 ± 9.11	13.01 ± 6.01	-3.99	.00*	0.32
Long Pass Completed	33.86 ± 9.01	30.87 ± 8.49	-2.25	.02*	0.18
Pass Completed	324.39 ± 115.24	285.86 ± 90.95	-1.88	.06	0.15
Offside	2.08 ± 1.90	1.66 ± 1.28	-0.87	.39	0.07
Aerial Duel Won	15.87 ± 6.54	15.24 ± 5.80	0.00	.78	0.02
Through Ball	1.00 ± 1.23	0.96 ± 1.14	0.00	.88	0.01
Long Pass Completed %	11.15 ± 3.16	11.44 ± 3.57	0.03	.97	0.00

Note. * = Significant at $p < .05$

Table 4 presents the technical performance metrics of bottom-tier teams according to match location. At home, these teams attempted significantly more total shots (p = .00, ES = 0.37, moderate effect) and had a higher number of successful take-ons (p = .03, ES = 0.18, small effect). They also performed more tackles in the attacking third (p = .00, ES = 0.27, small effect), along with more crosses (p = .00, ES = 0.32, moderate effect) and long passes (p = .02, ES = 0.18, small effect). In away games, bottom-tier teams displayed better shooting accuracy (p = .03, ES = 0.17, small effect). Additionally, they blocked more shots (p = .00, ES = 0.28, small effect) and completed more clearances (p = .01, ES = 0.21, small effect).

Table 5. Binary logistic regression results for top-tier teams.

Variable	B	Odds Ratio (OR)	*p*	Lower 95% CI	Upper 95% CI
Cross	-0.36	0.70	.00*	0.57	0.86
Aerial Duel Won	0.31	1.37	.00*	1.10	1.69
Shot on Target	0.50	1.65	.01*	1.12	2.42
Shot on Target Against	-0.61	0.55	.01*	0.34	0.88
Tackle Attacking 3rd	-0.57	0.57	.02*	0.35	0.93
(Intercept)			.03		
Through Ball	-0.32	0.73	.16	0.47	1.13
Blocked Shot	-0.33	0.72	.17	0.45	1.15
Clearance	-0.11	0.90	.20	0.77	1.06
Yellow Card	-0.46	0.63	.20	0.31	1.28
Shot Distance	-0.20	0.82	.27	0.57	1.17
Tackle Defensive 3rd	-0.08	0.93	.60	0.69	1.24
Successful Take-On	-0.05	0.95	.66	0.75	1.20
Pass Completed	0.00	1.00	.73	0.99	1.01
Long Pass Completed	0.01	1.01	.74	0.94	1.09
Shot	0.03	1.03	.80	0.82	1.29
Offside	-0.05	0.95	.81	0.63	1.44

Note. * = Significant at $p < .05$

Table 5 presents the binary logistic regression results for top-tier teams, indicating five significant metrics: Aerial Duel Won, Shot on Target, Cross, Tackle Attacking 3rd, and Shot on Target Against. Each additional Aerial Duel Won (p = .00) and Shot on Target (p = .01) increased the odds of winning in a game by 37% and 65%, respectively. On the other hand, per increase for Cross (p = .00), Tackle Attacking 3rd (p = .02), and Shot on Target Against (p = .01), the odds of winning decreased by 30%, 45%, and 43%, respectively. The Hosmer-Lemeshow goodness-of-fit test returned a nonsignificant p-value of .46, and Nagelkerke R^2 was .71.

Table 6. Binary logistic regression results for bottom-tier teams.

Variable	B	Odds Ratio (OR)	*p*	Lower 95% CI	Upper 95% CI
Shot on Target Against	-0.46	0.63	.00*	0.48	0.84
Clearance	0.12	1.13	.01*	1.03	1.23
Shot	0.19	1.21	.10	0.96	1.52
Pass Completed	-0.01	0.99	.13	0.98	1.00
Through Ball	0.36	1.43	.16	0.87	2.36
Successful Take-Ons	-0.12	0.89	.20	0.74	1.07
Cross	-0.08	0.93	.22	0.82	1.05
Long Pass Completed	0.06	1.06	.22	0.97	1.16
Blocked Shot	-0.17	0.84	.27	0.62	1.14
Shot on Target	0.19	1.21	.31	0.84	1.76
Shot Distance	0.10	1.10	.32	0.91	1.33
Tackle Defensive 3rd	-0.09	0.92	.34	0.77	1.09
Yellow Card	-0.20	0.82	.36	0.53	1.26
Aerial Duel Won	-0.05	0.95	.37	0.86	1.06
(Intercept)			.45		
Offside	0.13	1.14	.52	0.77	1.70
Tackle Attacking 3rd	-0.06	0.94	.77	0.63	1.42

Note. * = Significant at $p < .05$

As seen in Table 6, the binary logistic regression of bottom-tier teams revealed only two significant metrics: Clearance and Shot on Target Against. Per increase in a game, Clearance (p = .01) increased winning odds by 13%, while Shot on Target Against (p = .00) decreased them by 37%. The Hosmer-Lemeshow goodness-of-fit test returned a non-significant p-value of .16, and Nagelkerke R^2 had a value of .47.

DISCUSSION

The objective of this study was threefold: (1) to compare the technical performance of top- and bottom-tier teams in the 2023–24 English Premier League season; (2) to identify the technical metrics affected by match location; and (3) to determine the statistically significant performance indicators associated with winning. K-means clustering, Mann–Whitney U tests, and binary logistic regression were implemented in the analyses.

Regarding the first aim, the results showed that top-tier teams had a higher number of total and on-target shots, as well as for the number of successful take-ons. Previous studies have also found similar findings (Andrzejewski et al., 2022; González-Rodenas et al., 2015; Lago-Ballesteros & Lago-Peñas, 2010; Liu et al., 2015b; Liu et al., 2015c; Liu et al., 2016; Souza et al., 2019). However, Shot Distance and Shooting Accuracy % did not display statistically significant differences between the tiers. Considering the importance of the distance of a shot on scoring, and thus shot quality, (González-Rodenas et al., 2020b; Pollard et al., 2004) the lack of significance for Shot Distance may have contributed to the similar result in Shooting Accuracy %, which measures the average quality of shots in a game. Collectively, these findings indicate that the quantity of shots (Shot) better differentiates the top and bottom tiers than average shot quality (Shooting Accuracy %). In line with this claim, research conducted on the 2008–09 season of the Spanish La Liga reported

significant differences between top, middle, and bottom teams for the number of total shots, but not for shooting accuracy (Lago-Ballesteros & Lago-Peñas, 2010).

Defensively, bottom-tier teams conceded a greater number of shots on target, consistent with past research (Andrzejewski et al., 2022; Delgado Bordonau et al., 2013; Souza et al., 2019). Moreover, they made a higher frequency of clearances, blocked shots, and tackles in the defensive third of the pitch. These teams also received more yellow cards, in accordance with the negative correlation between disciplinary counts and league position (Sapp et al., 2017). Meanwhile, among top-tier teams, the only defensive metric they had significantly higher values been the number of tackles in the attacking third. Previous studies have established that such tackling in advanced areas of the pitch are intended to gain possession closer to the opponent's goal, further linking this to offensive success (Almeida et al., 2014; Fernández-Navarro et al., 2016; González-Rodenas et al., 2020c; T, 2019; Liu et al., 2016).

Taking into consideration the metrics related to passing and organizing, top-tier teams completed nearly twice as many total passes, along with more through balls and long passes. Some of these findings are supported by other studies (Andrzejewski et al., 2022; Liu et al., 2015b; Liu et al., 2015c; Liu et al., 2016). Although crossing has been negatively associated with win rates during the 2012–13 La Liga season (Liu et al., 2016), the present study showed that top-tier teams attempted more crosses. This contrast in results may suggest changing tactical strategies or may simply stem from league-specific characteristics. The current investigation also demonstrated a more direct style of play for bottom-tier teams, as they relied on a greater proportion of long passes relative to their total passing. According to Liu et al. (2016), teams that won more aerial duels tended to win more games over the 2012–13 La Liga season, attributing this to the control of attacking and defensive phases in a match this advantage provides. Therefore, the fact that, in the present study, bottom-tier teams won more aerial duels than top-tier teams is of considerable interest. A plausible explanation for this inconsistency is that in the context of the 2023–24 English Premier League season, bottom-tier teams placed extra emphasis on aerial training due to their heavy reliance on long balls, thereby enhancing aerial ability despite their lower ranking.

With respect to the second objective, in both tiers, home matches were associated with greater offensive outputs, particularly in shots and crosses. Similar findings have been made in past studies (Carmichael & Thomas, 2005; Fernández-Navarro et al., 2018; Gómez et al., 2018; González-Rodenas et al., 2015; González-Rodenas et al., 2020c; Lago-Peñas & Lago-Ballesteros, 2011; Tucker et al., 2005). Expanding on this, top-tier teams produced additional on-target attempts, while bottom-tier teams completed more successful take-ons and long passes (Carmichael & Thomas, 2005; Lago-Peñas & Lago-Ballesteros, 2011; Tucker et al., 2005).

By contrast, away matches impacted primarily defensive actions, prompting more clearances, blocked shots, and tackles (Carmichael & Thomas, 2005; Lago-Peñas & Lago-Ballesteros, 2011; Tucker et al., 2005). The specific location of these tackles differed between the tiers, however: top-tier teams tackled more in the defensive third, whereas the bottom tier showed an increased number of attacking-third tackles. Further investigation can examine why this may be the case. Interestingly, bottom-tier teams had better shooting accuracy away from home, yet no past studies have made similar findings—likely because shooting accuracy has not been studied in relation to match location. As such, future research should incorporate this metric to determine if this trend holds true in other contexts.

The impact of match location on disciplinary consequences has remained inconclusive in existing literature. While some note a greater number of yellow cards for away sides (Carmichael & Thomas, 2005; Lago-Peñas

& Lago-Ballesteros, 2011; Sapp et al., 2017; Thomas et al., 2006), others find no significant differences (Tucker et al., 2005). In the present study, the location of a match did not significantly affect the number of yellow cards received, but this should be interpreted with caution due to the exclusion of mid-table teams in the analysis.

These findings also support the conclusions of Lago-Peñas & Lago-Ballesteros (2011) and Liu et al. (2015c), both of whom indicated that stronger and weaker teams did not experience the same home advantage. In the present study, top-tier teams recorded higher values in Shot, Shot on Target, and Cross at home, while bottom-tier teams had higher totals for Shot, Successful Take-On, Cross, and Long Pass Completed. The greater number of significantly different metrics between home and away matches for bottom-tier teams aligns particularly well with Liu et al. (2015c), who reported that stronger teams tend to maintain more consistent technical performance across match location.

For the final objective, binary logistic regression was conducted to determine the metrics that had a statistically significant impact on winning. Among top-tier teams, Aerial Duel Won and Shot on Target were identified to be the significant positive predictors. Per increase in these metrics, the odds of winning increased by 37% and 65%, respectively, per event. The association between aerial duels and winning a match coincides with previous studies (Liu et al., 2015a), though the result in the present study is particularly noteworthy as the Mann–Whitney U test revealed that top-tier teams were less dominant in the air compared to bottom-tier teams. Therefore, it is recommended that coaches of top-tier teams improve their team's aerial ability by implementing more heading exercises to maximize the chances of winning. The pronounced effect of Shot on Target has also been reported in past studies (Bilek & Ulas, 2019; Castellano et al., 2012; Lago-Peñas et al., 2010; Liu et al., 2015a; Liu et al., 2016; Mao et al., 2016; Stafylidis et al., 2024). However, Shot did not significantly affect winning, reinforcing the notion that creating a shot with high quality (Shot on Target) matters more than the sheer overall quantity of shots (Shot) in generating favourable results (Liu et al., 2015a; Liu et al., 2016; Yue et al., 2014).

In the same model, Cross, Tackle Attacking 3rd, and Shot on Target Against appeared as negative predictors, reducing the odds of winning by 30%, 43%, and 45%, respectively, per increase in metric. Previous studies have similarly observed the detrimental effect of crossing, noting its unpredictability and risk of conceding counterattacks (Fernández-Navarro et al., 2016; Lago-Peñas et al., 2010; Liu et al., 2015a; Liu et al., 2016). The substantial negative effect of Tackle Attacking 3rd is surprising given previous claims that acquiring possession in advanced areas of the pitch—for example, through tackling—is advantageous despite the risks of fouls (Almeida et al., 2014; Fernández-Navarro et al., 2016; González-Rodenas et al., 2020c; Jamil, 2019; Liu et al., 2016). However, the findings of the present study suggest that, for top-tier teams, the risks involved in tackling in the attacking third outweighed its benefits. The result of Shot on Target Against is consistent with past research (Castellano et al., 2012), underscoring the critical need to limit high-quality shooting opportunities for opponents.

Among bottom-tier teams, Clearance was the only significant positive factor, raising winning odds by 12% per instance. This performance metric was not significant in the regression for top-tier teams, highlighting the importance of effective ball clearing for weaker sides, who often face stronger opposition (Bilek & Ulas, 2019). Again, Shot on Target Against was identified as a significant negative predictor, reducing the odds of winning by 37% per increase in metric. This was the only variable to achieve statistical significance in both models, emphasizing its pivotal influence on match success regardless of team quality.

CONCLUSION

In summary, this study identified significant differences in technical performance between top- and bottom-tier teams, highlighted the influence of match location, and uncovered the key performance indicators significantly associated with winning. Future research can continue to incorporate the newly explored metrics—Tackle Defensive 3rd, Tackle Attacking 3rd, Long Pass Completed % and Shot Distance—in a similar context to enhance the understanding of team performance in football.

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The author declares that the study complies with the current laws of the Republic of Korea.

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