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Match success in football: insights from raw and possession-normalized key performance indicators in the Turkish professional league

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Abstract

Background Match-performance indicators are widely used to explain success in football; however, traditional analyses based solely on absolute key performance indicators (KPIs) may overlook contextual factors such as ball possession and phase of play. This study aimed to examine match-performance indicators associated with winning in Turkish professional football using two complementary approaches: a raw KPI model based on absolute match actions and a possession- and phase-of-play-normalized KPI model accounting for contextual opportunity.

Methodology Match data were obtained from a validated event-based database covering six consecutive seasons, yielding 2,728 team observations from 1,364 win-loss matches. Descriptive comparisons between winning and losing teams were conducted, followed by multivariate binary logistic regression analyses to identify performance indicators independently associated with match success under both modeling approaches.

Results At the descriptive level, winning teams demonstrated higher values for shots, shots on target, accurate passes, opponent-half accurate passes, accurate crosses (%), and opponent-half accurate passes (%), whereas total possession and total passes did not differ significantly between groups. In terms of disciplinary indicators, losing teams received significantly more yellow and red cards, whereas fouls committed were significantly higher in winning teams ($p = 0.014$). However, the normalized indicator (fouls committed per out-of-possession) did not differ significantly between groups. In the raw KPI model, positive predictors of match success included shots on target (OR = 1.58), accurate crosses (OR = 1.10), opponent-half accurate passes (OR = 1.01), and fouls committed (OR = 1.04). Negative predictors were total crosses (OR = 0.92), yellow cards (OR = 0.89), and red cards (OR = 0.49). In the possession-normalized model, significant positive predictors were shots on target per possession, accurate crosses per possession, and fouls committed per out-of-possession. Significant negative predictors included crosses per possession, accurate crosses (%), yellow cards per out-of-possession, and red cards per out-of-possession.

Conclusions The findings indicate that combining absolute performance indicators with context-sensitive normalized metrics may provide a more comprehensive perspective on match success in football. Offensive efficiency and disciplinary control emerged as key correlates of winning, particularly when evaluated relative to possession and phase-of-play contexts. These findings suggest the potential value of integrating contextualized performance analysis into match evaluation and performance analysis frameworks.

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Keywords Football, Match analysis, Performance indicators, Logistic regression, Possession-based analysis, Match success

Introduction

Identifying the performance indicators that explain match success has been a longstanding objective of football performance analysis. With the increasing availability of detailed event-based match data, researchers have examined a wide range of technical, tactical, and disciplinary variables to differentiate winning from losing teams [1]. Metrics such as shots, passing actions, possession, crosses, and fouls are routinely treated as key performance indicators (KPIs) and interpreted as direct reflections of team performance [2–4]. A wide variety of performance indicators have been used in the sports industry and in research for analyzing different aspects of football [5], alongside broader player-related characteristics that may also influence performance [6]. While these studies consistently identify similar categories of performance indicators, their findings vary in the extent to which these variables explain match success, partly due to differences in methodological approaches and contextual considerations.

However, an important methodological limitation persists in much of this literature. Most KPIs are analyzed as absolute counts of actions (e.g., total shots, total crosses, total fouls), implicitly assuming that higher frequencies directly reflect superior or inferior performance [7, 8]. In invasion sports such as football, these actions are inherently constrained by contextual exposure, including time spent in possession or defending [9]. Consequently, raw counts may conflate opportunity with effectiveness, potentially leading to misleading interpretations [10]. For example, a team may record a high number of defensive actions simply because it spends more time without possession, rather than reflecting superior defensive performance. In particular, normalization has been proposed as a sport-specific preprocessing strategy that incorporates contextual information directly into performance indicators. In this context, phase-of-play normalization refers to the adjustment of performance indicators according to whether a team is in possession or out of possession, thereby accounting for differences in tactical exposure and opportunity across attacking and defensive phases of play. By scaling KPIs relative to contextual factors such as possession or phase of play, normalization distinguishes action frequency from action efficiency. Their findings demonstrated that the direction and magnitude of relationships between KPIs and team performance can change substantially after normalization, highlighting that raw indicators alone may obscure the true tactical or functional value of match behaviors [9]. Moreover, combining raw and normalized indicators may provide

additional contextual insight into match behaviors and may contribute to a more nuanced interpretation of performance indicators. These variations further suggest that how KPIs are operationalized can influence the observed relationships with match outcomes.

Although normalization provides a compelling conceptual and methodological framework, its application in match outcome research remains limited. Many studies continue to rely exclusively on either absolute indicators or efficiency-based measures, rarely examining how these two representations complement or differ from one another within the same analytical structure. Paradoxically, while normalization is routine in most areas of sport science to ensure fair comparison and interpretability of performance metrics [11, 12], its systematic application in match-performance analysis remains surprisingly scarce [10]. Moreover, few studies have directly compared raw and normalized KPIs within the same dataset and statistical framework, making it difficult to determine whether normalization fundamentally changes the interpretation of performance indicators or simply refines their contextual meaning. As a result, it remains unclear whether match success is better explained by action volume, contextualized efficiency, or the joint contribution of both. Therefore, the present study adopts a dual-model approach that directly integrates these perspectives. This approach allows a direct comparison of raw and normalized KPIs within the same dataset, offering a clearer understanding of how each contributes to explaining match success. Match-performance indicators are evaluated using two complementary frameworks: (1) a raw KPI model based on absolute match actions and (2) a possession- and phase-of-play-normalized KPI model reflecting contextualized performance efficiency. By integrating these two perspectives within the same dataset and statistical framework, the study aims to identify performance indicators associated with match outcomes and to examine how contextual normalization enriches their interpretation. The selection of performance indicators included in both models was guided by previous literature identifying offensive, passing, and disciplinary variables as key determinants of match success, while also enabling direct comparison between absolute and context-adjusted representations of the same underlying actions.

Materials and methods

Study design

This study employed a retrospective observational design using match-performance data from professional football

competitions. The primary aim of the study was to identify key match-performance indicators associated with winning in professional football by analyzing six consecutive seasons of match data from the Turkish leagues.

To account for the multidimensional nature of match performance and the influence of contextual factors, two complementary analytical models were constructed. First, a raw KPI model was used to examine absolute, volume-based match-performance indicators. Second, a possession- and phase-of-play-normalized KPI model was employed to evaluate efficiency- and context-adjusted performance indicators [10]. Together, these models were designed to capture both absolute match output and context-adjusted performance quality associated with winning.

Initially, winning and losing teams were compared across a wide range of offensive, possession-related, passing, and disciplinary indicators. Subsequently, multivariate binary logistic regression analyses were conducted to determine which performance indicators independently predicted the likelihood of winning.

Data source

Data were obtained from the www.mackolik.com database (OPTA Client System), whose performance statistics have been validated for high accuracy and reliability in previous research [13]. The dataset included all matches from the top-tier Turkish professional football league (Süper Lig) across six consecutive seasons (2013–2014 to 2018–2019). This ensured large-scale and multi-season coverage of team performance indicators. Prior to analysis, the dataset was screened for completeness and consistency. All variables were checked for outliers and data entry errors, and no extreme or implausible values were identified in the final dataset.

Inclusion and exclusion criteria

All matches from the six-season period ($n = 1,836$) were screened for eligibility based on the completeness of their statistical records. Matches were included if full performance data were available for both competing teams. No matches were excluded due to missing or incomplete statistical data. Matches that ended in a draw ($n = 472$) were excluded to establish a binary outcome structure suitable for logistic regression (win vs. loss). Accordingly, 1,364 win–loss matches were retained, yielding 2,728 team-level observations.

Sample size and variables

After applying the inclusion and exclusion criteria, 1,364 matches resulting in a win or loss were retained for analysis. As each match contributed two team-level observations, the final dataset comprised 2,728 observations,

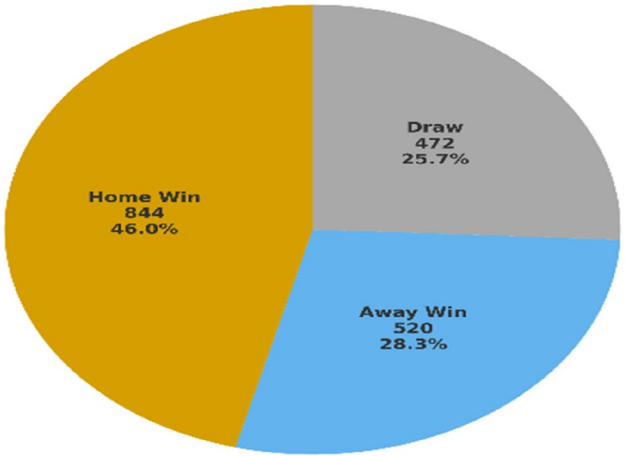


Fig. 1 Distribution of match outcomes (home win, away win, draw) across all analyzed seasons prior to exclusion of draw matches for statistical analysis

Table 1 Raw and possession-normalized key performance indicators included in the logistic regression models

Category	Raw KPI Model (Absolute Indicators)	Normalized KPI Model (Context-Adjusted Indicators)
Offensive	Shots	Shots per possession
	Shots on target	Shots on target per possession
	Crosses	Crosses per possession
	Accurate crosses	Accurate crosses (%)
	Corners	Corners per possession
Possession / Passing	Total passes	Accurate passes (%)
	Accurate passes	Opponent-half accurate passes (%)
		Opponent-half accurate passes
		Ball possession (%)
Defensive / Disciplinary	Fouls committed	Fouls committed per out-of-possession
	Yellow cards	Yellow cards per out-of-possession
	Red cards	Red cards per out-of-possession

Raw KPIs represent absolute match actions. Normalized KPIs are calculated relative to match context, including possession and phase of play. Detailed formulations of normalized indicators are provided in the Methods section

including 1,364 winning-team and 1,364 losing-team performances (Fig. 1).

The dependent variable was match outcome (WIN), coded as 1 for winning teams and 0 for losing teams. Performance indicators (independent variables) were classified into raw KPIs and normalized KPIs according to their level of contextualization (Table 1). Raw KPIs represented absolute counts of match actions without adjustment for match context. Normalized KPIs incorporated sport-specific contextual information either by adjusting indicators relative to match exposure (i.e., ball possession or phase of play) or by expressing performance as percentage-based efficiency measures. This classification

was adopted to distinguish absolute match output from context-adjusted performance characteristics while avoiding redundancy between raw counts and derived indicators [10].

Normalized performance indicators were calculated to account for contextual exposure. Possession-based indicators were expressed relative to total team ball possession, while defensive-phase indicators were normalized based on the proportion of time spent out of possession. The general formulations were as follows:

- Indicator per possession = (raw count) / (team ball possession proportion).
- Indicator per out-of-possession = (raw count) / (1 – team ball possession proportion).

Percentage-based indicators (e.g., accurate crosses (%), accurate passes (%)) were calculated as the proportion of successful actions relative to total attempts.

Statistical analysis

All statistical analyses were performed using IBM SPSS Statistics version 22 (IBM Corp., Armonk, NY, USA).

Descriptive statistics were calculated for all match-performance indicators and are presented as mean $\pm$ standard deviation. Normality assumptions were assessed prior to parametric testing. Differences between winning and losing teams were initially examined using independent samples t-tests. Although some variables represented count-based measures, independent samples t-tests were used due to the large sample size, which ensures the robustness of parametric tests to moderate deviations from normality according to the central limit theorem. The magnitude of between-group differences was quantified using Cohen's *d* effect sizes, calculated based on pooled standard deviations and interpreted according to conventional thresholds (small = 0.20, medium = 0.50, large = 0.80) [14] (Table 2).

To identify the performance indicators independently associated with match success, binary logistic regression analyses were conducted with match outcome (WIN; 1 = win, 0 = loss) as the dependent variable. In line with the study design, two separate multivariate logistic regression models were constructed. For each model, all selected predictors (Table 1) were simultaneously entered using the Enter method to assess their independent effects

Table 2 Descriptive comparison of raw and normalized key performance indicators between winning and losing teams

Model	Variable	Losing teams (Mean $\pm$ SD)	Winning teams (Mean $\pm$ SD)	<i>p</i>	Cohen's <i>d</i>
Raw KPI Model	Shots	11.81 $\pm$ 4.85	13.49 $\pm$ 4.99	0.000	0.34
	Shots on target	3.60 $\pm$ 2.15	5.50 $\pm$ 2.41	0.000	0.85
	Crosses	20.73 $\pm$ 11.38	17.89 $\pm$ 12.18	0.000	–0.25
	Accurate crosses	3.16 $\pm$ 5.30	3.02 $\pm$ 7.44	0.569	–0.02
	Corners	4.89 $\pm$ 2.82	4.69 $\pm$ 2.92	0.072	–0.08
	Total passes	410.70 $\pm$ 90.25	416.48 $\pm$ 104.51	0.123	0.06
	Accurate passes	321.17 $\pm$ 88.36	328.67 $\pm$ 107.47	0.047	0.08
	Opponent-half accurate passes	215.34 $\pm$ 78.62	227.38 $\pm$ 105.74	0.000	0.13
	Ball possession (%)	49.88 $\pm$ 9.76	49.83 $\pm$ 9.78	0.893	–0.01
	Fouls committed	14.96 $\pm$ 4.83	15.39 $\pm$ 4.36	0.014	0.10
	Yellow cards	2.31 $\pm$ 1.38	2.15 $\pm$ 1.36	0.003	–0.11
	Red cards	0.19 $\pm$ 0.47	0.09 $\pm$ 0.31	0.001	–0.26
Normalized KPI Model	Shots pP	0.238 $\pm$ 0.089	0.272 $\pm$ 0.089	0.000	0.38
	Shots on target pP	0.073 $\pm$ 0.043	0.112 $\pm$ 0.049	0.000	0.84
	Crosses per possession	0.413 $\pm$ 0.219	0.357 $\pm$ 0.216	0.000	–0.26
	Accurate crosses (%)	14.22 $\pm$ 12.18	15.80 $\pm$ 13.82	0.002	0.12
	Accurate crosses pP	0.062 $\pm$ 0.115	0.060 $\pm$ 0.136	0.609	–0.02
	Corners pP	0.098 $\pm$ 0.052	0.093 $\pm$ 0.054	0.036	–0.08
	Accurate passes (%)	78.20 $\pm$ 19.45	78.90 $\pm$ 7.13	0.610	–0.02
	Opponent-half accurate passes (%)	65.54 $\pm$ 7.33	67.01 $\pm$ 17.51	0.004	0.11
	Fouls committed poP	0.310 $\pm$ 0.120	0.316 $\pm$ 0.100	0.143	0.06
	Yellow cards poP	0.048 $\pm$ 0.030	0.044 $\pm$ 0.029	0.001	–0.13
	Red cards poP	0.0037 $\pm$ 0.0093	0.0017 $\pm$ 0.0063	0.000	–0.26

Values are presented as mean $\pm$ standard deviation. Shots: total number of shots; Shots on target: shots directed on goal; Crosses: total number of crosses; Accurate crosses: number of successful crosses; Accurate crosses (%): proportion of successful crosses; Total passes: total number of passes; Accurate passes: number of successful passes; Opponent-half accurate passes: successful passes in the opponent's half; Opponent-half accurate passes (%): proportion of successful passes in the opponent's half; Ball possession (%): percentage of ball possession; Fouls committed: total fouls; Yellow cards: number of yellow cards; Red cards: number of red cards

pP per possession, poP per out-of-possession

Bold values indicate statistically significant differences ($p < 0.05$)

while statistically controlling for the remaining variables in the model. Regression coefficients (β), odds ratios ($OR = e^{\beta}$), 95% confidence intervals, and corresponding p -values were reported for all predictors. Prior to the logistic regression analyses, multicollinearity diagnostics were assessed using auxiliary linear regression models. Tolerance values and Variance Inflation Factors (VIF) were examined, with tolerance values > 0.20 and $VIF < 5$ considered indicative of acceptable multicollinearity levels [15]. Model fit was evaluated using standard goodness-of-fit statistics. Statistical significance was set at $p < 0.05$ for all analyses. Forest plots illustrating odds ratios and 95% confidence intervals for significant predictors were generated using Python (version 3.12).

Results

Table 2 gives descriptive findings were used to characterize win–loss differences at the univariate level. In the raw KPI model variables, statistically significant differences were observed for shots, shots on target, crosses, accurate passes, opponent-half accurate passes, fouls committed, yellow cards, and red cards. In the normalized KPI model variables, significant group differences were identified for shots per possession, shots on target per possession, crosses per possession, accurate crosses (%), corners per possession, opponent-half accurate passes (%), yellow cards per out-of-possession, and red cards per out-of-possession ($p < 0.05$).

Collinearity diagnostics indicated no problematic multicollinearity among predictors. Prior to logistic regression analyses, multicollinearity among predictors was assessed using an auxiliary linear regression model. Variance inflation factors (VIF) and tolerance values were obtained from this model to evaluate potential collinearity among independent variables. Predictors with tolerance values greater than 0.20 and VIF values below 5

were considered acceptable, indicating no severe multicollinearity (Table 3).

In the raw KPI model, shots on target markedly increased the probability of winning. Specifically, each additional shot on target was associated with a 58.2% increase in the odds of winning ($OR = 1.582$, 95% CI: 1.496–1.672, $p < 0.001$). Accurate crosses also increased winning probability, with each unit increase corresponding to 10.3% higher odds of winning ($OR = 1.103$, 95% CI: 1.068–1.138, $p < 0.001$). Similarly, opponent-half accurate passes showed a small but statistically significant effect, with each additional accurate pass in the opponent half increasing the odds of winning by 0.7% ($OR = 1.007$, 95% CI: 1.000–1.015, $p = 0.046$). Fouls committed were also positively associated with match outcome, corresponding to a 3.5% increase in the odds of winning per foul ($OR = 1.035$, 95% CI: 1.014–1.057, $p = 0.001$).

In contrast, crosses were negatively associated with winning, with each additional cross reducing the odds of winning by 7.9% ($OR = 0.921$, 95% CI: 0.905–0.937, $p < 0.001$). Disciplinary actions substantially reduced winning probability: receiving a red card decreased the odds of winning by 51.1% ($OR = 0.489$, 95% CI: 0.383–0.624, $p < 0.001$), while each yellow card reduced the odds of winning by 10.6% ($OR = 0.894$, 95% CI: 0.837–0.954, $p = 0.001$) (Table 4).

In the normalized KPI model, shots on target per possession showed a strong positive association with match outcome ($OR = 1.96 \times 10^9$, 95% CI: 1.39×10^8 – 2.77×10^{10} , $p < 0.001$). Accurate crosses per possession were also positively associated with winning ($OR = 1004.457$, 95% CI: 165.30–6103.74, $p < 0.001$). Conversely, crosses per possession were negatively associated with match outcome ($OR = 0.007$, 95% CI: 0.003–0.020, $p < 0.001$). Accurate crosses (%) also demonstrated a statistically significant negative association with winning ($OR = 0.985$, 95% CI:

Table 3 Binary logistic regression results for the raw KIP model

Predictor	B	SE	Wald	OR (Exp(B))	95% CI for OR	p -value
Shots	-0.028	0.015	3.665	0.973	0.945–1.001	0.056
Shots on target	0.458	0.028	263.346	1.582	1.496–1.672	< 0.001
Crosses	-0.083	0.009	88.600	0.921	0.905–0.937	< 0.001
Accurate crosses	0.098	0.016	36.454	1.103	1.068–1.138	< 0.001
Total passes	0.002	0.003	0.608	1.002	0.997–1.008	0.435
Accurate passes	-0.008	0.005	2.410	0.992	0.982–1.002	0.121
OH accurate passes	0.007	0.004	3.975	1.007	1.000–1.015	0.046
Ball possession (%)	0.002	0.009	0.051	1.002	0.984–1.021	0.821
Corners	0.001	0.020	0.001	1.001	0.962–1.041	0.979
Red cards	-0.716	0.124	33.111	0.489	0.383–0.624	< 0.001
Yellow cards	-0.112	0.034	11.215	0.894	0.837–0.954	0.001
Fouls committed	0.035	0.011	10.396	1.035	1.014–1.057	0.001

B Regression coefficient, SE Standard error, OR Odds ratio, CI Confidence interval

WIN (dependent variable): 1 = win, 0 = loss

Bold values indicate statistically significant differences ($p < 0.05$)

Table 4 Binary logistic regression results for the normalized key performance indicator model

Predictor	B	SE	Wald	OR (Exp(B))	95% CI for OR	p-value
Shots pP	-0.879	0.714	1.516	0.415	0.102–1.683	0.218
Shots on target pP	21.395	1.351	250.673	1.96×10^9	1.39×10^8 – 2.77×10^{10}	< 0.001
Crosses pP	-4.903	0.517	90.104	0.007	0.003–0.020	< 0.001
Accurate crosses (%)	-0.015	0.005	10.496	0.985	0.976–0.994	0.001
Accurate crosses pP	6.912	0.921	56.369	1004.457	165.298–6103.744	< 0.001
Accurate passes (%)	-0.014	0.014	0.986	0.986	0.959–1.014	0.321
OH accurate passes (%)	0.020	0.012	2.687	1.020	0.996–1.045	0.101
Corners pP	0.671	1.004	0.447	1.957	0.274–13.997	0.504
Red cards poP	-35.583	6.147	33.509	< 0.001	< 0.001–< 0.001	< 0.001
Yellow cards poP	-4.969	1.559	10.151	0.007	< 0.001–0.148	0.001
Fouls committed poP	1.595	0.445	12.855	4.928	2.061–11.784	< 0.001

B regression coefficient, SE Standard error, OR Odds ratio, CI Confidence interval, pP per possession, poP per out-of-possession

WIN (dependent variable): 1 = win, 0 = loss

Bold values indicate statistically significant differences ($p < 0.05$)

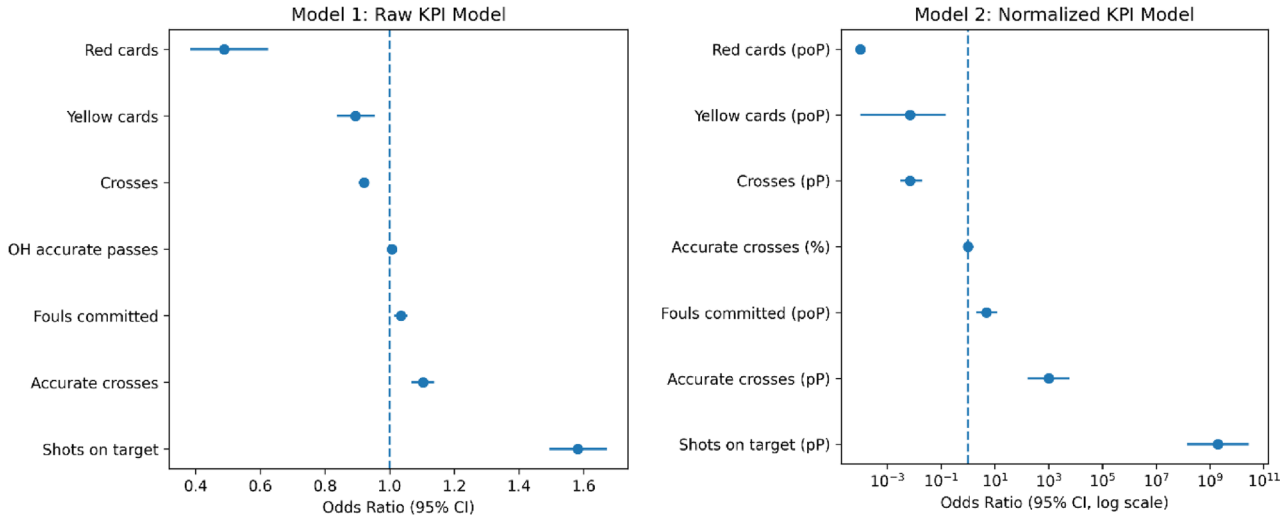


Fig. 2 Odds ratios (95% confidence intervals) for significant predictors of match outcome in the raw and normalized KPI models. OH: Opponent half, poP: per out of possession, pP: per possession

0.976–0.994, $p = 0.001$). Disciplinary indicators showed strong associations with match outcome. Red cards per out-of-possession were strongly and negatively associated with winning ($OR < 0.001$, $p < 0.001$); however, the extremely small odds ratios should be interpreted with caution, as they likely reflect the low frequency and sparse distribution of such events. Similarly, yellow cards per out-of-possession were negatively associated with match outcome ($OR = 0.007$, 95% CI: < 0.001 – 0.148 , $p = 0.001$). In contrast, fouls committed per out-of-possession were positively associated with match outcome ($OR = 4.93$, 95% CI: 2.06 – 11.78 , $p < 0.001$). Overall, the extremely large odds ratios observed for certain normalized variables (e.g., shots on target per possession and accurate crosses per possession) should be interpreted with caution, as they likely reflect scaling effects and the distributional properties of these indicators rather than purely substantive effects.

As it seen in Fig. 2, two models reveal both convergent and model-specific patterns in the relative prominence of performance indicators. Although the magnitude of odds ratios cannot be directly compared between the two models due to differences in scaling, their directional effects, and patterns of convergence or divergence across models can still be meaningfully interpreted. In the raw KPI model, red cards emerge as a particularly strong negative predictor of match outcome, standing out clearly from other disciplinary variables. In contrast, in the normalized KPI model, the negative effects of yellow cards per out-of-possession and crosses per possession appear to converge toward the prominence of red cards. With respect to offensive indicators, the models emphasize different dimensions of attacking performance: while opponent-half accurate passes are retained as a significant positive predictor in the raw model, the normalized model highlights accurate cross efficiency, with accurate

crosses (%) and accurate crosses per possession showing significant associations. Notably, fouls committed and accurate crosses display consistent positive associations across both models and occupy comparable relative positions, indicating robust relationships that persist regardless of contextual normalization. Finally, the positive association of shots on target becomes more apparent in the normalized model, suggesting that adjusting for possession may help clarify the contextual relationship between shooting efficiency and winning rather than merely reflecting higher attacking volume.

Discussion

The present study examined match-performance indicators associated with winning in Turkish professional football using two complementary analytical approaches: a raw KPI model based on absolute match actions and a possession- and phase-of-play-normalized KPI model capturing context-adjusted efficiency. Together, these models suggest that offensive efficiency and disciplinary control are consistently associated with match success, while overall possession and passing volume offer limited independent explanatory value. Recent evidence from elite competitions such as the UEFA Champions League also highlights that variations in match-performance characteristics may influence overall match dynamics, supporting the multifactorial nature of performance in professional football [16].

Winning teams recorded substantially more shots on target and shots on target per possession than losing teams. Across both models, shots on target emerged as the most influential positive determinant of match outcome. In the raw model, additional shot on target increased the likelihood of winning by approximately 58%, suggesting that shooting accuracy may be more strongly associated with match success than total shot volume. Although odds ratio magnitudes are not directly comparable across models, shots on target appear more prominently separated from the null value in the normalized model relative to other positive predictors, highlighting the salience of shooting efficiency when possession context is considered. This result is consistent with earlier findings suggesting that shooting accuracy may be more influential than shooting volume alone in professional football [17]. Although total shots showed a moderate effect size in the descriptive comparison (Table 2), they did not retain significance in the regression models, indicating that shot quantity was not independently associated with match success once efficiency is considered. However, some variables that appeared significant at the descriptive level did not retain their significance in the regression models, likely due to the effects of multivariate adjustment and shared variance among predictors. In addition, several variables that did not reach

statistical significance may still provide useful contextual information and should not be disregarded in the interpretation of match performance. Moreover, other studies have shown that, in addition to shots on goal, total shots can also significantly discriminate winning teams in professional league settings, indicating that attacking volume may contribute to match success under certain competitive conditions [3, 18]. Recent studies have also shown that improvements in technical execution and decision-making under game-like conditions can influence performance outcomes, supporting the importance of efficiency-based indicators in match analysis [19]. In one study focusing on elite goal scorers across Europe's top five leagues, results indicated that high-performing players consistently combine greater shooting frequency with superior scoring efficiency, suggesting that shot volume becomes meaningful primarily when supported by effective execution [20]. Similarly, in women's international football, evidence from World Cup competitions across multiple age categories demonstrated that total shots, shots on goal, and shooting efficacy reliably differentiated winning teams, reinforcing the central role of shot production and efficiency across competitive levels [21]. Taken together, these findings suggest that while shooting efficiency appears to be the dominant determinant of match success, the relative contribution of shot volume may vary depending on league characteristics, competition format, and contextual factors. Notably, this emphasis on shot-based indicators is also reflected in applied practice, as the performance indicators identified as the most discriminative in the present analysis largely overlap with those most frequently used and valued by practitioners [22]. However, these findings may also be influenced by contextual factors such as match status, opponent strength, and tactical strategies, which were not explicitly modeled in the present study. This pattern may reflect underlying tactical dynamics, where efficient shot selection and shot quality, rather than sheer attacking volume, play a more decisive role in determining match outcomes.

Crossing volume was higher among losing teams in the descriptive analysis (Table 1), whereas raw accurate crosses did not differ significantly between groups. Notably, although losing teams recorded a higher absolute number of accurate crosses, winning teams exhibited higher crossing accuracy ratios (%). Multivariate models revealed a clear separation between volume and efficiency effects. In both the raw and normalized models, higher crossing volume was negatively associated with match outcome, whereas indicators of accurate crossing showed positive associations. In the raw model, the absolute number of accurate crosses showed a small yet independent association with winning, whereas in the normalized model, measures of crossing efficiency

(accurate crosses (%)- Accurate crosses pP) gained prominence after accounting for possession and opportunity. This apparent discrepancy reflects the distinction between frequency and execution quality: losing teams may attempt more crosses, yet such actions do not translate into winning outcomes. These findings align with previous research suggesting that frequent crossing may be associated with less effective attacking patterns, particularly when teams struggle to penetrate centrally or generate high-quality scoring opportunities [23]. Findings from the Greek Super League suggest that crossing volume alone does not differentiate successful from less successful teams [7]. Importantly, evidence from the English Premier League indicates that goal conversion from open-play crosses is extremely low ($\approx 1.09\%$), and substantially inferior to attacking actions progressing through central or half-space entries into the final third ($\approx 1.88\%$) [24]. Some evidence from elite football suggests that crossing may have limited effectiveness as an attacking strategy. A comprehensive observational analysis reported a negative association between open-play crosses and scoring probability, with each additional cross linked to a small reduction in goal expectancy [24]. However, these findings should be interpreted with caution, as they are partly based on non-peer-reviewed evidence. Longitudinal analyses from professional leagues have also indicated a potential tactical shift away from crossing, with reductions in crossing frequency reported over time. Although temporal trends were not a focus in the present study, crossing volume remained relatively stable across six consecutive seasons in the Turkish league, suggesting possible league-specific differences in tactical adaptation.

At the descriptive level (Table 2), both raw and normalized passing-related indicators showed slightly higher mean values for winning teams, including accurate passes and opponent-half accurate passes; however, among the percentage-based measures, only opponent-half accurate passes (%) differed significantly between winning and losing teams. Overall, the existing literature indicates that ball possession and passing-related indicators are consistently higher in more successful teams at the descriptive level, particularly in terms of passing volume, pass accuracy, and the ability to progress possession into advanced areas [4, 7, 25–28]. In the multivariate analyses, opponent-half accurate passes emerged as a significant predictor in the raw KPI model, whereas the corresponding percentage-based indicator did not retain significance in the normalized model. Importantly, ball possession itself was not associated with winning in the raw model and was treated as a contextual scaling factor in the normalized model. Some studies have also reported that ball possession does not always differentiate winning from losing teams when match outcomes are

considered directly, with possession showing limited or non-significant differences between winners and losers at the univariate level [4, 27]. The absence of differences in ball possession between winning and losing teams may be explained by the tendency of both successful and unsuccessful teams to maintain longer possession phases when they are losing, likely reflecting an increased effort to regain and retain possession in pursuit of scoring [27]. Possession is significantly greater when teams were losing than when winning or drawing [4], indicating that possession and passing-based control were strongly shaped by situational context rather than match outcome alone. Evidence from prior research indicates that ball possession in soccer is primarily a context-dependent variable shaped by situational and structural factors rather than a direct determinant of match success. Using data from 170 La Liga matches (340 team observations), Lago and Martín [8] demonstrated that possession was significantly influenced by evolving match status, match location, and team-opponent identity, with these factors jointly explaining approximately 65–66% of the variance in possession, and showing that teams systematically increased possession when losing ($\approx +1\%$ possession for every 11 min spent losing) and when playing at home ($\approx +6\%$ possession). In line with this evidence, and consistent with recent contextual-performance frameworks [8, 10], possession in the present study was not treated as an independent performance indicator but rather as a contextual scaling factor in Model 2, allowing action-based KPIs to be normalized for exposure and opportunity. This approach acknowledges that raw action counts are inherently constrained by possession dynamics; however, the present findings suggest that once possession-related exposure is accounted for, the independent explanatory contribution of possession-normalized passing indicators is reduced, indicating that the associations observed in raw models may be more closely related to contextual opportunity than to passing execution or efficiency alone. These findings may suggest that overall possession volume alone may not fully capture performance differences unless the spatial characteristics of possession, particularly in advanced areas, are also taken into account [29, 30]. In line with this view, the Success-Score framework showed that scoring likelihood increases when ball circulation and spatial dominance are jointly achieved through structured passing actions in advanced zones [1]. These differences may be explained by variations in dataset characteristics, competition level, and methodological approaches across studies.

At the descriptive level, disciplinary variables exhibited divergent patterns between winning and losing teams. While winning teams committed slightly more fouls on average, this difference was not statistically significant; in contrast, losing teams received significantly more yellow

and red cards. In the multivariate analyses, all disciplinary indicators independently entered both the raw and normalized models. Fouls were positively associated with match success; however, this finding should be interpreted with caution, as the observational nature of the data does not allow causal or intentional inferences. Yellow and red cards, in contrast, showed consistent negative associations across both models. Notably, a clear distinction between the two models was observed only for fouls, with their association with winning becoming more pronounced after normalization for defensive exposure. This pattern suggests that fouls may be influenced by contextual and situational aspects of match play, rather than indicating deliberate or systematically applied tactical behavior. These findings are largely consistent with previous match-level investigations. Lago-Peñas et al. [4] reported that winning teams committed slightly more fouls on average than losing teams ($\approx 14.6 \pm 4.3$ vs. $\approx 13.9 \pm 4.6$), although this difference was not statistically significant, while losing teams received significantly more yellow cards ($\approx 2.4 \pm 1.4$ vs. $\approx 2.1 \pm 1.3$) and red cards ($\approx 0.22 \pm 0.46$ vs. $\approx 0.10 \pm 0.30$) [4]. Similarly, Castellano et al. [17] found that losing teams committed more fouls (17.9 ± 5.2 vs. 16.1 ± 5.3) and received more red cards (0.20 ± 0.50 vs. 0.06 ± 0.30), whereas yellow cards did not significantly differ between successful and unsuccessful teams [17]. In contrast, season-level analyses comparing teams across league-ranking strata have generally failed to identify disciplinary variables as discriminative indicators. For example, Lago-Ballesteros and Lago-Peñas [3] observed no significant differences in fouls, yellow cards, or red cards when contrasting top-, middle-, and bottom-ranked teams over a full competitive season, a finding likely influenced by the comparison of extreme ranking groups rather than direct win–loss contexts [3]. Likewise, Stafylidis et al. [7] reported no significant differences in disciplinary variables across team ranking levels using univariate, season-based analyses [7]. Taken together, these discrepancies suggest that disciplinary effects on match outcome are more readily detected in match-level comparisons and multivariate frameworks that account for possession and defensive exposure, rather than in aggregated season-level or ranking-based approaches. Additionally, recent research suggests that performance outcomes are shaped by complex interactions between physical, technical, and contextual factors, reinforcing the need for multidimensional analytical approaches in football performance analysis [31].

It should also be noted that some normalized indicators produced very large or very small odds ratios, which likely reflect scaling characteristics and sparse event distributions rather than purely interpretable effect magnitudes, and may also reflect model instability or separation

effects. Therefore, these findings should be interpreted with caution.

Limitations

Several limitations should be acknowledged. First, the dataset includes repeated observations of the same teams across multiple matches, which may introduce non-independence of observations. Although logistic regression was applied at the match level, future studies could benefit from hierarchical or multilevel modeling approaches to better account for this structure. Second, the analysis did not include important contextual covariates such as match location, opponent strength, or in-match score dynamics, which may influence performance indicators and match outcomes. Finally, the normalized performance indicators exhibited scaling characteristics that resulted in extremely large or small odds ratios in some cases. These values likely reflect distributional properties and sparse event structures rather than purely interpretable effect magnitudes, and therefore should be interpreted with caution. In addition, the linearity of the logit for continuous predictors was not formally tested, which may affect model specification. Furthermore, overall model performance metrics were not reported, which may limit the evaluation of model fit. Future studies may consider rescaling normalized indicators or applying alternative modeling approaches to improve coefficient stability and interpretability.

Conclusions

Match success in professional football reflects not only what teams produce during a match but also how these actions are expressed relative to opportunity. Across six seasons, the raw KPI model suggested associations between offensive effectiveness, disciplinary outcomes, and winning, with shooting accuracy and disciplinary sanctions emerging as consistent correlates of winning, whereas overall possession and action volume showed limited independent relevance. When performance indicators were interpreted through possession- and phase-of-play-normalized measures, the same core patterns were retained, while the contextual expression of selected behaviors—particularly defensive actions—appeared more evident. In this sense, normalization may refine rather than alter the interpretation of key findings by accounting for exposure and match context. Collectively, these findings may support the view that incorporating contextual and efficiency-based perspectives alongside absolute performance indicators may provide a more nuanced perspective on match-performance analysis. However, these findings should be interpreted within the limitations of the observational design and should not be considered evidence of model superiority, as no direct comparison of model performance was conducted.

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Authors' contributions

O.S., Ç.Ö., and S.B. contributed to the conceptualization of the study. O.S. and S.B. were responsible for the methodology. O.S., Ö.A., and S.B. contributed to the formal analysis. Y.Ö. contributed to data curation and investigation. O.S., S.B., and Ö.A. prepared the original draft of the manuscript. All authors contributed to the review and editing of the manuscript. S.B. supervised the study.

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Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Ethics declaration: not applicable. This study is based on secondary data analysis and does not involve human participants or animals.

Consent for publication

Not applicable. This manuscript does not contain any individual person's data in any form.

Competing interests

The authors declare no competing interests.

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