

Absolute and relative performance indicators associated with match success across six European professional football leagues

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ABSTRACT

Football performance analysis has traditionally focused on identifying which match-performance indicators are associated with competitive success, while comparatively little attention has been paid to how performance itself should be represented analytically. This study examined whether match success in professional football is more informatively characterised by absolute indicators, team–opponent differences, or their combined representation. All 2,058 matches played during the 2023–2024 season across six European professional domestic leagues were analysed, yielding 4,116 team-match observations. Descriptive analyses and one-way analyses of variance compared wins, draws and losses. Victory versus non-victory discrimination was evaluated using L2-penalised logistic regression with nested five-fold cross-validation grouped by match. Full models included goal-derived conversion rates, whereas a sensitivity analysis excluded all variables containing goals. In the full analysis, the relative model outperformed the absolute model (AUC = 0.979 vs. 0.864; difference = 0.115, 95% CI [0.105, 0.125]), and the combined model provided only a small additional gain (AUC = 0.980). After removing goal-derived rates, discrimination decreased, but the relative advantage persisted (AUC = 0.798 vs. 0.740; difference = 0.058, 95% CI [0.048, 0.069]), while the combined process-only model did not improve on the relative model. A secondary three-indicator explanatory model remained materially stable after adjustment for team fixed effects. These findings distinguish production from superiority: absolute indicators describe what a team produced, whereas opponent-referenced differences describe how that production compared within the same competitive interaction. Relative representation therefore retains meaningful discriminatory information beyond isolated production, although very high model-performance estimates are substantially influenced by variables mathematically proximal to goals. The results support purpose-aligned use of absolute indicators for description, relative indicators for competitive comparison, and internally validated process-only models for forward-looking applications.

Keywords: performance analysis; football performance analysis; competitive success; match-performance indicators; relative performance indicators; performance modelling; logistic regression.

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INTRODUCTION

Football is characterised by continuous interactions between teammates, opponents and contextual constraints that shape match performance. Although the final outcome of a match is ultimately expressed through goals scored and conceded, competitive success emerges from a multidimensional combination of technical, tactical, physical and psychological processes operating simultaneously throughout the game. Understanding the determinants of successful performance has become one of the central objectives of contemporary football research, giving rise to a rapidly expanding body of literature devoted to performance analysis, match statistics and predictive analytics.

Over the past three decades, advances in data collection technologies and analytical methodologies have profoundly transformed football performance analysis. The availability of comprehensive event databases and tracking systems has enabled researchers to examine match behaviour with an unprecedented level of detail, leading to the identification of numerous technical and tactical indicators associated with competitive success (Carling et al., 2005; Hughes & Bartlett, 2002; Mackenzie & Cushion, 2013; Rein & Memmert, 2016). Variables such as ball possession, passing accuracy, total passes, shots, shots on target, offensive efficiency, defensive actions and set-piece performance have consistently been investigated across different competitions and competitive standards (Castellano et al., 2012; Lago-Peñas & Dellal, 2010; Liu et al., 2015; Sarmiento et al., 2014). Collectively, these studies have improved understanding of the characteristics associated with successful performance while providing practitioners with increasingly sophisticated tools for performance evaluation and tactical decision-making.

Despite these advances, evidence accumulated over the last decade reveals an important limitation. Although numerous studies have identified performance indicators associated with winning, their findings remain partially inconsistent regarding the relative importance of individual variables. Ball possession, for example, has been reported as a decisive indicator of success in some competitions but of limited practical importance in others. Similar inconsistencies have been observed for passing variables, offensive production and several defensive indicators. Rather than reflecting contradictions in the literature, these discrepancies suggest that competitive success cannot be explained by isolated match statistics alone but instead emerges from the interaction of multiple performance dimensions operating within specific competitive contexts. The challenge facing contemporary football performance analysis is therefore no longer simply identifying which indicators differ between winning and losing teams but determining how competitive performance itself should be represented.

This distinction is fundamentally methodological. Absolute match-performance indicators describe what an individual team produced during a match, independently of the opponent's performance. Football is not an individual production system but an interactive and adaptive competitive system in which every technical and tactical action is conditioned by the behaviour of the opposing team (Araújo et al., 2006; Davids et al., 2013; McGarry et al., 2002). Within this perspective, the competitive meaning of any performance indicator cannot be fully understood in isolation. Fifteen shots, 60% ball possession or 600 successful passes do not necessarily represent the same competitive performance across different matches because their significance depends on the corresponding performance of the opponent. Consequently, absolute statistics quantify production, whereas relative indicators quantify competitive superiority. Although seemingly subtle, this distinction reflects two fundamentally different ways of representing football performance.

The importance of this issue extends beyond conceptual considerations. Contemporary performance analysis is increasingly expected not only to describe what occurred during competition but also to explain

observed outcomes and, where appropriate, to discriminate between outcomes in unseen data. Regardless of the statistical model employed, analytical performance depends on the quality and contextual relevance of the variables entering the model (Memmert, 2025; Rein & Memmert, 2016). This distinction also requires attention to outcome proximity. Indicators containing goals in their numerator may explain a completed match well because they are mathematically close to the criterion defining victory, but that proximity limits their interpretation as independent or forward-looking predictors. Consequently, both variable representation and distance from the outcome must be considered when evaluating model performance.

Surprisingly, relatively little research has addressed this methodological question directly. The vast majority of previous investigations have relied predominantly on absolute match statistics, implicitly assuming that these variables provide an adequate representation of competitive performance. Far fewer studies have examined team–opponent differentials as the primary analytical framework, while direct comparisons between absolute indicators, relative indicators and integrated analytical models remain remarkably scarce, particularly across multiple elite domestic competitions using a unified statistical approach. As a result, an important gap persists regarding whether competitive success is more accurately explained by what teams produce in absolute terms, by how much they outperform their opponents, or by the integration of both perspectives.

Addressing this question has both scientific and practical relevance. From a theoretical perspective, clarifying how football performance should be analytically represented contributes to the methodological development of performance analysis by strengthening the conceptual relationship between match statistics and competitive success. From an applied perspective, coaches, performance analysts, recruitment departments and sporting directors increasingly rely on quantitative information to support tactical preparation, player evaluation, opponent scouting and strategic decision-making. Identifying the analytical representation that most accurately captures competitive superiority has direct implications for both research and professional practice.

To address these limitations, the present study analysed match-performance indicators across six European professional domestic leagues during the 2023–2024 season, comprising 2,058 official matches and 4,116 team-match observations. Three complementary analytical perspectives were examined: absolute performance indicators, describing each team’s own match statistics; relative performance indicators, representing team–opponent differentials; and combined analytical models, integrating both approaches within a common discrimination framework. Using descriptive analyses, inferential statistics and internally validated penalised logistic modelling, the study compares these alternative representations under equivalent analytical conditions.

Therefore, the primary aim of this study was to determine whether competitive success in elite football is more informatively represented by absolute match-performance indicators, relative performance indicators or a combination of both approaches. The study specifically examined: (i) how absolute and relative indicators differed across wins, draws and losses; (ii) whether relative and combined representations retained superior discrimination under grouped internal validation and penalised modelling; and (iii) whether any advantage remained after removing goal-derived, outcome-adjacent indicators. It was hypothesised that relative indicators would provide greater discriminatory information than absolute indicators, but that the magnitude of model performance would decrease when goal-derived rates were excluded.

Rather than identifying additional indicators associated with winning, the study addresses the more fundamental methodological question of how competitive performance should be represented when

explaining and modelling match success. By systematically comparing absolute, relative and combined analytical approaches across six European professional domestic leagues, the study seeks to clarify how match-performance data should be represented when investigating competitive superiority in professional football.

MATERIALS AND METHODS

Study design

This retrospective observational study used a comparative and explanatory design, supplemented by internally validated discrimination analyses, to examine how match performance should be analytically represented when investigating competitive success in professional football. The study compared three approaches: absolute indicators, relative team–opponent differences and a combined representation integrating both. The analyses quantify association and out-of-fold discrimination; they do not estimate causal effects or establish externally validated prediction.

The individual team within each match constituted the primary unit of analysis. Accordingly, every match generated two team-match observations, one for each competing team. This structure enabled the performance of each team to be classified according to its competitive outcome while preserving the direct relational structure of the match. Because the two observations derived from the same fixture were not statistically independent, this dependency was considered in the multivariable analyses by estimating standard errors clustered at match level.

The analytical design was developed to distinguish between two conceptually different representations of performance. Absolute indicators quantified the production of a team during a match, such as its possession, shots, shots on target or passing performance. Relative indicators quantified the degree to which that team outperformed or was outperformed by its opponent, calculated as the difference between corresponding values. The combined approach examined whether integrating these representations provided incremental discriminatory information beyond either approach separately.

Competitive outcome was examined from two related perspectives. First, descriptive and inferential analyses compared winning, drawing and losing performances to characterise how absolute and relative indicators varied across the three possible match outcomes. Second, logistic models examined victory versus non-victory. Model performance was estimated from held-out observations using nested cross-validation grouped by match, thereby distinguishing internally validated discrimination from apparent fit estimated on the same observations used for model development.

This design therefore addressed not only which match-performance indicators were associated with success, but also whether their analytical representation influenced explanatory association and internally validated discrimination. Goal-derived rates were evaluated separately from process-only indicators, penalised modelling was used for the principal model comparisons, and team fixed effects were examined in a sensitivity analysis of the secondary explanatory model. The complete analytical sequence is summarised in Figure 1.

Sample and match selection

The study included all eligible matches played during the 2023–2024 season in six European professional domestic leagues: the English Premier League, Spanish LaLiga, Italian Serie A, German Bundesliga, French Ligue 1 and Portuguese Primeira Liga. These competitions were selected because they represent

established top-tier professional leagues operating within comparable European competitive structures, while differing in tactical traditions, competitive balance and league format.

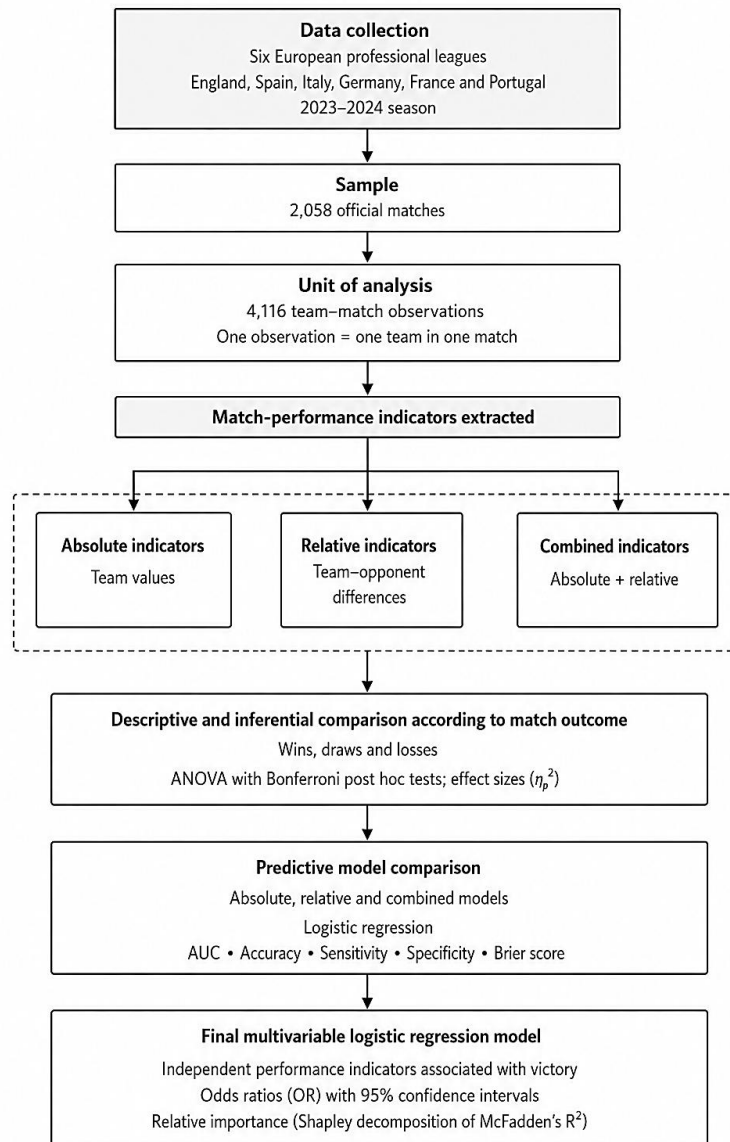


Figure 1. Analytical framework used to compare absolute, relative and combined representations of match performance across the three stages of the analytical strategy.

The Premier League, LaLiga and Serie A comprised 20 teams competing over 38 match days, resulting in 380 matches per competition. The Bundesliga, Ligue 1 and Primeira Liga comprised 18 teams competing over 34 match days, resulting in 306 matches per competition. Overall, the dataset contained 2,058 official league matches.

Each match contributed two observations, one for each participating team. Consequently, the final analytical sample comprised 4,116 team-match observations, including 1,520 winning observations, 1,076 drawing observations and 1,520 losing observations. The equality between the number of wins and losses reflects the paired structure of match outcomes, whereas each drawn match contributed two draw observations.

All completed regular-season league matches for which the required match-performance indicators were available were eligible for inclusion. Cup competitions, continental competitions, friendly matches, play-offs and matches from other competitive seasons were not considered. No sampling procedure was applied because the study was designed as a census of all eligible matches played in the six selected leagues during the specified season. Accordingly, an a priori sample-size calculation was not required.

The distribution of matches and team-match observations across competitions is presented in Table 1.

Table 1. Characteristics of the study sample across the six European professional leagues.

League	Country	Competition format	Matches	Team-match observations	Wins	Draws	Losses	Sample (%)
Premier League	England	20 teams/38 match days	380	760	298	164	298	18.5
Serie A	Italy	20 teams/38 match days	380	760	268	224	268	18.5
Primeira Liga	Portugal	18 teams/34 match days	306	612	231	150	231	14.9
Bundesliga	Germany	18 teams/34 match days	306	612	225	162	225	14.9
Ligue 1	France	18 teams/34 match days	306	612	225	162	225	14.9
LaLiga	Spain	20 teams/38 match days	380	760	273	214	273	18.5
Total	—	—	2,058	4,116	1,520	1,076	1,520	100.0

Note. The study included 2,058 official matches from six European professional football leagues during the 2023–2024 season, corresponding to 4,116 team-match observations (one observation per team per match). Each match generated two observations, one for each competing team. Therefore, the number of wins equals the number of losses, while draws represent matches in which both teams recorded a draw.

Data source, extraction and quality control

Match-performance data were retrieved from Zerozero.pt, a publicly accessible football information platform providing match results and team-level performance statistics across domestic and international competitions. Data were extracted after completion of the 2023–2024 season using a predefined data-extraction protocol applied consistently across all six leagues. For each match, the same set of team-level variables was recorded separately for both competing teams.

The initial extraction was conducted by one researcher and organised using a unique match identifier linking the two team-match observations generated by each fixture. The database was subsequently screened for duplicate records, incomplete observations, impossible logical relations, inconsistent team–opponent pairings and failure of paired relative values to sum to zero. A renewed audit identified one out-of-range corner entry (507). Because its true value could not be verified from the archived dataset, it was treated as missing rather than replaced by an assumed value; the corresponding paired corner difference was also treated as missing.

Absolute indicators were retained as reported by the source platform. Derived indicators were calculated using predefined formulas applied uniformly across the complete dataset. Relative indicators were calculated as the value recorded by the focal team minus the corresponding value recorded by its opponent. All derived and relative variables were generated computationally after completion of the absolute-data quality checks, thereby reducing manual calculation and transcription errors.

Following quality control, no duplicate records or missing values were identified in the variables used in the primary analyses, apart from the single corner entry described above. Descriptive corner statistics used the available observations. During cross-validation, the missing corner value and its paired difference were median-imputed using the corresponding outer-fold training data only; no information from held-out observations entered preprocessing.

The study involved the secondary analysis of publicly accessible, anonymised team-level competition data and did not include identifiable individual-level information. Consequently, no participants were recruited and no direct data collection involving human subjects was undertaken.

Match-performance variables

The match-performance variables were selected to represent complementary dimensions of team production during competition, including ball control, shooting, passing, attacking effectiveness and disciplinary behaviour. The original team-level indicators were ball possession, total shots, shots on target, corners, total passes, successful passes, red cards and goals scored. Three rates were derived: shot accuracy (shots on target/total shots $\times$ 100), shot conversion (goals/total shots $\times$ 100) and on-target conversion (goals/shots on target $\times$ 100). When a denominator was zero, the corresponding rate was coded as zero according to the prespecified database rule.

Absolute indicators corresponded to the values recorded by the focal team, independently of the performance of its opponent. They quantified the volume or effectiveness of the team's match activity and retained the original units in which the data were reported. Ball possession and pass accuracy were expressed as percentages, whereas shots, shots on target, corners, passes, successful passes, goals and red cards were expressed as event counts.

Derived indicators were calculated from the original match statistics using predefined formulas applied uniformly across the complete dataset. Shot accuracy was treated as a process indicator because it did not contain goals. Shot conversion and on-target conversion were explicitly classified as goal-derived, outcome-adjacent indicators because goals appeared in their numerators and match outcome was determined by the relationship between goals scored and conceded. This classification was used to separate explanatory value in completed matches from more defensible forward-looking discrimination.

For every match-performance dimension, a matched relative counterpart was generated by subtracting the value recorded by the opponent from the corresponding value recorded by the focal team within the same fixture. Differences for red cards and shot conversion were included so that absolute and relative model sets represented equivalent dimensions.

Relative indicator = focal-team value – opponent value

Positive values indicated that the focal team recorded a higher value than its opponent, zero indicated equality between teams, and negative values indicated a lower value. The sign of a relative indicator therefore reflected the direction of the team–opponent difference and did not, by itself, imply superior or inferior performance, as the functional meaning of higher values depended on the indicator considered. Accordingly, relative indicators represented the direction and magnitude of the competitive difference established between the two teams rather than the isolated production of either team. Percentage-based differences were expressed in percentage points, while differences between count variables retained their original event units.

The two team-match observations originating from the same fixture necessarily produced relative values of equal magnitude and opposite direction. This antisymmetric structure was verified computationally during the quality-control procedures described in Section 2.3. Relative indicators were calculated only after the absolute and derived variables had been checked, ensuring that all team–opponent differences originated from the same validated pair of match observations.

Match outcome was operationalised according to the purpose of each analytical stage. For descriptive and inferential comparisons, observations were classified as wins, draws or losses. For logistic modelling, the outcome was dichotomised as victory (1) versus non-victory (0), with draws and losses jointly constituting the reference category. This binary operationalisation was used to compare internally validated discrimination across representations and to estimate indicators conditionally associated with the odds of victory.

Analytical framework

The analytical framework was designed to directly compare three alternative representations while maintaining equivalent outcome definitions, validation procedures and performance criteria. Full models contained nine process indicators and two goal-derived conversion rates in each absolute or relative representation. Process-only sensitivity models excluded both goal-derived rates and retained the nine process indicators. Combined models included the corresponding absolute and relative sets.

The first approach considered absolute indicators only and represented performance through the values produced by the focal team independently of its opponent. The second approach considered matched relative indicators only and represented performance through focal-team minus opponent differences. The third approach combined the two representations. Because absolute values plus their corresponding differences can reconstruct opponent values, the combined model was interpreted as an information-rich benchmark rather than as evidence that two independent constructs had been added.

The same analytical sample, outcome definitions, modelling procedures and performance-evaluation criteria were applied across each direct comparison. This ensured that differences in discrimination reflected analytical representation rather than unequal validation or mismatched predictor dimensions.

The analytical strategy progressed from descriptive comparisons to penalised, cross-validated model evaluation and then to a secondary three-indicator explanatory analysis with team fixed-effects sensitivity testing. The secondary model was used to estimate conditional associations and was not used as the basis for claims of predictive performance.

Statistical analysis

The statistical analyses were designed to address the study objectives through a sequential strategy progressing from descriptive comparisons to internally validated model evaluation. Analyses used all eligible observations, with preprocessing and tuning restricted to training data whenever held-out performance was estimated.

Initially, descriptive statistics were calculated for all absolute and relative match-performance indicators according to competitive outcome (win, draw and loss). Continuous variables are presented as means and standard deviations, whereas categorical variables are reported as frequencies and percentages, as appropriate.

Differences between competitive outcomes were subsequently examined using one-way analyses of variance (ANOVA). Whenever a statistically significant overall group effect was identified, Bonferroni-adjusted pairwise comparisons were performed to determine which competitive-outcome groups differed from one another. Effect sizes were quantified using partial eta squared (η^2) and interpreted as small ($\eta^2 \geq .01$), medium ($\eta^2 \geq .06$) or large ($\eta^2 \geq .14$) to complement probability-based inference and facilitate the evaluation of practical significance.

To compare the discriminatory value of alternative representations while addressing correlated predictors, six L2-penalised logistic regression models were evaluated: absolute, relative and combined full models, and their three process-only counterparts. Variance inflation factors calculated before penalisation demonstrated severe redundancy in the full candidate sets (maximum VIF = 219.6 for the absolute set and 635.6 for the relative set; the combined set contained an exact linear dependency for possession). Penalisation was therefore preferred to backward stepwise selection for the principal comparisons because it stabilises estimation without selecting an arbitrary subset of correlated indicators.

Internal validation used nested stratified five-fold cross-validation. Both team observations from each fixture were assigned to the same outer fold. Within every outer training set, the regularisation parameter was selected by three-fold grouped cross-validation from $C = 0.01, 0.1, 1, 10$ or 100 . Continuous predictors were standardised and the single missing corner value was imputed within training data only. Held-out predictions were pooled to calculate AUC, accuracy, sensitivity, specificity and Brier score at a 0.50 threshold. Ninety-five per cent confidence intervals and paired AUC differences were estimated from 2,000 bootstrap resamples at match level.

A secondary explanatory logistic model included shots-on-target difference, on-target-conversion difference and absolute shot conversion. Predictors were standardised and standard errors were clustered by match. Collinearity was assessed in this reduced model (all VIFs ≤ 2.05). To address repeated observations from the same teams, a sensitivity model additionally included fixed effects for the 118 league-specific teams. Stability of the odds ratios, rather than model prediction, was the purpose of this analysis.

Outcome proximity was quantified using Pearson correlations between each goal-derived rate and the goal or outcome quantity to which it was mathematically closest. Because these correlations describe mathematical and empirical overlap rather than causal relations, they were used solely to qualify interpretation of the full models. One-way ANOVA results are reported as descriptive associations for the observed season; because observations were paired within matches and teams appeared repeatedly, the reported p values should not be interpreted as results of independent causal tests.

All reported analyses were implemented in Python 3.11 using pandas, NumPy, SciPy, scikit-learn and statsmodels. Fold assignments and random seeds were fixed for reproducibility.

RESULTS

Characterisation of match-performance indicators according to competitive outcome

Table 2 presents the descriptive statistics and inferential analyses of absolute and relative match-performance indicators according to competitive outcome, whereas Figure 2 graphically displays the distribution of selected relative indicators. The corrected outcome counts are 1,520 wins, 1,076 draws and 1,520 losses.

Overall, both absolute and relative match-performance indicators differed according to competitive outcome; however, opponent-referenced differences generally demonstrated stronger group separation. Among process-only indicators, the largest effects were observed for shots-on-target difference (partial $\eta^2 = .261$), shot-accuracy difference (partial $\eta^2 = .159$) and total-shot difference (partial $\eta^2 = .073$). Goal-derived rates produced still larger effects, particularly shot-conversion difference (partial $\eta^2 = .489$) and on-target-conversion difference (partial $\eta^2 = .398$), simultaneously demonstrating their explanatory value and their mathematical proximity to match outcome.

Table 2. Descriptive and inferential statistics for absolute and relative match-performance indicators according to competitive outcome (n = 4116 team-match observations unless otherwise indicated).

Variable		Win (Mean SD)	Draw (Mean SD)	Loss (Mean SD)	F	p	Partial η^2
Competitive Outcome descriptors	Goals scored	2.49 ± 1.19	1.12 ± 0.69	0.62 ± 0.75	1517.38	<.001	.425
	Goals conceded	0.62 ± 0.75	1.12 ± 0.69	2.49 ± 1.19	1517.38	<.001	.425
	Goal difference	1.87 ± 1.12	0.00 ± 0.00	-1.87 ± 1.12	5719.78	<.001	.736
Absolute Process indicators	Ball possession (%)	52.29 ± 11.70	50.00 ± 11.31	47.71 ± 11.70	59.35	<.001	.028
	Total shots	14.43 ± 5.47	12.76 ± 5.28	11.63 ± 4.95	109.66	<.001	.051
	Shots on target	5.81 ± 2.57	4.25 ± 2.28	3.51 ± 2.07	386.37	<.001	.158
	Shot accuracy (%)	41.53 ± 13.82	34.18 ± 15.49	31.00 ± 15.83	194.23	<.001	.086
	Corners	5.13 ± 2.87	4.95 ± 3.00	4.70 ± 2.83	8.44	<.001	.004
	Total passes	478.00 ± 136.70	439.35 ± 117.02	427.72 ± 111.83	68.43	<.001	.032
	Successful passes	399.02 ± 141.26	356.11 ± 120.04	347.04 ± 112.11	72.28	<.001	.034
	Pass accuracy (%)	81.77 ± 7.28	79.56 ± 7.12	79.78 ± 6.76	42.17	<.001	.020
	Red cards	0.07 ± 0.26	0.11 ± 0.34	0.15 ± 0.39	21.29	<.001	.010
Absolute goal-derived indicators	Shot conversion (%)	18.98 ± 10.18	9.97 ± 9.43	6.00 ± 8.13	775.50	<.001	.274
	On-target conversion (%)	47.02 ± 21.74	29.20 ± 26.65	18.28 ± 25.26	534.59	<.001	.206
Relative Process indicators	Ball-possession difference (pp)	4.58 ± 23.39	0.00 ± 22.61	-4.58 ± 23.39	59.35	<.001	.028
	Total-shot difference	2.80 ± 8.53	0.00 ± 8.58	-2.80 ± 8.53	163.04	<.001	.073
	Shots-on-target difference	2.30 ± 3.38	0.00 ± 3.19	-2.30 ± 3.38	724.90	<.001	.261
	Shot-accuracy difference (pp)	10.53 ± 20.78	0.00 ± 21.06	-10.53 ± 20.78	387.64	<.001	.159
	Corner difference	0.43 ± 4.61	0.00 ± 4.88	-0.43 ± 4.61	12.88	<.001	.006
	Total-pass difference	50.28 ± 222.40	0.00 ± 207.43	-50.28 ± 222.40	80.43	<.001	.038
	Successful-pass difference	51.98 ± 223.07	0.00 ± 208.21	-51.98 ± 223.07	85.40	<.001	.040
	Pass-accuracy difference (pp)	1.99 ± 10.35	0.00 ± 10.37	-1.99 ± 10.35	56.07	<.001	.027
Relative goal-derived indicators	Red-card difference	-0.08 ± 0.45	0.00 ± 0.44	0.08 ± 0.45	47.23	<.001	.022
	Shot-conversion difference (pp)	12.99 ± 11.96	0.00 ± 9.69	-12.99 ± 11.96	1970.40	<.001	.489
	On-target-conversion difference (pp)	28.74 ± 30.87	0.00 ± 29.05	-28.74 ± 30.87	1358.12	<.001	.398

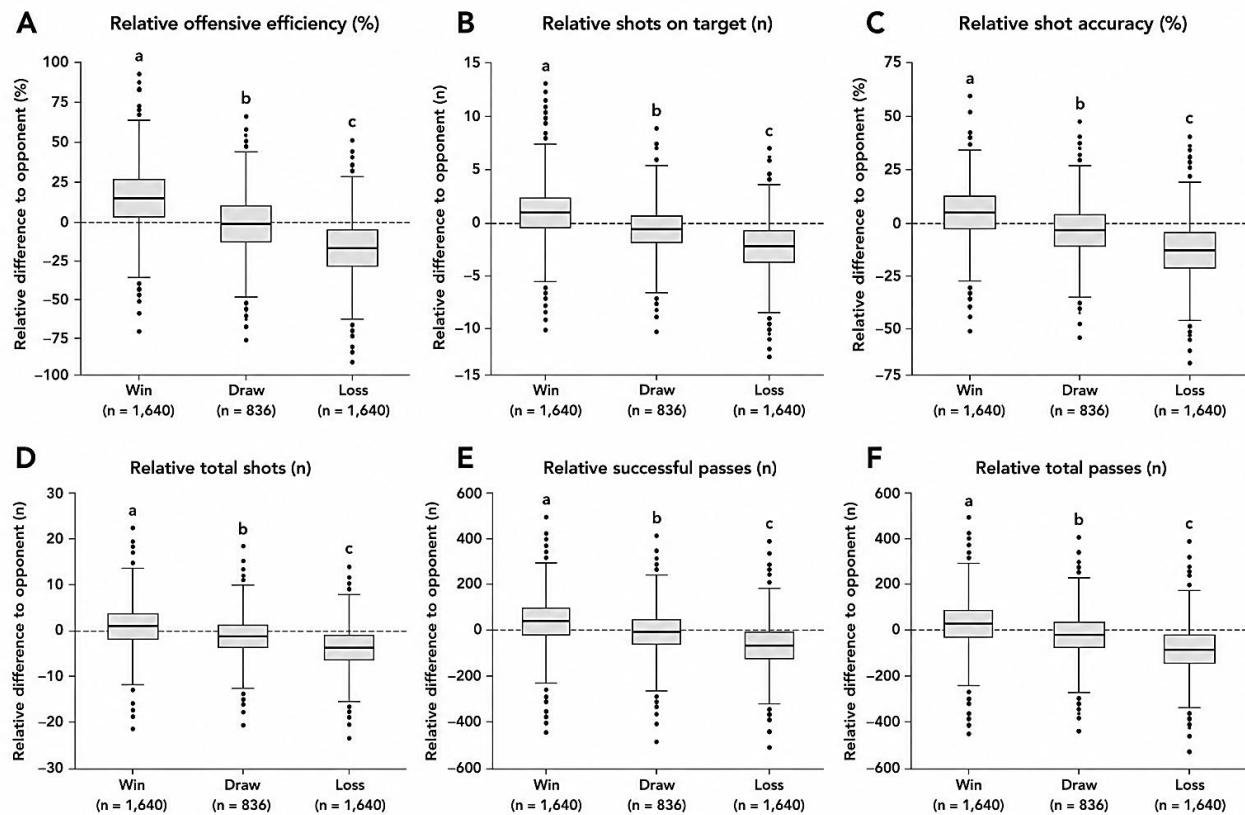
Note. Values are presented as mean ± standard deviation. Group differences were assessed using one-way ANOVA; partial η^2 is reported as the effect size. Because one out-of-range corner entry was treated as missing, absolute corner statistics used n = 4,115 and corner-difference statistics used n = 4,114.

Among the absolute process indicators, winning teams recorded higher values across the principal attacking variables. Group effects were observed for ball possession (partial η^2 = .028), total shots (partial η^2 = .051), shots on target (partial η^2 = .158), shot accuracy (partial η^2 = .086), corners (partial η^2 = .004), total passes (partial η^2 = .032), successful passes (partial η^2 = .034), pass accuracy (partial η^2 = .020) and red cards (partial η^2 = .010). Absolute shot conversion and on-target conversion produced larger effects (partial η^2 = .274 and partial η^2 = .206, respectively), but both contained goals and were therefore treated as outcome-adjacent.

The relative representation produced stronger separation for several matched dimensions. In addition to the process-only effects noted above, shot-conversion difference and on-target-conversion difference displayed the two largest non-outcome-descriptor effects. Their proximity to the criterion was quantitatively evident: absolute shot conversion correlated at r = .789 with goals scored, absolute on-target conversion correlated at r = .664, shot-conversion difference correlated at r = .762 with goal difference, and on-target-conversion difference correlated at r = .652. Their correlations with victory were r = .503, r = .427, r = .623 and r = .562, respectively.

These findings are reinforced by Figure 2, which shows progressive displacement from losses to draws and wins across selected relative indicators. Separation was most pronounced for on-target-conversion

difference, shots-on-target difference and shot-accuracy difference, whereas passing-related distributions overlapped more extensively. The distributions therefore illustrate both the stronger relational separation of attacking indicators and the need to distinguish outcome-adjacent conversion from process-only measures.



Note. Boxes show interquartile ranges and median lines; whiskers extend to 1.5 interquartile ranges. Outcome counts were 1,520 wins, 1,076 draws and 1,520 losses. pp = percentage points.

Figure 2. Distribution of selected team-opponent differences across wins, draws and losses.

The outcome-proximity analysis is essential to interpreting these distributions. Conversion rates containing goals are highly informative summaries of how a completed match was decided, but they are not analytically independent of the result. Their large effects should therefore not be compared uncritically with process indicators such as shots, passes or possession.

Comparison of model performance between analytical representations

Table 3 compares out-of-fold discrimination, classification and probabilistic accuracy for the penalised logistic models, while Figure 3 displays the pooled held-out receiver operating characteristic curves for the full and process-only analyses.

In the full analysis, the relative model achieved an out-of-fold AUC of 0.979, 95% CI [0.974, 0.982], compared with 0.864, 95% CI [0.852, 0.874], for the absolute model. The paired AUC difference was 0.115, 95% CI [0.105, 0.125]. The combined model reached an AUC of 0.980, 95% CI [0.976, 0.984], representing a small increment of 0.002, 95% CI [0.001, 0.003], beyond the relative model.

Table 3. Internally validated performance of penalised logistic models based on absolute, relative and combined representations.

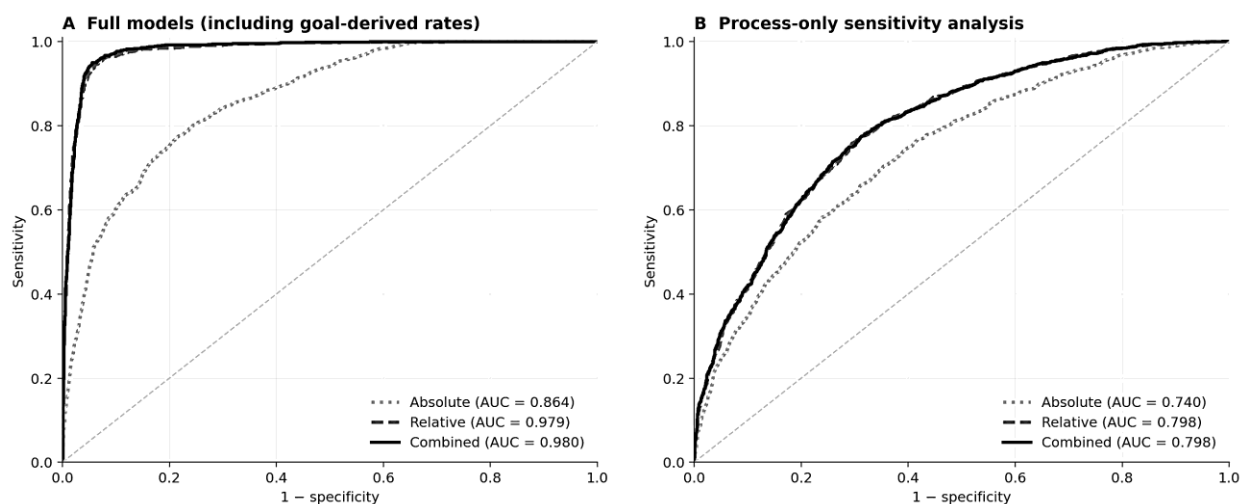
Internally validated model	AUC (95% CI)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Brier score
Full absolute (11)	0.864 (0.852–0.874)	78.4	65.8	85.8	0.144
Full relative (11)	0.979 (0.974–0.982)	93.9	91.2	95.4	0.050
Full combined (22)	0.980 (0.976–0.984)	94.5	93.0	95.5	0.047
Process-only absolute (9)	0.740 (0.725–0.755)	70.2	43.2	86.0	0.194
Process-only relative (9)	0.798 (0.781–0.814)	73.3	54.3	84.4	0.174
Process-only combined (18)	0.798 (0.781–0.814)	73.3	54.5	84.2	0.174

Note. Values are pooled held-out estimates from nested five-fold cross-validation grouped by match. Full models include two goal-derived conversion rates; process-only models exclude both. AUC = area under the receiver operating characteristic curve; CI = confidence interval. Sensitivity represents victories correctly classified; specificity represents non-victories correctly classified. The classification threshold was 0.50.

Excluding both goal-derived conversion rates reduced discrimination across all three representations. Nevertheless, the process-only relative model retained an AUC of 0.798, 95% CI [0.781, 0.814], compared with 0.740, 95% CI [0.725, 0.755], for the process-only absolute model. The paired difference remained 0.058, 95% CI [0.048, 0.069]. The process-only combined model achieved an AUC of 0.798, 95% CI [0.781, 0.814], and did not improve materially on the relative model (difference = 0.000, 95% CI [–0.001, 0.002]).

The same pattern was evident for accuracy and Brier score. In the full analysis, accuracy increased from 78.4% for the absolute model to 93.9% for the relative model and 94.5% for the combined model; the corresponding Brier scores were 0.144, 0.050 and 0.047. In the process-only analysis, accuracy was 70.2%, 73.3% and 73.3%, and Brier scores were 0.194, 0.174 and 0.174, respectively. Thus, the relational advantage persisted without variables containing goals, although the exceptionally high performance of the full models was substantially attributable to outcome proximity.

This pattern is illustrated in Figure 3: relative and combined curves were closely aligned within each analysis, whereas removing goal-derived rates shifted all curves downward and reduced the separation between representations.



Note. Full models include goal-derived conversion rates; process-only models exclude all variables containing goals. All curves are based on nested cross-validation grouped by match.

Figure 3. Pooled held-out receiver operating characteristic curves for full and process-only penalised models.

Independent indicators associated with victory

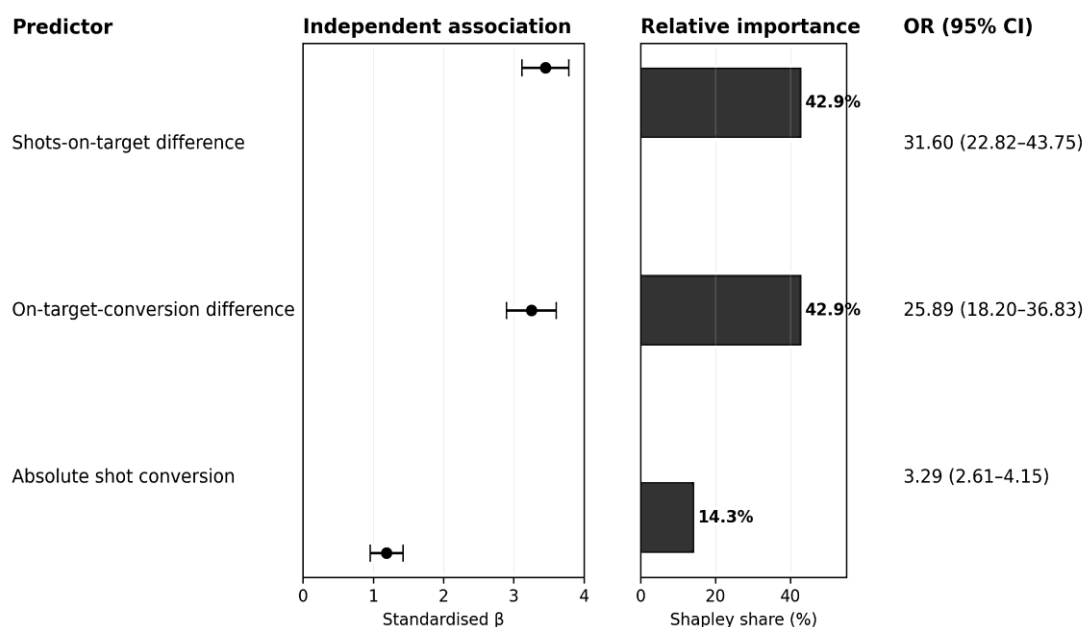
Table 4 presents the secondary three-indicator explanatory model. All three indicators were independently associated with victory, and the reduced model showed limited collinearity (all VIFs ≤ 2.05). These estimates describe conditional associations in the observed dataset and are not presented as validated causal or predictive effects.

Table 4. Secondary three-indicator explanatory logistic regression model for victory.

Predictor	β	SE	Wald χ^2	OR	95% CI	p
Shots-on-target difference	3.45	0.17	432.20	31.60	22.82–43.75	<.001
On-target-conversion difference	3.25	0.18	326.97	25.89	18.20–36.83	<.001
Absolute shot conversion	1.19	0.12	101.06	3.29	2.61–4.15	<.001

Note. Predictors were standardised before estimation; odds ratios represent the change in the odds of victory for a one-standard-deviation increase. Standard errors were clustered by match. β = regression coefficient; SE = standard error; OR = odds ratio; CI = confidence interval.

Independent performance indicators associated with victory



Secondary explanatory model; associations are not causal. Relative importance is the Shapley decomposition of McFadden's pseudo- R^2 .

Note. β = standardised regression coefficient; OR = odds ratio; CI = confidence interval. Relative importance was estimated using a Shapley/dominance decomposition of McFadden's pseudo- R^2 for the three-indicator explanatory model. The figure displays association, not causal effects or validated prediction.

Figure 4. Independent performance indicators associated with victory in the secondary explanatory model.

Shots-on-target difference showed the strongest association with victory (OR = 31.60, 95% CI [22.82, 43.75], $p < .001$), followed by on-target-conversion difference (OR = 25.89, 95% CI [18.20, 36.83], $p < .001$). Absolute shot conversion retained a complementary association (OR = 3.29, 95% CI [2.61, 4.15], $p < .001$). Because the two conversion variables contain goals, their effect sizes must be interpreted as outcome-adjacent explanatory associations rather than independent determinants of success.

Adjustment for league-specific team fixed effects produced materially consistent estimates for shots-on-target difference (OR = 38.14, 95% CI [26.32, 55.29]), on-target-conversion difference (OR = 34.78, 95% CI [23.14, 52.28]) and absolute shot conversion (OR = 3.47, 95% CI [2.68, 4.49]). The observed associations were therefore not explained solely by stable differences in team identity, quality or playing style.

Taken together, the primary cross-validated comparisons and the secondary explanatory model provide complementary evidence. The process-only sensitivity analysis supports a relational advantage beyond variables containing goals, whereas the secondary model shows why the full-model estimates are so high. Neither analysis establishes causation, and only the grouped out-of-fold results should be interpreted as internally validated discrimination.

DISCUSSION

The present study compared three alternative representations of match performance—absolute team values, team–opponent differences and their combination—to determine which most informatively characterises competitive success in professional football. The principal finding remained consistent after substantial robustness checks: opponent-referenced representation contained more discriminatory information than isolated team statistics. Importantly, the sensitivity analyses qualify the magnitude of that advantage. Goal-derived conversion rates produced exceptionally high discrimination because they are mathematically proximal to the goals defining victory; after their removal, the relational advantage persisted but was more moderate.

This conclusion is conceptually consistent with the relational nature of football performance. Football can be understood as a coupled, adaptive and self-organising system in which each team simultaneously enables and constrains the behaviour of the other (Araújo et al., 2006; Davids et al., 2013; McGarry et al., 2002). Absolute outputs therefore describe only one component of the competitive interaction. Opponent-referenced differences do not merely rescale those outputs; for most indicators they express the direction and magnitude of superiority established within the same match environment.

This perspective is increasingly reflected in the football performance-analysis literature. Systematic and critical reviews have highlighted the limitations of interpreting isolated match statistics and have called for greater incorporation of situational and interactional context when analysing performance (Mackenzie & Cushion, 2013; Sarmiento et al., 2014). Likewise, empirical studies have consistently shown that commonly used indicators, including ball possession, passing performance and shooting frequency, are strongly influenced by contextual factors such as match status, opposition quality, match location and tactical strategy (Bradley et al., 2013, 2014; Lago & Martín, 2007). Consequently, identical absolute values may represent markedly different competitive realities depending on the context in which they are produced.

From an ecological perspective, the relevant unit is not an isolated team output but the team–opponent relation under shared constraints. From a complex-systems perspective, the direction of influence is reciprocal and time dependent: a team may generate an advantage, respond to an opponent or alter its behaviour after the score changes. Relative indicators provide a parsimonious representation of this coupling, but they do not identify the causal sequence through which the observed difference emerged.

The present findings provide empirical support for this conceptual position. Absolute indicators quantified what a team produced during a match, whereas relative indicators quantified how that production compared with the direct opponent. This production–superiority distinction is the central contribution of the study. It aligns analytical representation with ecological and complex-systems accounts in which performance emerges from performer–environment relations rather than residing entirely within an isolated performer or team.

Importantly, this interpretation should not be understood as diminishing the value of absolute match-performance indicators. Rather, it suggests that absolute and relative indicators describe different dimensions of performance. Absolute measures remain essential for characterising how teams play and for monitoring technical and tactical development over time. Relative indicators, however, quantify the extent to which those performances establish superiority over the opponent, thereby capturing the competitive dimension through which match outcomes are ultimately determined. The superiority of the relative representation observed in the present study should therefore be interpreted as reflecting the relational structure of football competition rather than the replacement of one analytical approach by another.

This distinction also clarifies the boundary between descriptive and predictive analytics. Goal-derived rates can be excellent descriptive explanations because they summarise scoring efficiency in the match that has already occurred. Their usefulness does not make them appropriate stand-alone forecasts. The process-only sensitivity models offer a more conservative estimate of discrimination available before goals are incorporated into the predictors.

The superiority of the relative representation observed in the present study also provides a plausible explanation for one of the most persistent inconsistencies in football performance-analysis research. Over the past two decades, variables such as ball possession, passing performance, shooting frequency and shooting accuracy have repeatedly been identified as relevant indicators of success. However, their reported importance has varied considerably across competitions, competitive levels, analytical approaches and study designs. Rather than reflecting contradictory evidence, part of this variability may arise from differences in the way performance itself is represented and interpreted.

Within the present dataset, winning teams consistently recorded higher absolute values for several technical and offensive indicators, including possession, total shots, shots on target, passing volume and successful passes. These findings broadly agree with previous investigations reporting that successful teams generally produce greater attacking output than unsuccessful teams. However, the relatively modest effect sizes observed for several absolute indicators indicate that superior production alone provides only limited discrimination between competitive outcomes. Once these same indicators were expressed relative to the opponent, their ability to distinguish wins, draws and losses increased substantially. This finding suggests that competitive superiority is better characterised by the advantage established over the opposing team than by the absolute magnitude of a team's own production.

The recent work of Sever et al. (2026) provides an informative comparison in this respect. Although their study adopted a different methodological strategy by normalising performance according to possession and phase of play, it reached a conceptually similar conclusion: contextualising performance altered the interpretation of which indicators were most strongly associated with success. Together, these studies suggest that the principal limitation of many conventional match statistics may not lie in the variables themselves, but in the absence of an explicit competitive context within which those variables are interpreted. Whether contextualisation is achieved through opportunity normalisation, possession-adjusted metrics or team–opponent differences, the underlying methodological principle remains the same: football performance should be interpreted relative to the conditions under which it is produced.

This interpretation is particularly evident when comparing indicators describing match control with those reflecting attacking effectiveness. Possession and passing variables differentiated successful and unsuccessful teams, but their discriminatory capacity remained considerably lower than that of indicators directly associated with the creation and conversion of scoring opportunities. In contrast, shots on target and

offensive efficiency consistently emerged as the variables most strongly associated with competitive success, especially when expressed relative to the opponent. These findings are consistent with previous evidence demonstrating that shots on target represent one of the most robust technical indicators of match outcome, whereas the influence of possession is considerably more dependent on contextual factors such as opposition quality, match status and tactical strategy (Bradley et al., 2013; Lago & Martín, 2007; Liu et al., 2015).

Importantly, these findings should not be interpreted as suggesting that possession or passing are unimportant components of football performance. On the contrary, they remain fundamental expressions of how teams organise play, create numerical and positional advantages and control the rhythm of the game. Their influence on competitive success, however, is predominantly indirect. Possession and passing contribute to the processes through which scoring opportunities are created and prevented, whereas indicators such as shots on target and offensive efficiency represent outcome-proximal expressions of those underlying processes. Consequently, when multiple performance dimensions are considered simultaneously, variables located closer to the scoring process are expected to retain the strongest independent statistical associations with victory.

Viewed collectively, these findings reinforce a broader methodological implication. The analytical value of football performance indicators depends not only on what is measured, but also on how that information is represented. Absolute indicators describe the level of production achieved by a team, whereas relative indicators describe the competitive advantage established over its opponent. These perspectives are not mutually exclusive; they provide complementary information about different dimensions of the same competitive process. Nevertheless, when the objective is to characterise or discriminate match success, opponent-referenced differences provide the more informative representation in the present data.

Beyond the interpretation of individual performance indicators, the present findings have broader implications for the methodological design of football performance-analysis research. Studies investigating the determinants of match success have traditionally focused on identifying which variables are associated with winning. The present results suggest that an equally important methodological question concerns how those variables are represented analytically. The comparison between absolute and relative indicators demonstrated that the representation adopted before any statistical modelling is undertaken can substantially influence both the interpretation of performance and the explanatory capacity of the resulting analyses. Consequently, the choice between absolute and opponent-referenced indicators should not be regarded as a simple data-processing decision, but as a fundamental component of research design (Memmert, 2025).

This methodological perspective also has practical implications for applied analysis. Absolute values should remain in match reports when the purpose is to describe workload or production. For competitive review, analysts can add a matched opponent column and calculate focal-team minus opponent differences for shots, shots on target, shot accuracy, passing and disciplinary variables. Opposition reports can compare these differentials across recent matches, while tactical reviews can examine whether the team repeatedly establishes or concedes superiority in targeted dimensions. Recruitment dashboards should not transfer match differentials directly to individual evaluation without accounting for team role and context. For forward-looking models, practitioners should privilege process-only variables and evaluate performance on unseen matches; goal-derived conversion rates are better retained in retrospective explanation and finishing review.

The present findings should nevertheless be interpreted within the scope of the study design. Although the analysis comprised a census of one season across six European professional leagues, generalisation to

other seasons, competitive levels and data providers requires further validation. The study used team-level summary statistics and could not represent within-match temporal dynamics, score-state changes or tactical interactions directly. Goal-derived rates are partly constitutive of the observed outcome; the process-only analysis reduces but does not eliminate endogeneity because match statistics and match state co-evolve. Internal validation was grouped by match, but it was not external validation across seasons or independent competitions. Team fixed effects addressed time-invariant team identity in a sensitivity analysis, not all repeated, contextual or opponent-specific dependencies. Finally, one out-of-range corner entry could not be recovered and was treated conservatively as missing.

Future research should examine whether the relational advantage persists across seasons, competitive levels and independent providers, ideally using leave-one-league-out and temporal external validation. The framework can be extended to expected-goal models (Anzer & Bauer, 2021), tracking data and sport-specific tracking analyses (Torres-Ronda et al., 2022), spatial control, pressure, possession chains and passing networks, where opponent behaviour is integral to the meaning of the focal team's actions. Dynamic models should represent score state, venue, opposition strength and tactical phase, and multilevel or crossed-effects structures should distinguish within-team, between-team and opponent effects. Research should also test whether contextualised ratios, residualised indicators or interaction features add information beyond simple differences and whether relational dashboards improve analysts' decisions in applied settings.

Overall, the present study contributes to football performance analysis by shifting attention from the traditional question of which indicators accompany success to the methodological question of how competitive performance should be represented. The evidence supports opponent-referenced representation, but also demonstrates that representation, outcome proximity and validation must be considered together. Relative indicators capture competitive superiority; goal-derived rates explain completed outcomes but can inflate apparent prediction; and cross-validated process-only models provide the more defensible basis for forward-looking application.

CONCLUSION

The present study demonstrates that analytical representation is a fundamental methodological consideration when investigating match success in professional football. Across six European leagues, opponent-referenced differences discriminated victory more effectively than isolated absolute statistics under grouped internal validation. Crucially, this advantage persisted after every goal-derived rate was removed, although model performance decreased substantially, confirming that the highest estimates were partly driven by outcome proximity.

Absolute and relative indicators should therefore be used according to analytical purpose. Absolute indicators describe the level of production achieved by a team; relative indicators describe the superiority or inferiority established within the competitive interaction. Combined models added little beyond the relative representation once equivalent dimensions and validation procedures were used. Goal-derived conversion rates remain valuable for retrospective explanation but should not be presented as independent or forward-looking predictors of victory.

More broadly, the study preserves its original methodological proposition while defining its limits more precisely: football performance should be represented relationally when the question concerns competitive comparison, evaluated with process-only variables when the purpose is forward-looking, and interpreted as

association rather than causation. This purpose-aligned framework offers a more robust basis for research and applied performance analysis.

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CONFLICT OF INTEREST

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

AI USE DISCLOSURE

In accordance with current publishing ethics and transparency recommendations, artificial intelligence (AI) tools were used solely to assist with translation and language editing, with the aim of improving clarity and readability. No AI tools were used in the generation of scientific content, including the study design, data collection, analysis, interpretation of results, or the formulation of conclusions. The author retains full responsibility for the content of the manuscript and confirms its originality, integrity, and accuracy.

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