INTERNATIONAL JOURNAL of IJSETS SPORT, EXERCISE & TRAINING SCIENCES

e-ISSN 2149-8229 | Volume 12, 22–32, (2026) | Research Article

https://dergipark.org.tr/tr/pub/useeabd

The Relationship Between Expected Goals (xG) Based Performance Indicators and Match Outcomes in Elite Football: The 2024–2025 English Premier League Season

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Abstract

Aim: This study investigates whether expected goals (xG)–based performance indicators differ systematically across match outcomes in elite football.

Method: Match-level data were analyzed using 228 team–match observations (114 fixtures × 2 teams) from league fixtures involving the six teams that finished in the top six positions of the 2024–2025 English Premier League. Performance indicators included expected goals (xG), expected goals against (xGA), expected goals difference (xGD), non-penalty expected goals (npxG), finishing efficiency (goals/xG), total shots, key passes, xG per shot, and non-penalty xG per shot. Match outcome was coded as win ($n = 126$), draw ($n = 54$), or loss ($n = 48$). Assumption checks (normality diagnostics and Levene's test) were conducted; group differences were examined using one-way ANOVA, followed by Tukey HSD for variables meeting homogeneity and Games–Howell for variables with unequal variances. Effect sizes (partial η^2) were reported.

Results: Significant group differences were found across all performance variables (all $p < .001$). Net and process-oriented metrics showed particularly strong discrimination across outcomes, including xGD (partial $\eta^2 = .197$), finishing efficiency (partial $\eta^2 = .189$), and npxG (partial $\eta^2 = .147$). Post-hoc comparisons indicated that wins were consistently associated with stronger offensive production, higher shot quality, and better conversion efficiency, while losses displayed weaker profiles on both attacking and defensive dimensions.

Conclusion: Expected goals–based indicators meaningfully differentiate match outcomes among elite teams, supporting the value of process-based metrics for interpreting performance beyond final scorelines.

Key words: *Expected Goals, Football, Goals, Match Analysis, Performance.*

Submission Date : 02.01.2026 **Acceptance Date** : 15.03.2026 **Online Publication Date** : 27.03.2026

https://doi.org/10.18826/useeabd.1854908

INTRODUCTION

Football is the most popular sport worldwide, yet it involves a persistent tension between performance and outcome. Because the game is typically low scoring, random events can have a substantial impact on match outcomes and may obscure the true quality of a team's performance (Anderson & Sally, 2013; Pollard, 1986). Previous research has consistently shown that final scores do not fully reflect underlying performance dynamics, particularly when a single goal determines the outcome of a match (Wunderlich et al., 2021; Pappalardo et al., 2019). For this reason, the uncertainty inherent in football has led to the development of analytical frameworks that focus on the quality of scoring opportunities rather than relying solely on results. Within this context, the Expected Goals (xG) model has become a widely adopted tool for evaluating performance in modern football (Rathke, 2017; Mackenzie & Cushion, 2013; Brechot & Flepp, 2020).

The xG model calculates the probability that a given shot will result in a goal by assigning a value between 0 and 1 based on contextual and positional factors such as shot distance, shooting angle, body part used, and the type of attacking phase (e.g., open play, penalty, or set piece) (Spearman, 2018; Fernández et al., 2021). By aggregating these probabilities across all attempts, xG represents the number of goals a team would be expected to score under similar conditions, thus offering a more systematic assessment of attacking quality. In addition to xG, Expected Goals Difference (xGD) provides a composite measure by calculating the difference between expected goals created and conceded. In doing so, it reflects the overall balance of performance within a match, incorporating both offensive productivity and defensive effectiveness (Eggels et al., 2016; Rathke, 2017). Accordingly, these metrics shift the analytical focus away from final scores and toward the underlying processes that shape match performance. Recent research has extended the use of xG beyond purely descriptive purposes and has incorporated tactical and psychological dimensions into analytical models. For example, Spearman (2018) proposed a probabilistic framework linking shot quality to spatial positioning, while Kharrat et

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al. (2019) and Malikov and Kim (2024) examined how player-specific characteristics and contextual pressures interact with xG-based evaluations. In a similar vein, Lucey et al. (2013) showed that accounting for temporal dynamics can reduce prediction error, emphasizing that scoring opportunities emerge from coordinated team actions rather than isolated moments. Building on this perspective, scholars have also explored finishing efficiency, commonly defined as the ratio of actual goals to expected goals (Fu, 2024; Liu et al., 2016). Teams that consistently exceed their expected goals are typically interpreted as efficient in converting chances. Conversely, sustained underperformance relative to xG may point to limitations in finishing ability or decision-making under match conditions.

Key passes are defined as the final passes that directly precede a shot attempt and therefore represent a crucial connection between chance creation and shot execution (Mackenzie & Cushion, 2013). Empirical evidence indicates a strong association between key passes and the accumulation of expected goals, underlining their importance for attacking cohesion and the development of positional superiority in advanced areas of the field. When key passes are examined alongside expected goals, expected goals against, and finishing efficiency, a more comprehensive picture of performance emerges. Such an integrated approach allows for the evaluation of how frequently teams generate opportunities, how high the quality of those opportunities is, and how effectively they are converted into goals.

Evidence from Europe's top leagues suggests that xG-based metrics are also effective in explaining long-term competitive success. For example, Brechot and Flepp (2020) examined more than 7,000 matches across the Big Five leagues and reported that xGD showed a stronger association with future points per game than traditional goal difference. Their findings indicate that xG-derived measures provide a more stable representation of underlying team quality than results alone. Similarly, Eggels et al. (2016) demonstrated that incorporating expected goals metrics enhances match outcome prediction compared with models based solely on historical results. Focusing specifically on the Premier League, prior research has further shown that elite teams often outperform their expected goals through more effective shot selection and advantageous player positioning (Spearman, 2018; Anderson & Sally, 2013).

Although xG analysis has become increasingly common in both academic research and professional practice, important gaps remain in understanding how match-level dynamics shape team success over the course of a single season. Much of the existing literature treats xG primarily as a predictive variable, yet relatively few studies have explored how it interacts with key passes and finishing efficiency across different match outcomes (win, draw, loss). Furthermore, many investigations rely on aggregated seasonal data, which may obscure meaningful variation in shot quality and conversion at the individual match level (Mackenzie and Cushion, 2013; Liu et al., 2016).

Against this background, the present study analyzes 114 fixtures from the 2024–2025 English Premier League season involving the six teams that finished in the top six positions. These fixtures produced 228 team–match observations. The primary objective is to examine how match outcomes relate to expected goals–based performance indicators. In particular, the study investigates the association between match outcomes and expected goals metrics, the contribution of key passes to chance creation, and the role of finishing efficiency as an indicator of conversion quality. By considering production, prevention, and efficiency dimensions together, this study seeks to clarify how expected goals–based metrics collectively distinguish successful from unsuccessful match performances. In doing so, it aims to provide a more comprehensive understanding of elite team performance beyond conventional result-based statistics.

METHOD

Research model

This study adopted a cross-sectional and observational design to investigate the relationship between expected goals–based performance indicators and match outcomes in elite football. The analysis was carried out at the match level, allowing for a direct comparison of performance characteristics across win, draw, and loss categories. By focusing on team–match observations rather than aggregated seasonal data, the study aimed to enhance statistical sensitivity and to account for performance fluctuations within a single competitive season.

Population and sample

The dataset comprised 228 team–match observations, corresponding to 114 unique fixtures (each fixture contributing one observation per team). Unique fixtures refer to the set of Premier League league games in which at least one of the top-six teams participated; each fixture contributed two team-level observations.The sample consisted of 114 league fixtures involving the six teams that finished in the top six positions: Liverpool, Arsenal, Manchester City, Chelsea, Newcastle United, and Aston Villa.

Data collection tools

All data were obtained from FBref (https: Further details regarding the data extraction process, filtering criteria, and operational definitions of variables are outlined below. The dataset comprised match-level offensive and defensive performance indicators derived from the expected goals framework.

Data source and extraction procedure

Match-level performance data were obtained from FBref (https: All data were accessed and extracted on 21 December 2025. The dataset covered the 2024–2025 English Premier League season and was limited to league matches played by the six teams that finished in the top six positions: Liverpool, Arsenal, Manchester City, Chelsea, Newcastle United, and Aston Villa.

Filtering and inclusion criteria

The analysis included only regular-season Premier League matches. Cup fixtures, friendly matches, and games played outside the official 2024–2025 league calendar were excluded. The unit of analysis was defined as the team–match observation, such that each match generated two separate observations, one for each team. Variables were retained provided that data were available for all team–match observations. Values recorded as zero (e.g., xG = 0.00) were treated as valid performance outcomes rather than missing data. Listwise deletion was not implemented; if a value was missing for a specific team–match observation, that case was excluded solely from analyses involving the relevant variable.

In line with the objectives of the study, match outcome was specified as the dependent variable, representing competitive success at the match level. To account for the multidimensional structure of performance underlying match outcomes, a series of expected goals–based and attacking indicators were included as independent variables. These measures were selected to capture distinct aspects of performance, including chance creation and offensive volume, chance quality and overall performance balance, as well as finishing efficiency. All variables were computed at the match level to maintain consistency and comparability across outcome categories.

Table 1. Description of match outcome and performance variables

Variable Type	Variable	Description
Dependent Variable	Match outcome	Match outcome categorized as win, draw or loss
Match outcome categorized as win, draw, or loss	Expected goals (xG)	Total expected goals generated by the team in a match
	Expected goals against (xGA)	Expected goals conceded by the team
	Expected goal difference (xGD)	Difference between xG and xGA (xG − xGA)
	Non-penalty expected goals (npxG)	Expected goals excluding penalty kicks
	Goals scored	Total number of goals scored in the match
	Goal difference	Difference between goals scored and goals conceded
	Finishing efficiency	Ratio of goals scored to expected goals (Goals/xG)
	Total shots	Total number of shots attempted
	Key passes	Passes directly leading to a shot attempt
	xG per shot	Average expected goals value per shot (xG ÷ shots)
	Non-penalty xG per shot	Average non-penalty expected goals per shot (npxG ÷ shots)

Data analysis

All statistical analyses were performed using IBM SPSS Statistics. Prior to conducting inferential tests, descriptive statistics were calculated for each variable across match outcome categories, including means and standard deviations.

Prior to conducting group comparisons, the distribution of each match-level performance variable was evaluated to assess normality. Normality diagnostics indicated deviations from strict normality for some variables (Table 3); however, given the group sizes (Win = 126, Draw = 54, Loss = 48) and the well-documented robustness of one-way ANOVA under moderate-to-strong departures in large samples, analyses proceeded using parametric procedures.

Accordingly, one-way analysis of variance (ANOVA) was conducted to assess differences in expected goals–based and attacking performance indicators across match outcomes (win, draw, loss). For each variable, F-statistics and corresponding p-values were computed. Statistical significance was determined at the $p < 0.05$ level for all analyses.

Because the unit of analysis was the team–match observation, each team contributed multiple observations throughout the season. Although one-way ANOVA assumes independence of observations, the analysis was structured as a comparative assessment of performance differences across match outcomes rather than as a causal modeling approach. Given that each team played an equal number of matches (38), the potential impact of clustering was considered limited. Nonetheless, this constraint is recognized as a methodological limitation and is addressed in the Limitations section.

To reduce potential bias related to unequal group sizes and variance heterogeneity, the relevant statistical assumptions were examined and appropriate post-hoc procedures were applied when necessary. The findings were interpreted with caution, taking into account the clustered structure of the data.

RESULTS

Descriptive statistics were calculated to summarize the central tendency and variability of the offensive and defensive performance indicators included in the analysis. Expected goals metrics, finishing efficiency, and related match-level variables were first evaluated across the entire dataset, providing a quantitative baseline for subsequent comparisons between match outcome categories.

Table 2. Descriptive statistics of performance metrics by match outcomes

Variable	Match outcome	n	Mean	SD
xG	Win	126	2.11	0.99
	Draw	54	1.97	2.99
	Loss	48	1.19	0.62
xGA	Win	126	1.01	1.06
	Draw	54	1.20	0.66
	Loss	48	1.66	0.79
xGD	Win	126	1.10	1.49
	Draw	54	0.77	3.13
	Loss	48	-0.46	1.01
Goals	Win	126	2.54	1.24
	Draw	54	1.31	0.77
	Loss	48	0.54	0.62
Goal difference	Win	126	1.95	1.47
	Draw	54	0.00	0.00
	Loss	48	-1.81	1.05
Finishing efficiency	Win	126	1.33	0.67
	Draw	54	0.94	0.82
	Loss	48	0.48	0.64
Shots	Win	126	15.83	5.82
	Draw	54	14.74	6.44
	Loss	48	11.92	4.71
Key passes	Win	126	12.55	5.32
	Draw	54	11.54	5.30
	Loss	48	9.21	4.22
xG per shot	Win	126	0.136	0.050
	Draw	54	0.128	0.129

	Loss	48	0.103	0.048
npxG per shot	Win	126	0.126	0.043
	Draw	54	0.104	0.042
	Loss	48	0.098	0.035

xG = expected goals; xGA = expected goals against; xGD = expected goals difference; npxG = non-penalty expected goals; Finishing Efficiency = Goals/xG

Table 2 presents the descriptive statistics of the match-level performance variables across outcome categories. Matches that ended in a win showed higher mean values for expected goals (xG), goals scored, total shots, key passes, and shot quality measures such as xG per shot and non-penalty xG per shot. In contrast, losses were associated with the lowest averages across these offensive indicators. Expected goals against (xGA) displayed the opposite pattern, increasing from wins to losses. Similarly, expected goals difference (xGD) was positive in wins, close to zero in draws, and negative in losses. Finishing efficiency, calculated as goals divided by xG, decreased progressively from wins to losses. Goal difference followed the same overall trend, aligning closely with the direction of the expected goals–based metrics.

Table 3. Normality tests for match-level performance variables

Variable		Mean	CI		Variance	SD	Min	Max	Skewness	Kurtosis
			Lower	Upper						
xG	Stat.	1.793	1.671	1.915	0.872	0.934	0.000	6.200	1.065	2.551
	SE	0.062								
xGA	Stat.	1.188	1.063	1.313	0.917	0.958	0.070	11.000	5.087	48.382
	SE	0.063								
xGD	Stat.	0.604	0.418	0.790	2.026	1.423	-9.300	4.900	-1.329	10.173
	SE	0.094								
Goals	Stat.	1.829	1.656	2.002	1.764	1.328	0	6	0.808	0.578
	SE	0.088								
Goal difference	Stat.	0.697	0.466	0.929	3.155	1.776	-4	6	-0.086	0.208
	SE	0.118								
Finishing efficiency	Stat.	1.061	0.960	1.162	0.600	0.775	0.000	5.000	1.225	3.224
	SE	0.051								
Shots	Stat.	14.750	13.975	15.525	35.272	5.939	1	37	0.803	1.225
	SE	0.393								
Key passes	Stat.	11.605	10.920	12.290	27.544	5.248	1	35	1.093	2.624
	SE	0.348								
xG per shot	Stat.	0.123	0.116	0.130	0.003	0.050	0.000	0.300	0.896	1.064
	SE	0.003								
npxG per shot	Stat.	0.115	0.109	0.120	0.002	0.043	0.000	0.258	0.573	0.156
	SE	0.003								

CI= confidence interval; SD: standard deviation; Stat.= statistics; SE= standard error; xG = expected goals; xGA = expected goals against; xGD = expected goals difference; npxG = non-penalty expected goals; Finishing Efficiency = Goals/xG

Table 3 reports the descriptive statistics and normality indicators for the match-level performance variables. Across the full sample (N = 228), mean expected goals (xG) was 1.793 (SD = 0.934), whereas mean expected goals against (xGA) was 1.188 (SD = 0.958). The average expected goals difference (xGD) was 0.604 (SD = 1.423). An examination of skewness and kurtosis values showed that some variables deviated from perfect normality. In particular, xGA (skewness = 5.087; kurtosis = 48.382) and xGD (kurtosis = 10.173) displayed relatively high kurtosis, indicating the presence of extreme values in a small number of matches. Finishing efficiency also showed moderate positive skewness (1.225) and kurtosis (3.224).

By comparison, goals scored, goal difference, total shots, key passes, and shot-level quality measures showed relatively moderate skewness and kurtosis values, suggesting acceptable distributional characteristics for large-sample analysis. Although perfect normality was not observed for all variables, each outcome category included more than 30 observations (Win = 126, Draw = 54, Loss = 48). Given the group sizes, one-way ANOVA is generally robust to departures from normality in practice (Casella & Berger, 2002; Ross, 2014). Therefore, the findings should be interpreted as comparative associations at the match level, and results were supported by assumption checks and appropriate post-hoc procedures.

In addition to normality, one-way ANOVA assumes homogeneity of variances across groups. To examine this assumption, Levene's test (based on the mean) was performed to determine whether variance equality held across the win, draw, and loss categories. The results of this analysis are reported in Table 4.

Table 4. Levene's Test for Homogeneity of Variances

Variable	Levene F	df1	df2	p
xG	4.892	2	225	.008
xGA	0.228	2	225	.796
xGD	1.425	2	225	.243
npxG	2.742	2	225	.067
Goals	13.895	2	225	<.001
Goal difference	43.639	2	225	<.001
Finishing efficiency	1.266	2	225	.284
Shots	1.202	2	225	.302
Key passes	0.966	2	225	.382
xG per shot	1.206	2	225	.301
npxG per shot	2.196	2	225	.114

Note. Levene's test (based on mean) for equality of variances across match outcome groups (Win, Draw, Loss). df1 = 2, df2 = 225. p < .05 indicates violation of the homogeneity assumption.

The results of Levene's test showed that the assumption of homogeneity of variances was met for most variables ($p > .05$), including xGA, xGD, npxG, finishing efficiency, total shots, key passes, and shot-level quality measures. However, the assumption was not satisfied for expected goals (xG), goals scored, and goal difference ($p < .05$). Therefore, variance-robust post-hoc procedures were applied for these variables, while standard post-hoc tests were used for those that met the homogeneity criterion.

For variables with non-significant Levene's test results ($p > .05$), Tukey HSD was used for pairwise comparisons. For variables with significant Levene's test results ($p < .05$), Games–Howell was applied because it does not assume equal variances. Although the Levene result for npxG was marginal ($p = .067$), it remained above the .05 threshold and was therefore analyzed using Tukey HSD.

Based on the assumption checks outlined above, one-way ANOVA was conducted to examine differences in expected goals–based and related performance indicators across match outcomes. The detailed ANOVA results are presented in Table 5.

Table 5. One-Way ANOVA results for match-level performance metrics by match outcomes

Variable	Source	Sum of Squares	df	Mean Square	F	p	η²
xG	BG	32.047	2	16.023	21.742	<.001	0.162
	WG	165.822	225	0.737			
xGA	BG	16.082	2	8.041	9.325	<.001	0.077
	WG	194.020	225	0.862			
xGD	BG	91.625	2	45.813	27.635	<.001	0.197
	WG	372.996	225	1.658			
npxG	BG	24.969	2	12.485	19.321	<.001	0.147
	WG	145.388	225	0.646			
Goals	BG	157.463	2	78.731	72.939	<.001	0.393
	WG	242.866	225	1.079			
Goal difference	BG	527.092	2	263.546	313.701	<.001	0.736
	WG	189.027	225	0.840			
Finishing efficiency	BG	25.914	2	12.957	26.285	<.001	0.189
	WG	110.912	225	0.493			
Shots	BG	533.213	2	266.606	8.027	<.001	0.067
	WG	7473.537	225	33.216			
Key passes	BG	387.917	2	193.958	7.441	<.001	0.062
	WG	5864.557	225	26.065			
xG per shot	BG	0.047	2	0.024	10.224	<.001	0.083
	WG	0.521	225	0.002			
npxG per shot	BG	0.036	2	0.018	10.606	<.001	0.086
	WG	0.379	225	0.002			

Note. BG = Between Groups; WG = Within Groups; df = degrees of freedom; η² values represent partial eta squared. N = 228 team–match observations.

The one-way ANOVA results indicated statistically significant differences across match outcome groups (win, draw, loss) for all performance variables examined ($p < .001$). Expected goals (xG) varied significantly between groups, $F(2, 225) = 21.742$, $p < .001$, demonstrating that the quality of scoring opportunities differed systematically according to match outcome. Likewise, expected goals against (xGA) showed significant differences across outcome categories, $F(2, 225) = 9.325$, $p < .001$, indicating that defensive performance was also associated with match outcomes.

Net performance indicators showed particularly strong differences across groups. Expected goals difference (xGD) significantly distinguished match outcomes, $F(2, 225) = 27.635$, $p < .001$. In addition, non-penalty expected goals (npxG) varied significantly across win, draw, and loss categories, $F(2, 225) = 19.321$, $p < .001$. Together, these results underscore the combined role of offensive production and defensive control in determining competitive success.

Marked differences were also found for traditional outcome-based variables. Goals scored and goal difference showed strong between-group effects, $F(2, 225) = 72.939$, $p < .001$ and $F(2, 225) = 313.701$, $p < .001$, respectively. Although these indicators are inherently linked to match outcomes, they serve as useful reference points when interpreting the explanatory value of xG-based process measures. Finishing efficiency also varied significantly across outcome categories, $F(2, 225) = 26.285$, $p < .001$, indicating systematic differences in conversion effectiveness between wins, draws, and losses. In addition, indicators of offensive volume and creativity demonstrated significant group effects. Both total shots, $F(2, 225) = 8.027$, $p < .001$, and key passes, $F(2, 225) = 7.441$, $p < .001$, differed across match outcomes, pointing to variations in attacking intensity and chance production.

Finally, shot-level quality measures also differed significantly across match outcomes. Expected goals per shot, $F(2, 225) = 10.224$, $p < .001$, and non-penalty expected goals per shot, $F(2, 225) = 10.606$, $p < .001$, both varied according to result category.

Table 6. Tukey HSD post-hoc comparisons (Homogeneous Variances)

Variable	Group 1	Group 2	Mean Diff	Lower CI	Upper CI	p	Cohen's d
xGA	Draw	Loss	0.482	0.047	0.916	.026	-0.658
	Draw	Win	-0.198	-0.555	0.158	.389	0.207
	Loss	Win	-0.680	-1.052	-0.308	<.001	0.682
xGD	Draw	Loss	-0.877	-1.480	-0.274	.002	0.886
	Draw	Win	0.718	0.224	1.212	.002	-0.533
	Loss	Win	1.595	1.080	2.110	<.001	-1.161
npxG	Draw	Loss	-0.325	-0.702	0.051	.105	0.524
	Draw	Win	0.476	0.167	0.784	.001	-0.556
	Loss	Win	0.801	0.479	1.123	<.001	-0.950
Finishing efficiency	Draw	Loss	-0.452	-0.781	-0.124	.004	0.612
	Draw	Win	0.393	0.124	0.663	.002	-0.548
	Loss	Win	0.846	0.565	1.127	<.001	-1.278
Shots	Draw	Loss	-2.824	-5.521	-0.127	.038	0.496
	Draw	Win	1.093	-1.119	3.304	.475	-0.182
	Loss	Win	3.917	1.610	6.223	<.001	-0.707
Key passes	Draw	Loss	-2.329	-4.718	0.061	.058	0.483
	Draw	Win	1.011	-0.949	2.970	.444	-0.190
	Loss	Win	3.339	1.296	5.382	<.001	-0.662
xG per Shot	Draw	Loss	-0.009	-0.031	0.014	.633	0.189
	Draw	Win	0.024	0.006	0.043	.006	-0.504
	Loss	Win	0.033	0.014	0.052	<.001	-0.669
npxG per Shot	Draw	Loss	-0.005	-0.025	0.014	.784	0.140
	Draw	Win	0.022	0.007	0.038	.003	-0.525
	Loss	Win	0.028	0.011	0.044	<.001	-0.681

Note. Tukey HSD was used when Levene's test was non-significant ($p > .05$). Cohen's d was calculated using the pooled standard deviation. All analyses were conducted with N = 228 (Win = 126, Draw = 54, Loss = 48).

Tukey HSD post-hoc tests were performed for variables that met the homogeneity of variances assumption (see Table 6). With respect to expected goals against (xGA), losses differed significantly from both draws ($p = .026$) and wins ($p < .001$). In contrast, no significant difference was found between draws and wins ($p = .389$).

Expected goals difference (xGD) revealed significant pairwise differences across all match outcomes (all $p \leq .002$), reflecting a clear gradient from losses to draws and from draws to wins. In a similar vein, non-penalty expected goals (npxG) differed significantly between wins and both draws ($p = .001$) and losses ($p < .001$). However, the contrast between draws and losses did not reach statistical significance ($p = .105$). Finishing efficiency displayed a comparable progressive pattern, with significant differences observed across all outcome categories (all $p \leq .004$). This trend indicates that conversion effectiveness increased steadily from losses to wins. In terms of offensive volume, total shots differed significantly between losses and wins ($p < .001$) as well as between draws and losses ($p = .038$), whereas the difference between draws and wins was not significant ($p = .475$). A broadly similar tendency emerged for key passes. Only the comparison between losses and wins reached statistical significance ($p < .001$), while the draw–loss contrast approached, but did not achieve, significance ($p = .058$). Shot-level quality indicators also showed consistent patterns. Expected goals per shot differed significantly between wins and both draws ($p = .006$) and losses ($p < .001$), yet no significant difference was detected between draws and losses ($p = .633$). Non-penalty expected goals per shot mirrored this structure, with significant differences between wins and the other two outcomes ($p \leq .003$), but not between draws and losses ($p = .784$).

Table 7. Games–Howell post-hoc comparisons (Unequal Variances)

Variable	Group 1	Group 2	Mean Diff	Lower CI	Upper CI	p	Cohen's d
xG	Win	Draw	0.137	-0.697	0.970	.744	0.061
	Win	Loss	0.915	0.666	1.164	<.001	1.105
	Draw	Loss	0.778	-0.056	1.613	.067	0.360
Goals	Win	Draw	1.225	0.923	1.527	<.001	1.183
	Win	Loss	1.998	1.717	2.279	<.001	2.035
	Draw	Loss	0.773	0.500	1.047	<.001	1.105
Goal difference	Win	Draw	1.952	1.759	2.145	<.001	2.523
	Win	Loss	3.765	3.439	4.090	<.001	3.733
	Draw	Loss	1.812	1.547	2.078	<.001	2.803

Note. Games–Howell was used when Levene's test was significant (p < .05). Cohen's d was calculated using a variance-robust standardizer (non-pooled). All analyses were conducted with N = 228 (Win = 126, Draw = 54, Loss = 48).

For variables that violated the homogeneity of variances assumption, Games–Howell post-hoc tests were applied (see Table 7). Regarding expected goals (xG), winning matches differed significantly from losses ($p < .001$), with higher xG values recorded in wins. In contrast, no significant difference emerged between wins and draws ($p = .744$) or between draws and losses ($p = .067$). This pattern indicates that the clearest distinction in chance creation was observed between wins and losses. Goals scored showed significant differences across all pairwise comparisons ($p < .001$). Winning matches yielded more goals than both draws and losses, and draws, in turn, produced more goals than losses. A similar structure was evident for goal difference. All comparisons were statistically significant ($p < .001$), with wins associated with markedly higher goal differences than draws and losses and draws demonstrating higher values than losses.

DISCUSSION

Based on match-level data from the 2024–2025 English Premier League season, this study examined whether performance indicators derived from the expected goals framework differentiate match outcomes among top-six teams. The findings indicate that process-oriented metrics—particularly expected goals difference (xGD), non-penalty expected goals (npxG), shot quality measures, and finishing efficiency—differ significantly across win, draw, and loss categories. Overall, these results emphasize the importance of evaluating underlying performance processes rather than relying solely on final scorelines when assessing competitive success.

Among the variables analyzed, expected goals difference (xGD) stood out as one of the most powerful indicators of match outcome, with considerable effect sizes across groups. Because it combines offensive production (xG) and defensive resistance (xGA), xGD reflects the overall balance of performance within a match. This finding is consistent with previous research indicating that net expected goals metrics offer a more reliable representation of team quality than traditional goal-based measures (Rathke, 2017; Mead et al., 2023). In the present study, xGD clearly separated wins from losses and also distinguished draws from both outcomes, underscoring its sensitivity to differences in competitive performance levels.

Offensive production, as measured by xG and non-penalty xG, also varied across match outcomes. Nevertheless, the size of these differences indicates that generating chances alone is not sufficient to explain results. Although wins were generally associated with higher expected goals values, draws and losses showed some degree of overlap. This suggests that the volume of opportunities should be considered together with defensive solidity and finishing performance. Such a pattern is consistent with previous research showing that match outcomes in football arise from the interaction of chance creation, chance prevention, and situational efficiency rather than from isolated attacking indicators (Wright et al., 2017; Umami et al., 2021).

Defensive performance, captured through expected goals against (xGA), also varied consistently across match outcomes and further emphasized the joint role of attacking and defensive dimensions. The results point to a balanced performance structure in which reducing the quality of opponents' chances is just as important as creating scoring opportunities. In this respect, the findings align with earlier studies that underline the explanatory value of defensive indicators within expected goals models (Mead et al., 2023).

Finishing efficiency (goals/xG) also differed meaningfully across match outcomes, with higher values recorded in winning performances. This measure captures the extent to which the quality of created chances is translated into actual goals and therefore reflects execution rather than simply the number of opportunities generated. At the same time, finishing efficiency should be interpreted with caution. Previous research has demonstrated that conversion rates are shaped by contextual and situational factors, including defensive pressure and goalkeeper positioning (Hewitt & Karakuş, 2023). Accordingly, although efficiency plays an important role in competitive success, it likely functions in conjunction with broader performance dynamics rather than as an isolated determinant.

Measures of offensive volume and creativity, including total shots and key passes, also differed significantly across match outcomes. At the same time, shot-level quality indicators such as xG per shot and non-penalty xG per shot offered further insight into qualitative differences in chance creation. The findings indicate that successful performances are defined not only by generating a greater number of attempts but also by producing opportunities with higher scoring probability. In this sense, the results clearly support the distinction between quantity-based and quality-based attacking metrics. It should also be acknowledged that traditional outcome-based variables, namely goals scored and goal difference, inherently separate match outcome categories. For this reason, they were included as reference measures rather than as primary explanatory variables. The main emphasis of the analysis remains on process-oriented indicators derived from the expected goals framework, which are intended to reflect underlying performance quality beyond the final score. Overall, the study demonstrates that these process-based metrics consistently differentiate performance profiles across win, draw, and loss outcomes.

Taken together, these findings support a process-oriented view of performance in elite football. Match outcomes seem to stem from consistent differences in chance creation, defensive solidity, and finishing efficiency rather than from isolated statistical indicators. Nevertheless, given the observational nature of the study and its match-level comparative design, the conclusions should be interpreted as reflecting associations rather than causal relationships. Future studies that apply multilevel or predictive modeling techniques could provide a more detailed understanding of the explanatory capacity of expected goals–based metrics in competitive football settings.

CONCLUSION

The results of this study show that match outcomes in elite football are linked to consistent differences in chance creation, defensive performance, net expected goals, and finishing efficiency. Taken together, these findings indicate that expected goals–based metrics provide a valuable framework for understanding how underlying performance processes relate to competitive results. At the same time, the persistence of variability across outcomes highlights the ongoing role of uncertainty in football matches.

LIMITATIONS

This study has several methodological limitations that should be taken into account when interpreting the results. The unit of analysis was the team–match observation. Since each team contributed multiple observations over the course of the season, the assumption of independence required for one-way ANOVA may not have been fully satisfied because of potential clustering effects. Although the analysis was designed to compare performance profiles rather than to establish causal relationships, repeated observations from the same teams may have affected the estimation of standard errors.

Another limitation relates to the lack of explicit control for contextual factors, including home versus away status and opponent strength. Such variables are known to influence both performance indicators and match outcomes. As a result, their exclusion may limit the explanatory scope of the findings. Moreover, the statistical approach was based on group comparisons rather than multilevel or mixed-effects models. Methods that explicitly address hierarchical data structures and account for clustering at the team or opponent level would offer a more rigorous and detailed examination of performance variability.

Additionally, several univariate ANOVAs were performed across different performance indicators. Although suitable post-hoc procedures were applied within each analysis to control for familywise error, conducting multiple separate tests may still increase the overall risk of Type I error. For this reason, future studies could consider multivariate techniques, such as MANOVA, which allow correlated performance variables to be examined simultaneously within a single analytical framework.

Ethical Approval and Permission Information

Ethics Committee:	Inonu University Scientific Research and Publication Ethics Board — Social Sciences and Humanities Scientific Research and Publication Ethics Committee
Protocol/Number:	25/1

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