applied sciences

MDPI

Article

Decoding Success: Predictive Analysis of UEFA Euro 2024 to Uncover Key Factors Influencing Soccer Match Outcomes

Andreas Stafylidis *, Athanasios Mandroukas, Yiannis Michailidis and Thomas I. Metaxas

Laboratory of Evaluation of Human Biological Performance, Department of Physical Education and Sports Sciences, Aristotle University of Thessaloniki, 57001 Thessaloniki, Greece; amandrou@phed.auth.gr (A.M.); ioannimd@phed.auth.gr (Y.M.); tommet@phed.auth.gr (T.I.M.)

* Correspondence: astafylidis@phed.auth.gr; Tel.: +30-2310992248

Abstract: This study presents the analysis of the UEFA Euro 2024 in Germany, focusing on the impact of the first goal on match outcomes, goal distribution between halves and quarters, and the relationship between offensive, defensive, and goalkeeping metrics and match outcomes. Moreover, a regression model is developed to identify the key factors that significantly contribute to teams' success. The analysis of the 36 group stage matches revealed that scoring the first goal significantly increased the likelihood of a positive match outcome. There were no significant differences between goals scored in the first and second halves or per 15 min of the game. Kruskal–Wallis tests highlighted that winning teams had more assists, attempts on target and runs into the penalty area. Defensive metrics showed that winning teams recovered more balls, while goalkeeping metrics revealed that winning teams had more clean sheets. The logistic regression model identified "Attempts on Target" and "Passes into Attacking Third" as significant positive predictors of winning, while "Attempts on Target Outside Area" and "Crosses Attempted" were negative predictors. These findings offer valuable insights for coaching staff to develop strategies focusing on key performance indicators that enhance the likelihood of winning.

Keywords: soccer metrics; video analysis; logistic regression; success prediction; performance indicators; football; technical demands; physical demands; notational analysis; total distance

check for updates

Citation: Stafylidis, A.; Mandroukas, A.; Michailidis, Y.; Metaxas, T.I. Decoding Success: Predictive Analysis of UEFA Euro 2024 to Uncover Key Factors Influencing Soccer Match Outcomes. *Appl. Sci.* **2024**, *14*, 7740. https://doi.org/10.3390/app14177740

Academic Editor: Matej Supej

Received: 26 July 2024
Revised: 15 August 2024
Accepted: 28 August 2024
Published: 2 September 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Soccer match performance analysis is crucial for enhancing training prescriptions and match strategies in elite soccer, providing essential insights for coaching staff to boost team success [1–3]. Effective soccer performance is closely tied to the ability of coaching staff to observe, interpret, and improve key performance indicators and tactical behavior through game interventions [2]. Numerous studies have explored the relationship between playing styles and statistical indicators across various tournaments and competitions [4–23], highlighting the value of performance analysis methods for understanding athletic performance and identifying areas for targeted coaching interventions [1–3]. Recent research also emphasizes the role of artificial intelligence and factor analysis in understanding playing styles in soccer [24].

The statistical analysis of UEFA European Championship [14–23] tournaments has provided valuable insights into the dynamics of soccer, with comprehensive studies spanning various editions, including UEFA Euro 1996 and Euro 2000 [14], Euro 2004 [15], Euro 2008 and Euro 2016 [16], Euro 2012 [17–20], Euro 2016 [20,21], and Euro 2020 [22,23].

The variables selected for this study—attacking, distribution, goalkeeping, and disciplinary metrics—are grounded in their established significance within soccer performance analysis [14–23]. Attacking metrics such as goals scored, attempts on target, assists, and runs into the penalty area are critical for assessing a team's offensive effectiveness. Previous research has consistently demonstrated that teams excelling in these areas tend

to perform better, underscoring the importance of creating and capitalizing on scoring opportunities [15,17,19]. For instance, higher offensive efficiency, reflected in metrics like shots and attempts on target, has been repeatedly linked to successful match outcomes [14,21]. Distribution metrics like ball possession and passing accuracy are fundamental for maintaining control over the game. Effective distribution, including strategic backward passes, allows teams to manage the pace and direction of play, which is increasingly crucial in modern soccer, where possession-based tactics dominate [16,20,22]. Goalkeeping metrics are another essential component, providing insights into a team's defensive stability through measures like goals conceded, clean sheets, and saves. Disciplinary metrics, while not always directly influencing match outcomes, can significantly affect the flow and dynamics of a game. Actions such as corners, fouls, and yellow and red cards can disrupt a team's momentum and lead to disadvantageous situations, making these metrics an important aspect of comprehensive performance analysis [19,21].

In the present study, a holistic approach is provided by integrating all these metrics—attacking, distribution, goalkeeping, and disciplinary—together, highlighting the critical role of team cooperation in achieving success in elite soccer. These metrics have consistently influenced team rankings and match outcomes. For instance, the findings from Luhtanen et al. [14] highlighted that in UEFA Euro 1996, teams' rankings were influenced by the number of executions such as ball possession, passes, runs with the ball, and defensive actions like interceptions and tackles, with higher-ranked teams showing a balanced mix of offensive and defensive strengths. In UEFA Euro 2000, a similar analysis indicated that France emerged as the top team due to superior performance in ball possession, passes, and interceptions. Furthermore, there was a shift in the importance of specific metrics, with defensive actions being significant predictors of success in 1996, while offensive efficiency, particularly successful passes and goal-scoring trials, became more crucial in UEFA Euro 2000 [14].

Continuing this analysis, the study by Yiannakos and Armatas [15] provides a comprehensive analysis of goal-scoring patterns during the UEFA European Championship in Portugal in 2004, revealing that most goals were scored in the second half of matches compared to the first half, indicating a statistically significant difference in goal frequency across halves. In terms of offensive strategies, it was observed that a substantial proportion of goals resulted from organized offensive moves, followed by set plays and counter-attacks, with significant differences noted between these offensive types. The actions leading to goals varied, with long passes, combination play, and individual actions being the most common, each showing significant differences in their effectiveness. Additionally, set plays such as corner kicks, free kicks, penalties, and throw-ins were analyzed, with corner kicks being the most frequent source of goals, followed by free kicks and penalties. Lastly, the location of goal-scoring attempts highlighted that the majority of goals were scored inside the penalty area, with significant differences observed compared to those scored outside the penalty area. These findings underscore the diverse tactical approaches and situational contexts contributing to goal-scoring in high-level football tournaments [15].

Building on these observations, the study by Maneiro et al. [16] investigated offensive transitions in high-performance football by comparing the UEFA Euro 2008 and UEFA Euro 2016 championships. The analysis revealed significant differences between the two tournaments in several key variables, including the start of possession, interaction context, defensive organization, intention, number of passes, final interaction context, and match status, all of which significantly impacted the success of offensive transitions. In Euro 2008, the significant predictor of success was the final interaction context, while in Euro 2016, multiple variables, including defensive organization, final interaction context, interaction context, number of passes, and start of possession, were significant. These differences suggest an evolution in the dynamics of attack play. In Euro 2016, a higher frequency of offensive transitions and a shift towards more open and fluid game patterns were noted compared to Euro 2008. This shift indicates a trend towards utilizing wider spaces and shorter offensive actions, reflecting changes in tactical approaches over the eight years [16].

Further expanding on these findings, the study by Michailidis et al. [17] analyzed goal-scoring patterns during the UEFA European Championship 2012, which revealed that although more goals were scored in the second half compared to the first half, this difference was not statistically significant [17], controversy with previous analysis of the Euro 2004 [15]. The distribution of goals across 15 min intervals was relatively even, with no significant deviations except during extra time and the initial 15 min of each half [17]. Regarding how goals were scored, the majority were from shots, followed by goals scored using the inner part of the foot and headers, with significant differences between these methods and other less common methods like penalties and own goals. The location of goals revealed that most were scored inside the penalty box, with significant differences compared to goals scored inside the goal box and outside the penalty box. Additionally, the study found that most goals were scored following a long pass, followed by short passes and individual actions. However, there were no significant differences between these types of assists. Notably, the analysis showed that teams scoring the first goal were significantly more likely to win the match, highlighting the critical impact of the first goal on match outcomes [17].

The analysis [20] for the UEFA European Championships of 2012 and 2016 revealed also that teams scoring the first goal finally won the game in the UEFA European Championships of 2012 and 2016 (71% and 72%, respectively), with no significant differences between the two tournaments. In 2012, goals were most frequently scored following through passes and crosses, whereas in 2016, crosses, long shots, and through passes were more common, though patterns differed significantly between types of goals. Set play scoring patterns revealed no significant differences, with corner kicks and indirect fouls being prominent in both tournaments. Regarding open play, 79% of goals in 2012 and 70% in 2016 were scored in this manner. Timing analysis showed that goals were evenly distributed across halves with no significant differences. The most frequent goal-scoring periods in 2012 were between the 46th and 60th min, while in 2016, goals were more evenly distributed across various intervals. Lastly, a significant proportion of goals in both tournaments resulted from ball recovery in the offensive third of the field [20].

In another related analysis, the study by Winter and Pfeiffer [18] examined the tactical behavior of the teams in UEFA Euro 2012, where significant differences in tactical metrics across winners, drawers, and losers were noted. The ball recovery time had a mean of 4.68 s for winners, 3.98 s for drawers, and 4.65 s for losers. Offensive efficiency had a mean of 2.14% for winners, 0.67% for drawers, and 0.43% for losers. These metrics and others, such as the ball recovery index and the prevented transition index, demonstrated significant variations, with winners generally exhibiting superior values compared to drawers and losers [18]. Factor analysis revealed four key dimensions accounting for 75.55% of the variance: game speed across various situations (24.46%), transitions after losing possession (20.05%), transitions after gaining possession (16.84%), and open play efficiency (14.19%), highlighting the significance of transition play after losing possession and efficiency in open play in Euro 2012 [18].

Furthering the analysis of UEFA Euro 2012, a similar study [19] examined differences in goal-scoring and passing patterns between winning and losing teams. Significant differences were noted in goal-scoring times between winning and losing teams, with more goals scored in the second half, particularly between the 75th and 90th min. However, there were no significant differences in the total shots on goal between winning and losing teams [19].

The analysis also revealed significant differences in goals scored from corners and open play, with the winning teams showing superiority in these aspects. The pitch area analysis indicated a notable difference in goals scored inside the penalty box. Regarding player positions, attackers and midfielders were significant differentiators between winning and losing teams. Additionally, passing sequences showed significant differences, with winning teams having more short passing sequences than losing teams [19].

The analysis from Konefał et al. [21] about the shot frequency concerning match outcomes in UEFA Euro 2016 revealed significant effects in several areas. Specifically, the frequency of shots on target and shots taken inside the penalty box had a large effect size. Additionally, medium effect sizes were found for the frequency of overall shots and shots from open play. However, no significant effects were observed regarding the frequency of shots concerning match status. In contrast, pass frequency did not show significant effects concerning match outcome, but significant effects were noted concerning match status. Specifically, the frequency of passes, short passes, and crosses, as well as the percentage of ball possession, all demonstrated medium effect sizes. These findings indicate that while shot-related activities are crucial for determining match outcomes, pass-related activities and ball possession are more influential when teams attempt to change an unfavorable match status.

Finally, the study of de Amorim Mendes et al. [22] examined the association between goal-kick strategies and offensive outcomes in UEFA Euro 2020. The results indicated significant associations between the type of goal kick and the result of the offensive sequence. Specifically, the regression analysis revealed that the model could accurately predict 64% of the offensive outcomes based on the goal-kick strategy. The short goal-kick strategy was found to be related to unsuccessful offensive sequences. In contrast, contrary to the initial hypothesis, the long goal-kick strategy was associated with successful offensive sequences. The study concluded that the long goal-kick strategy showed more efficiency than the short goal-kick strategy in obtaining possession of the ball in the offensive half. The logistic regression indicated that 64% of the outcome is predicted by the type of goal kick, with significant associations between goal kick strategy and offensive success. Short goal kicks increased the frequency of unsuccessful offensive sequences, while long goal kicks increased the frequency of successful offensive sequences. These findings suggest that the strategy to start the offensive phase is crucial in predicting the outcome of the upcoming attacking unit. Furthermore, the study highlights the need for coaches and match analysts to consider goal-kick strategies in their tactical planning, as the long goal-kick proves more effective in elite soccer [22]. Similarly, logistic regression models from other studies noted shot and passing metrics, counterattacks, and offensive duels as critical factors influencing the likelihood of winning [25], or a more direct style of play, with fewer passes and more shots [26,27]. While many studies have examined match outcomes (win, draw, lose), a relatively small proportion of research is dedicated to developing regression models that illustrate the relationship between performance indicators and the prediction of match outcomes [25].

This study aimed to: (a) investigate the impact of scoring the first goal on match outcomes, whether it results in a win, loss, or draw; (b) analyze the differences in goals scored between the first and second halves, as well as the distribution of goals across each quarter of the match; (c) examine the relationship between various factors—attacking, distribution, goalkeeping, and disciplinary metrics—and match outcomes; and (d) employ a regression model (win vs. no win) to identify statistically significant key factors that contribute to teams' success in the UEFA Euro 2024.

2. Materials and Methods

2.1. Sample

A total of 36 matches from the group stage of EURO 2024 were analyzed. This stage featured 24 European national teams divided into six groups of four, each playing three matches in a round-robin format. Matches from the knockout phase were excluded from the analysis due to the inclusion of extra time in some of them. The study focused on 72 match outcomes, categorized as wins (n = 22), draws (n = 28), and losses (n = 22).

2.2. Data Collection and Analysis Procedures

Thirty-six matches from the EURO 2024 group stage were analyzed. All statistical performance indicators and match data presented in this study were sourced from the

official UEFA website (https://www.uefa.com/euro2024/, accessed on 14 July 2024).The UEFA statistics page categorizes key stats into attacking, distribution, defending, goalkeeping, and disciplinary. Attacking included variables such as: goals, attempts on target, total attempts, assists, attacks, corners taken, offsides, dribbles, runs into attacking third, runs into key play area, and runs into penalty area. Distribution covered the variables: possession, passing accuracy, passes completed, passes attempted, free kicks taken, passes into attacking third, passes into key play area, passes into penalty area, crosses completed, and crosses attempted. Defending encompassed: tackles, balls recovered, blocks, clearances completed, clearances attempted, and penalties conceded. Goalkeeping involved: saves, clean sheets, claims, high claims, low claims, and punches made. Disciplinary recorded: fouls committed, fouls committed in defensive third, fouls committed in own half, yellow cards, and red cards. The above teams' statistics, as well as the total distance covered (km) for each match, were publicly available on the UEFA website throughout the competition. This data is typically derived from video-based and GPS-tracking methods that record players' positions over time. The data collection and assessment process involved two UEFA A licensed coaches and one UEFA Pro coach, conducted from 14 June to 15 July 2024. Similar research methodologies using this platform have been employed in previous studies [28], with data that was publicly available on the UEFA official website (https://www.uefa.com/euro2024) throughout the competition.

2.3. Statistical Analysis

The analysis for this study was performed using IBM SPSS Statistics for Windows, Version 26.0 (IBM Corp., Armonk, NY, USA) [29]. Effect sizes were calculated following Cohen's criteria [30,31], and statistical power and effect sizes were evaluated using G*Power: Statistical Power Analyses for Windows, Version 3.1.9.7 [32,33]. Effect sizes (η^2) were categorized as small (η^2 = 0.01–0.06), moderate (η^2 = 0.06–0.14), and large ($\eta^2 > 0.14$). Descriptive statistics included the computation of mean (M), standard deviation (SD), frequencies, and minimum and maximum values for all performance indicators.

To investigate the impact of scoring the first goal on match outcomes, a chi-square test of independence was applied to determine the relation between scoring the first goal and the final result. Additionally, to analyze the differences in goals scored between the first and second halves, as well as the distribution of goals across each quarter of the match, chi-square tests were used to examine the temporal patterns of goal scoring to identify critical periods and shifts in scoring trends. Non-parametric tests (Kruskal–Wallis tests) were used to compare performance indicators across different match outcomes (win, lose, draw). Mann–Whitney U tests with Bonferroni correction were applied for cases where significant differences were detected to further analyze the group's differences.

To identify factors that significantly predict match outcomes, a generalized linear model for predicting binary outcomes was employed, utilizing logistic regression analysis with the binary match outcome (win vs. draw/lose) as the dependent variable, as used in previous studies [25–27]. Model predictive capacity was evaluated using Cox and Snell R^2 and Nagelkerke R^2, with the -2 log likelihood serving as a goodness-of-fit test. The omnibus test of model coefficients was used to assess model fit, and several predictor variables were tested for their effect on match outcomes using the Wald chi-square test. Stepwise logistic regression was conducted to develop a model that effectively predicts match outcomes (win vs. draw/lose), adding variables based on their contribution to improving model fit. The level of statistical significance was set at $p \leq 0.05$.

3. Results

A chi-square test of independence was conducted to examine the relationship between scoring the first goal and the final match outcome. The results indicated a significant association between these variables: $\chi^2(2, N = 36) = 8.167$, $p = 0.017$. The observed frequencies were as follows: teams that scored the first goal lost 4 matches, drew 15, and won 17 games. The expected frequencies were 12 for each outcome, indicating that teams that scored the

first goal were less likely to lose and more likely to draw or win compared to what would be expected by chance. The significant chi-square test result suggests that scoring the first goal is associated with the final match outcome, as teams scoring the first goal tend to avoid losses and are more likely to achieve draws or wins (Table 1).

Table 1. Goals scored by match time intervals.

Goals Scored	M ± SD	Min	Max	Sum
1st half goals	1.08 ± 0.93	0	3	39
2nd half goals	1.19 ± 1.16	0	4	43
0–15 min	0.36 ± 0.54	0	2	13
15–30 min	0.44 ± 0.60	0	2	16
30–45 min	0.28 ± 0.51	0	2	10
45–60 min	0.36 ± 0.63	0	2	13
60–75 min	0.31 ± 0.52	0	2	11
75–90 min	0.53 ± 0.60	0	2	19

Note: M ± SD—mean ± standard deviation, Min—minimum, Max—maximum, Sum—summation.

In order to examine the relationship between goals scored in the first half and the second half, a chi-square test of independence was also conducted (Table 1), which indicated no significant association between the goals scored in the first half and the second half, $\chi^2(12, N = 36) = 10.869$, $p = 0.540$. Additionally, a chi-square test for goodness of fit was conducted to examine whether the distribution of goals scored in six 15 min intervals of soccer matches differed significantly. Although the final interval (75–90 min) had the highest number of goals, no significant differences were noted regarding the goals scored across the six 15 min intervals, $\chi^2(5, N = 82) = 4.049$, $p = 0.542$, $p > 0.05$.

The Kruskal–Wallis tests revealed significant differences among winning, drawing, and losing teams concerning several key attacking metrics (Table 2). Winning teams demonstrated superior performance in "Goals Scored", "Total Attempts", "Attempts on Target", "Assists", and "Runs into the Penalty Area", indicating their offensive efficiency. Additionally, metrics like "Dribbles" and "Runs into Attacking Third" also significantly favored winning teams. Interestingly, while winning teams tended to cover more distance on average, this difference was not statistically significant. This could suggest that while higher distance coverage may be a characteristic of winning teams, total distance covered was not a decisive factor in determining match outcome.

Table 2. Attacking metrics and their impact on match outcomes.

Variable	Win (n = 22)	Draw (n = 28)	Lose (n = 22)	H	p	η^2
	M ± SD	M ± SD	M ± SD			
Distance covered (km)	114.28 ± 2.71	113.09 ± 4.71	113.76 ± 4.16	1.471	0.479	0.021
Goals Scored	2.18 ± 1.01	0.79 ± 0.57	0.50 ± 0.60	34.584	0.001 *†	0.487
Goals inside area	1.50 ± 0.86	0.64 ± 0.56	0.41 ± 0.59	21.186	0.001 *†	0.298
Goals outside area	0.45 ± 0.74	0.11 ± 0.32	0.05 ± 0.21	7.509	0.023 *	0.106
Total attempts	14.82 ± 4.70	12.14 ± 5.16	10.45 ± 5.10	8.016	0.018 *	0.113
Attempts on target	5.59 ± 2.22	4.04 ± 2.15	3.09 ± 1.93	13.116	0.001 *†	0.185
Attempts off target	5.18 ± 2.89	4.46 ± 2.50	4.09 ± 2.22	1.910	0.385	0.027
Blocks	3.27 ± 2.14	3.68 ± 2.53	4.05 ± 1.91	1.462	0.482	0.021
Woodwork	0.27 ± 0.63	0.21 ± 0.42	0.14 ± 0.35	0.502	0.778	0.007
Crossbar	0.14 ± 0.35	0.04 ± 0.19	0.09 ± 0.29	1.635	0.442	0.023
Post	0.14 ± 0.35	0.18 ± 0.39	0.05 ± 0.21	2.005	0.367	0.028
On target outside area	1.73 ± 1.35	1.54 ± 1.35	1.36 ± 1.14	0.726	0.696	0.010
Off target outside area	2.18 ± 1.37	1.64 ± 1.22	1.50 ± 0.91	3.692	0.158	0.052

Table 2. *Cont.*

Variable	Win (n = 22)	Draw (n = 28)	Lose (n = 22)	H	p	η^2
	M ± SD	M ± SD	M ± SD			
Assists	1.59 ± 0.80	0.46 ± 0.51	0.36 ± 0.58	29.287	0.001 *†	0.413
Penalties scored	0.14 ± 0.35	0.14 ± 0.36	0.00 ± 0.00	3.370	0.185	0.047
Penalties missed	0.00 ± 0.00	0.04 ± 0.19	0.05 ± 0.21	0.935	0.626	0.013
Penalties awarded	0.09 ± 0.29	0.14 ± 0.36	0.05 ± 0.21	1.327	0.515	0.019
Attacks	48.64 ± 17.69	43.75 ± 16.47	37.05 ± 18.32	6.234	0.044 *	0.088
Clear chances	0.45 ± 0.60	0.50 ± 0.64	0.68 ± 0.89	0.471	0.790	0.007
Corners taken	5.09 ± 2.99	5.18 ± 3.28	4.09 ± 2.98	1.669	0.434	0.024
Offsides	2.00 ± 1.66	1.43 ± 1.57	0.95 ± 0.95	4.583	0.101	0.065
Dribbles	16.23 ± 6.40	11.82 ± 5.31	12.00 ± 5.81	7.084	0.029 †	0.100
Runs into attacking third	16.55 ± 6.49	13.07 ± 7.39	11.73 ± 7.28	7.503	0.023 *	0.106
Runs into key play area	14.23 ± 6.76	10.57 ± 8.26	10.59 ± 7.06	5.486	0.064	0.077
Runs into penalty area	7.95 ± 4.50	4.61 ± 4.05	3.27 ± 2.25	16.893	0.001 *†	0.238

Note: M ± SD—mean ± standard deviation, H—Kruskal–Wallis H statistic, p—p-value, η^2—eta squared. * Win ≠ lose ($p < 0.05$); † win ≠ draw ($p < 0.05$).

Regarding the distribution metrics analysis (Table 3), winning teams displayed significantly higher numbers of "Backward Passes Completed" and showed a tendency towards greater ball possession (with an average of over 53%) and higher passing accuracy. Although the differences in possession and passing accuracy were not statistically significant, the successful teams demonstrated a strategic use of backward passes. These findings suggest that effective ball distribution, particularly through controlled and strategic backward passes, maybe plays a crucial role in achieving match success.

Table 3. Distribution metrics and their impact on match outcomes.

Variable	Win (n = 22)	Draw (n = 28)	Lose (n = 22)	H	p	η^2
	M ± SD	M ± SD	M ± SD			
Possession	53.32 ± 10.33	50.00 ± 9.20	46.68 ± 10.33	5.357	0.069	0.075
Passing accuracy	86.95 ± 5.56	85.21 ± 5.19	84.14 ± 5.59	3.748	0.154	0.053
Passes completed	453.05 ± 152.55	414.21 ± 133.42	369.14 ± 119.67	3.983	0.136	0.056
Passes attempted	512.77 ± 148.64	479.79 ± 132.14	432.36 ± 119.54	3.933	0.140	0.055
Short passes completed	122.45 ± 54.72	107.39 ± 42.90	95.41 ± 36.48	2.389	0.303	0.034
Medium passes completed	294.95 ± 106.38	272.96 ± 92.95	242.91 ± 89.48	2.794	0.247	0.039
Long passes completed	35.73 ± 9.71	33.86 ± 8.55	30.82 ± 7.42	2.882	0.237	0.041
Backward passes completed	89.64 ± 29.70	81.29 ± 25.96	67.00 ± 24.59	7.722	0.021 *	0.109
Passes completed to left	125.23 ± 47.75	112.07 ± 39.10	102.68 ± 34.55	2.577	0.276	0.036
Passes completed to right	123.73 ± 49.23	114.96 ± 42.77	101.64 ± 35.31	2.756	0.252	0.039
Free kicks taken	12.41 ± 3.59	12.21 ± 3.51	12.91 ± 3.78	0.460	0.795	0.006
Passes into attacking third	38.23 ± 15.73	34.54 ± 15.24	29.41 ± 16.99	5.238	0.073	0.074
Passes into key play area	28.59 ± 17.50	24.75 ± 12.50	18.23 ± 12.19	5.546	0.062	0.078
Passes into penalty area	11.55 ± 5.24	10.64 ± 5.88	8.36 ± 3.86	4.205	0.122	0.059
Crossing accuracy	28.36 ± 13.09	24.75 ± 12.98	23.00 ± 11.17	1.686	0.430	0.024
Crosses completed	4.36 ± 2.22	4.39 ± 2.78	3.77 ± 2.02	0.738	0.692	0.010
Crosses attempted	15.86 ± 6.12	17.32 ± 9.19	16.50 ± 7.15	0.148	0.929	0.002
Times in possession	170.45 ± 16.56	172.39 ± 20.91	171.18 ± 17.38	0.204	0.903	0.003

Note: M ± SD—mean ± standard deviation, H—Kruskal–Wallis H statistic, p—p-value, η^2—eta squared. * Win ≠ lose ($p < 0.05$).

The analysis of defensive play metrics revealed significant tendencies among winning, drawing, and losing teams (Table 4). The Kruskal–Wallis tests showed that winning teams recovered significantly more balls (M = 38.91, SD = 5.27) compared to losing teams (M = 34.23, SD = 7.52), with a notable effect size (H = 6.430, p = 0.040, η^2 = 0.09057).

Other metrics, such as blocks, tackles, and clearances, did not show statistically significant differences across match outcomes. However, these metrics provide insight into teams' defensive strategies with different match outcomes. Notably, the number of blocks (H = 1.462, p = 0.482), tackles (H = 0.460, p = 0.794), and clearances completed (H = 0.118, p = 0.942) were similar among winning, drawing, and losing teams, suggesting that while defensive actions are crucial, their impact might be more nuanced and dependent on specific match contexts.

Table 4. Defensive metrics and their impact on match outcomes.

Variable	Win (n = 22)	Draw (n = 28)	Lose (n = 22)	H	p	η^2
	M ± SD	M ± SD	M ± SD			
Balls recovered	38.91 ± 5.27	38.46 ± 6.46	34.23 ± 7.52	6.430	0.040 *	0.091
Blocks	3.27 ± 2.14	3.68 ± 2.53	4.05 ± 1.91	1.462	0.482	0.021
Penalties conceded	0.05 ± 0.21	0.18 ± 0.39	0.14 ± 0.35	2.005	0.367	0.028
Tackles	13.36 ± 4.76	13.32 ± 3.94	14.23 ± 4.32	0.460	0.794	0.006
Tackles won	5.59 ± 3.79	4.82 ± 2.72	5.27 ± 2.49	0.242	0.886	0.003
Tackles lost	7.77 ± 2.39	8.50 ± 2.95	8.95 ± 3.46	1.703	0.427	0.024
Clearances completed	14.73 ± 5.43	16.11 ± 8.76	14.68 ± 6.94	0.118	0.942	0.002
Clearances attempted	18.41 ± 7.04	20.07 ± 9.61	19.00 ± 8.05	0.192	0.908	0.003

Note: M ± SD—mean ± standard deviation, H—Kruskal–Wallis H statistic, p—p-value, η^2—eta squared. * Win ≠ lose ($p < 0.05$).

The analysis of goalkeeping metrics also revealed significant differences regarding the match outcome (Table 5). Winning teams conceded fewer goals (M = 0.50, SD = 0.60) compared to drawing (M = 0.79, SD = 0.57) or losing teams (M = 2.18, SD = 1.01), with a notable effect size (H = 34.584, $p < 0.001$, η^2 = 0.48709). Similarly, winning teams had more clean sheets (M = 0.55, SD = 0.51, $p < 0.05$). Furthermore, own goals conceded were significantly lower in winning teams (M = 0.05, SD = 0.21) compared to losing teams (M = 0.23, SD = 0.43) (H = 6.033, p = 0.049, η^2 = 0.08497). While saves, saves from direct free kicks, and saves from penalties did not show significant differences, the overall trends suggest that better defensive performance, indicated by fewer goals conceded and more clean sheets, is associated with higher chances of winning. The analysis also showed non-significant differences in metrics such as claims, high claims, low claims, and punches made, implying these may not be strong indicators of match outcomes.

Table 5. Goalkeeping metrics and their impact on match outcomes.

Variable	Win (n = 22)	Draw (n = 28)	Lose (n = 22)	H	p	η^2
	M ± SD	M ± SD	M ± SD			
Goals conceded	0.50 ± 0.60	0.79 ± 0.57	2.18 ± 1.01	34.584	0.001 *†	0.487
Own goals conceded	0.05 ± 0.21	0.04 ± 0.19	0.23 ± 0.43	6.033	0.049	0.085
Clean sheets	0.55 ± 0.51	0.29 ± 0.46	0.00 ± 0.00	16.101	0.001 *‡	0.227
Saves	2.68 ± 1.94	3.32 ± 2.09	3.68 ± 1.99	1.753	0.416	0.025
Saves from direct free kicks	0.18 ± 0.40	0.07 ± 0.26	0.09 ± 0.29	1.628	0.443	0.023
Saves from penalties	0.05 ± 0.21	0.04 ± 0.19	0.00 ± 0.00	0.935	0.626	0.013
Claims	2.86 ± 1.73	2.14 ± 1.84	2.09 ± 1.23	3.119	0.210	0.044
High claims	1.41 ± 1.05	0.96 ± 1.20	1.14 ± 1.04	3.034	0.219	0.043
Low claims	1.45 ± 1.22	1.14 ± 1.21	0.95 ± 0.95	1.978	0.372	0.028
Punches made	0.45 ± 0.67	0.79 ± 1.03	0.55 ± 0.67	1.254	0.534	0.018

Note: M ± SD—mean ± standard deviation, H—Kruskal–Wallis H statistic, p—p-value, η^2—eta squared. * Win ≠ lose ($p < 0.05$); † win ≠ draw ($p < 0.05$); ‡ lose ≠ draw ($p < 0.05$).

The analysis of disciplinary metrics indicated no significant differences across match outcomes for yellow cards, red cards, fouls committed, fouls committed in the defensive third, and fouls committed in own half, as shown in Table 6.

Table 6. Disciplinary metrics and their impact on match outcomes (win, draw, lose).

Variable	Win (n = 22)	Draw (n = 28)	Lose (n = 22)	H	p	η^2
	M ± SD	M ± SD	M ± SD			
Yellow cards	2.23 ± 2.22	2.36 ± 1.45	2.09 ± 1.74	1.108	0.575	0.016
Red cards	0.00 ± 0.00	0.00 ± 0.00	0.14 ± 0.47	4.609	0.100	0.065
Fouls committed	11.00 ± 3.35	11.04 ± 3.21	11.68 ± 3.79	0.303	0.860	0.004
Fouls committed in defensive third	1.59 ± 0.91	2.00 ± 1.19	1.95 ± 1.62	1.380	0.502	0.019
Fouls committed in own half	4.09 ± 2.16	4.43 ± 1.95	5.09 ± 2.47	1.480	0.477	0.021

Note: M ± SD—mean ± standard deviation, H—Kruskal–Wallis H statistic, p—p-value, η^2—eta squared.

The logistic regression model was applied to predict the outcome of soccer matches as either a win or no-win (draw/lose). The model summary indicates that the final model achieved a −2 log likelihood of 61.919. The Cox and Snell R^2 and Nagelkerke R^2 values were 0.310 and 0.438, respectively, suggesting a moderate fit of the model. Notably, the model could classify 80.6% of the cases correctly. Specifically, the variable "Attempts on target" significantly positively affected the likelihood of winning (B = 1.037, S.E. = 0.320, Wald = 10.507, p = 0.001), with an odds ratio of 2.821. "Passes into attacking third" also indicated a positive effect (B = 0.056, S.E. = 0.027, Wald = 4.361, p = 0.037), with an odds ratio of 1.058. Finally, the variables "Attempts on target outside area" and "Crosses attempted" had a significant negative effect (B = −1.206, S.E. = 0.485, Wald = 6.193, p = 0.013) with an odds ratio of 0.299 and (B = −0.173, S.E. = 0.062, Wald = 7.690, p = 0.006), with an odds ratio of 0.841, respectively (Table 7). These findings highlight that increasing attempts on target and passes into the attacking third significantly enhances the chances of winning. In contrast, attempts on target outside the area and crosses attempted are negatively associated with winning.

Table 7. Binary logistic regression analysis results for the key predictors of match outcome (win/lose).

Variable	B	S.E.	Wald	p	Exp(B)	95% CI for Exp(B)	
						Lower	Upper
On target outside area	−1.206	0.485	6.193	0.013 *	0.299	0.116	0.774
Passes into attacking third	0.056	0.027	4.361	0.037 *	1.058	1.003	1.116
Attempts on target	1.037	0.320	10.507	0.001 *	2.821	1.507	5.280
Crosses attempted	−0.173	0.062	7.690	0.006 *	0.841	0.744	0.950
Constant	−2.726	0.959	8.075	0.004 *	0.065		

* $p < 0.05$.

4. Discussion

The analysis of UEFA Euro 2024 revealed several key findings regarding goal-scoring patterns and match outcomes. Firstly, the study's findings indicate that scoring the first goal significantly impacts match outcomes, confirming existing literature that suggests early scoring enhances match success [15,17,20]. Specifically, teams that scored first were less likely to lose and more likely to win or draw. While this study did not directly analyze opponents' tactical adjustments after conceding the first goal, it is well recognized that teams often alter their strategies, either by opening their defense to equalize or by increasing their offensive pressure, as indicated in studies of previous UEFA European Championships [16,18]. The history of scoring the first goal is a well-established predictor of success, with studies across multiple UEFA EURO Championships consistently showing that teams scoring first have a higher likelihood of winning the match [17,20]. Moreover,

although this study did not specifically measure the impact of fan support, prior research suggests that crowd presence could also positively influence team performance and create a psychologically challenging environment for the opposing team [34].

Secondly, the analysis of the 82 goals scored in the 36 matches from the group stage of EURO 2024 showed no significant association between goals scored in the first (39 goals) and second halves (43 goals), indicating independent goal distribution across these periods, similarly to Michailidis et al. [17], who also observed more goals in the second half but no significant association. While no relationship was found between the timing of the first goal and match outcomes in this study, it is generally advantageous to score early to control the game's pace and force opponents into a reactive stance. However, the optimal timing may depend on the team's strategy and defensive capabilities, as seen in various UEFA tournaments [15,17]. Yiannakos and Armatas [15] found a significant difference in goal frequency across halves. Additionally, although the final interval (75–90 min) had the highest number of goals, the overall distribution did not deviate significantly in goals scored in the UEFA Euro 2024. This aligns with Tousios et al. [20], who found no significant differences in goal timing across intervals, but contrasts with Luhtanen et al. [14], who emphasized the importance of specific goal-scoring periods.

Thirdly, regarding performance metrics, winning teams scored significantly more goals per game (M = 2.18) than drawing or losing teams, emphasizing the importance of goal efficiency. This finding is consistent with studies that underscore the significance of offensive efficiency [14,15,19]. Additionally, winning teams had higher averages in "Goals Inside Area" and "Attempts on Target", confirming the critical role of shot quality and quantity in match success [15,21]. The importance of assists, with winners averaging 1.59 assists per game, highlights the value of team coordination and collaboration in creating scoring opportunities, supporting previous findings on the significance of team play [1,16,18,21,35–44]. It is also important to be mentioned that previous analyses have demonstrated that key players also play a critical role in match-defining moments, particularly in high-stakes tournaments like the UEFA European Championship [21].

Regarding the total distance covered in km, winning teams tend to cover more total distance on average (M = 114.28 $\pm$ 2.71 km), although this difference was not statistically significant. This suggests that while higher distance coverage may be a characteristic of winning teams, total distance covered was not decisive in determining match outcome in UEFA Euro 2024. Similar to previous research [45–50], examining the differences in distance covered among different running speed zones, player positions, or formations could provide deeper insights into the physical and tactical demands contributing to match outcomes.

Regarding ball possession and passing, winning teams demonstrated higher averages, with possession at 53.32% and passes completed at 453.05, suggesting that controlling the ball and effective distribution are essential for favorable outcomes. This aligns with studies emphasizing the importance of ball control and passing accuracy in achieving success [14,16,18,51]. Interestingly, the analysis also revealed that winning teams made more backward passes and maintained a higher average possession, suggesting a strategic element in their playstyle. This fact maybe indicates a strategic approach to maintaining possession and resetting play, reflecting modern tactical trends observed in elite soccer [14,16]. Over the last 20 years, soccer has seen a significant evolution in playing styles, characterized by a shift towards possession-based tactics, high pressing, and increased use of data analytics to optimize performance. This trend is well documented in studies analyzing tournaments from UEFA Euro 1996 to UEFA Euro 2020, where the importance of ball possession, passing accuracy, and offensive transitions has grown steadily [14–23].

Defensively, winning teams recovered significantly more balls (M = 38.91) compared to losing teams, illustrating the importance of regaining possession and disrupting opponents' plays. This finding is consistent with research highlighting the significance of defensive actions in soccer success [14,19]. Goalkeeping metrics also showed that winning teams conceded fewer goals (M = 0.50) and had more clean sheets (M = 0.55), underscoring the

importance of strong defensive and goalkeeping performance, which aligns with existing literature [14,18]. Although other goalkeeping metrics like saves and claims did not show significant differences, the overall trend suggests that preventing goals is vital for winning matches. Disciplinary metrics, including yellow cards, red cards, and fouls committed, did not show significant differences across match outcomes, suggesting that these factors may not be as influential in determining the final result of the matches during the UEFA Euro 2024. These significant differences observed in the metrics between teams highlight the critical role of overall team cooperation in achieving success. These findings emphasize the importance of a holistic analysis, incorporating attacking, distribution, goalkeeping, and disciplinary metrics, to gain a comprehensive understanding of the factors that contribute to team performance.

Lastly, the logistic regression model identified "Attempts on Target", "On Target Outside Area", "Passes into Attacking Third", and "Crosses Attempted" as significant predictors of match outcomes. These findings highlight that increasing attempts on target and passes into the attacking third significantly enhances the chances of winning. In contrast, attempts on target outside the area and crosses attempted are negatively associated with winning. This supports previous research identifying similar key performance indicators for predicting match success [14,21,22,25].

5. Conclusions

This study aimed to understand the factors influencing match outcomes in UEFA Euro 2024, offering valuable insights into match performance and extending the aspects of existing literature. Firstly, the analysis confirmed that scoring the first goal significantly impacts match outcomes, with teams scoring first being less likely to lose. This finding highlights the strategic importance of early scoring, which can dictate game control and force opponents into a reactive stance. Secondly, the study revealed that winning teams demonstrate superior offensive efficiency, marked by higher averages in attempts on target and assists. These metrics underscore the importance of creating and capitalizing on scoring opportunities through coordinated team efforts and precise shot selection. Thirdly, the analysis of ball possession and passing metrics emphasized the strategic role of effective distribution in match success. Winning teams tended to have higher possession and passing accuracy, particularly through backward passes, reflecting a modern approach focused on maintaining control and resetting play. Defensively, the study showed that winning teams excel in recovering possession and preventing goals, reinforcing the need for a balanced approach that integrates both offensive prowess and defensive resilience. Furthermore, the logistic regression model identified key predictors of match outcomes, such as attempts on target and passes into the attacking third, which significantly enhance the likelihood of winning. Conversely, crosses attempted and attempts on target outside the area were negatively associated with winning, emphasizing the importance of shot quality and tactical decision making.

In summary, this research offers a holistic analysis of match performance, incorporating attacking, distribution, goalkeeping, and disciplinary metrics to provide a comprehensive understanding of the factors contributing to team success in elite soccer. The findings present actionable insights for coaching strategies, highlighting the need for a balanced approach that leverages both offensive and defensive strengths for optimizing team performance in elite tournaments like the UEFA European Championship.

Author Contributions: A.S., A.M. and T.I.M., designed the study and provided critical feedback on the manuscript; A.S. and Y.M., collected and processed. A.S. and Y.M. analyzed data. A.S., A.M. and Y.M. revised the first draft; A.S. and Y.M. conducted the statistical analysis. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Guimarães, J.P.A.; Rochael, M.; de Andrade, A.G.P.; Bredt, S.G.; Praça, G.M. How reaching the pitch's final third is related to scoring opportunities in soccer? *Retos Nuevas Tend. En Educ. Física Deporte Y Recreación* **2022**, *43*, 171–176.
2. Carling, C.; Williams, A.M.; Reilly, T. *Handbook of Soccer Match Analysis: A Systematic Approach to Improving Performance*; Routledge: London, UK, 2007. [CrossRef]
3. Peixoto, D.; Praça, G.M.; Bredt, S.; Clemente, F.M. Comparison of network processes between successful and unsuccessful offensive sequences in elite soccer. *Hum. Mov. Spec. Issues* **2017**, *18*, 48–54. [CrossRef]
4. Castellano, J.; Casamichana, D.; Lago, C. The use of match statistics that discriminate between successful and unsuccessful soccer teams. *J. Hum. Kinet.* **2012**, *31*, 137–147. [CrossRef]
5. Hughes, M.; Churchill, S. Attacking profiles of successful and unsuccessful teams in Copa America 2001. In *Science and Football V: The Proceedings of the Fifth World Congress on Science and Football*; Routledge: London, UK, 2005; pp. 219–224.
6. Hook, C.; Hughes, M.D. Patterns of play leading to shots in Euro 2000. In *Performance Analysis of Sport V*; UWIC: Cardiff, UK, 2001; pp. 295–302.
7. Hughes, M.; Franks, I. Analysis of passing sequences, shots and goals in soccer. *J. Sports Sci.* **2005**, *23*, 509–514. [CrossRef] [PubMed]
8. Jones, P.D.; James, N.; Mellalieu, S.D. Possession as a performance indicator in soccer. *Int. J. Perform. Anal. Sport* **2004**, *4*, 98–102. [CrossRef]
9. Konefał, M.; Chmura, P.; Zacharko, M.; Baranowski, J.; Andrzejewski, M.; Błażejczyk, K.; Chmura, J. The influence of thermal stress on the physical and technical activities of soccer players: Lessons from the 2018 FIFA World Cup in Russia. *Int. J. Biometeorol.* **2021**, *65*, 1291–1298. [CrossRef]
10. Kubayi, A.; Toriola, A. Match performance indicators that discriminated between winning, drawing and losing teams in the 2017 AFCON Soccer Championship. *J. Hum. Kinet.* **2020**, *72*, 215–221. [CrossRef]
11. Stafylidis, A.; Mandroukas, A.; Papadopoulou, S.D.; Michailidis, Y.; Kyranoudis, A.; Gissis, I.; Metaxas, T. Analysis of game-related performance indicators in the Greek soccer league: Insights from the 2020–2021 season. *Trends Sport Sci.* **2024**, *31*, 1–4. [CrossRef]
12. Stafylidis, A.; Michailidis, Y.; Mandroukas, A.; Gissis, I.; Metaxas, T. Analysis of goal scoring and performance indicators in the 2020–2021 Greek soccer league. *J. Phys. Educ. Sport* **2022**, *22*, 91–99. [CrossRef]
13. Vergonis, A.; Michailidis, Y.; Mikikis, D.; Semaltianou, E.; Mavrommatis, G.; Christoulas, K.; Metaxas, T. Technical and tactical analysis of goal scoring patterns in the 2018 FIFA World Cup in Russia. *Facta Univ. Ser. Phys. Educ. Sport* **2019**, *17*, 181–193. [CrossRef]
14. Luhtanen, P.; Belinskij, A.; Häyrinen, M.; Vänttinen, T. A comparative tournament analysis between the EURO 1996 and 2000 in soccer. *Int. J. Perform. Anal. Sport* **2001**, *1*, 74–82. [CrossRef]
15. Yiannakos, A.; Armatas, V. Evaluation of the goal scoring patterns in European Championship in Portugal 2004. *Int. J. Perform. Anal. Sport* **2006**, *6*, 178–188. [CrossRef]
16. Maneiro, R.; Casal, C.A.; Álvarez, I.; Moral, J.E.; López, S.; Ardá, A.; Losada, J.L. Offensive transitions in high-performance football: Differences between UEFA Euro 2008 and UEFA Euro 2016. *Front. Psychol.* **2019**, *10*, 1230. [CrossRef]
17. Michailidis, Y.; Michailidis, C.; Primpa, E. Analysis of goals scored in European Championship 2012. *J. Hum. Sport Exerc.* **2013**, *8*, 367–375. [CrossRef]
18. Winter, C.; Pfeiffer, M. Tactical metrics that discriminate winning, drawing and losing teams in UEFA Euro 2012®. *J. Sports Sci.* **2016**, *34*, 486–492. [CrossRef]
19. Muhamad, S.; Norasrudin, S.; Rahmat, A. Differences in goal scoring and passing sequences between winning and losing team in UEFA-EURO Championship 2012. *Int. J. Humanit. Soc. Sci.* **2013**, *7*, 332–337.
20. Tousios, T.; Michailidis, Y.; Mandroukas, A.; Mikikis, D.; Metaxas, T. Differences in goal scoring and minutes of scoring between two European Championships, one among 16 teams (Euro 2012) and the other among 24 teams (Euro 2016). *Facta Univ. Ser. Phys. Educ. Sport* **2018**, *2018*, 365–373. [CrossRef]
21. Konefał, M.; Chmura, P.; Zacharko, M.; Chmura, J.; Rokita, A.; Andrzejewski, M. Match outcome vs match status and frequency of selected technical activities of soccer players during UEFA Euro 2016. *Int. J. Perform. Anal. Sport* **2018**, *18*, 568–581. [CrossRef]
22. de Amorim Mendes, M.H.; Rezende, V.H.S.; Praça, G.M. Association between goal-kick strategies and the offensive outcome in the UEFA Euro 2020. *Hum. Mov.* **2020**, *24*, 125924. [CrossRef]
23. Fedrizzi, G.; Canal, L.; Micciolo, R. UEFA EURO 2020: An exciting match between football and probability. *Teach. Stat.* **2022**, *44*, 119–125. [CrossRef]
24. Plakias, S.; Moustakidis, S.; Kokkotis, C.; Papalexi, M.; Tsatalas, T.; Giakas, G.; Tsaopoulos, D. Identifying soccer players' playing styles: A systematic review. *J. Funct. Morphol. Kinesiol.* **2023**, *8*, 104. [CrossRef]

25. Stafylidis, A.; Mandroukas, A.; Michailidis, Y.; Vardakis, L.; Metaxas, I.; Kyranoudis, A.E.; Metaxas, T.I. Key Performance Indicators Predictive of Success in Soccer: A Comprehensive Analysis of the Greek Soccer League. *J. Funct. Morphol. Kinesiol.* **2024**, *9*, 107. [CrossRef]
26. Harrop, K.; Nevill, A. Performance indicators that predict success in an English professional League One soccer team. *Int. J. Perform. Anal. Sport* **2014**, *14*, 907–920. [CrossRef]
27. Kite, C.S.; Nevill, A. The predictors and determinants of inter-seasonal success in a professional soccer team. *J. Hum. Kinet.* **2017**, *58*, 157–167. [CrossRef]
28. Moura, F.A.; Santana, J.E.; Vieira, N.A.; Santiago, P.R.P.; Cunha, S.A. Analysis of soccer players' positional variability during the 2012 UEFA European championship: A case study. *J. Hum. Kinet.* **2015**, *47*, 225–236. [CrossRef] [PubMed]
29. SPSS, I. *Corp Ibm SPSS Statistics for Windows, version 26.0*; IBM Corp: Armonk, NY, USA, 2018.
30. Cohen, J. Statistical power analysis. *Curr. Dir. Psychol. Sci.* **1992**, *1*, 98–101. [CrossRef]
31. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*; Routledge: New York, NY, USA, 2013. [CrossRef]
32. Faul, F.; Erdfelder, E.; Buchner, A.; Lang, A.G. Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behav. Res. Methods* **2009**, *41*, 1149–1160. [CrossRef] [PubMed]
33. Faul, F.; Erdfelder, E.; Lang, A.G.; Buchner, A. G* Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods* **2007**, *39*, 175–191. [CrossRef]
34. McCarrick, D.; Bilalic, M.; Neave, N.; Wolfson, S. Home advantage during the COVID-19 pandemic: Analyses of European football leagues. *Psychol. Sport Exerc.* **2021**, *56*, 102013. [CrossRef]
35. Zhou, C.; Zhang, S.; Lorenzo Calvo, A.; Cui, Y. Chinese soccer association super league, 2012–2017: Key performance indicators in balance games. *Int. J. Perform. Anal. Sport* **2018**, *18*, 645–656. [CrossRef]
36. Lago-Peñas, C.; Lago-Ballesteros, J.; Dellal, A.; Gómez, M. Game-related statistics that discriminated winning, drawing and losing teams from the Spanish soccer league. *J. Sports Sci. Med.* **2010**, *9*, 288. [PubMed]
37. Lago-Peñas, C.; Lago-Ballesteros, J. Game location and team quality effects on performance profiles in professional soccer. *J. Sports Sci. Med.* **2011**, *10*, 465. [PubMed]
38. Rodenas, J.G.; Malavés, R.A.; Desantes, A.T.; Ramírez, E.S.; Hervás, J.C.; Malavés, R.A. Past, present and future of goal scoring analysis in professional soccer. *Retos Nuevas Tend. En Educ. Física Deporte Y Recreación* **2020**, *37*, 774–785. [CrossRef]
39. Michailidis, Y.; Nenos, I.; Metaxas, I.; Mandroukas, A.; Metaxas, T. Correlations of passes and playing formations with technical-tactical elements during the 2022 FIFA World Cup. *J. Sports Med. Phys. Fit.* **2023**, *63*, 1309–1316. [CrossRef]
40. Cao, S. Passing path predicts shooting outcome in football. *Sci. Rep.* **2024**, *14*, 9572. [CrossRef]
41. Paixão, P.; Sampaio, J.; Almeida, C.H.; Duarte, R. How does match status affects the passing sequences of top-level European soccer teams? *Int. J. Perform. Anal. Sport* **2015**, *15*, 229–240. [CrossRef]
42. Pulling, C.; Eldridge, D.; Ringshall, E.; Robins, M.T. Analysis of crossing at the 2014 FIFA World Cup. *Int. J. Perform. Anal. Sport* **2018**, *18*, 657–677. [CrossRef]
43. Redwood-Brown, A. Passing patterns before and after goal scoring in F.A. Premier League Soccer. *Int. J. Perform. Anal. Sport* **2008**, *8*, 172–182. [CrossRef]
44. Kyranoudis, E.; Papadimitriou, K.; Kyranoudis, A.; Giannakopoulos, A.; Konstantinidou, X. Final pass and its relationship with final action for the creation of goal-scoring opportunities at EURO 2020. *J. Hum. Sport Exerc.* **2024**, *19*, 499–509. [CrossRef]
45. Ponce-Bordón, J.C.; López-Gajardo, M.A.; Lobo-Triviño, D.; Pulido, J.J.; García-Calvo, T. Longitudinal match running performance analysis of soccer in professional European leagues: A systematic review. *Int. J. Perform. Anal. Sport* **2024**, 1–25. [CrossRef]
46. Metaxas, T.I. Match running performance of elite soccer players: VO2max and players position influences. *J. Strength Cond. Res.* **2021**, *35*, 162–168. [CrossRef] [PubMed]
47. Plakias, S.; Michailidis, Y. Factors Affecting the Running Performance of Soccer Teams in the Turkish Super League. *Sports* **2024**, *12*, 196. [CrossRef] [PubMed]
48. Silva, H.; Nakamura, F.Y.; Loturco, I.; Ribeiro, J.; Marcelino, R. Analyzing soccer match sprint distances: A comparison of GPS-based absolute and relative thresholds. *Biol. Sport* **2024**, *41*, 223–230. [CrossRef] [PubMed]
49. Morgans, R.; Orme, P.; Bezuglov, E.; Di Michele, R. Technical and physical performance across five consecutive seasons in elite European Soccer. *Int. J. Sports Sci. Coach.* **2023**, *18*, 839–847. [CrossRef]
50. Modric, T.; Versic, S.; Stojanovic, M.; Chmura, P.; Andrzejewski, M.; Konefał, M.; Sekulic, D. Factors affecting match running performance in elite soccer: Analysis of UEFA Champions League matches. *Biol. Sport* **2022**, *40*, 409–416. [CrossRef]
51. Vantarakis, A.; Stafylidis, A. Attributes of crosses and their impact on goal scoring in soccer leagues. *J. Phys. Educ. Sport* **2023**, *23*, 3084–3090. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.