

Longitudinal analysis of performance indicators in winning and losing teams in rugby union

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Abstract:

Analyzing performance indicators in rugby is essential for improving training programs and optimizing team strategies. A key method involves comparing these indicators between winning and losing teams to identify factors critical to success. However, much of the existing research tends to focus on single tournaments or short periods, lacking a systematic examination of long-term trends. This study analyzes performance indicator trends of winning and losing teams in English Premiership Rugby over multiple competitive seasons. Data from 1,001 matches spanning eight full seasons (2016–17 to 2023–24) were analyzed. Absolute (e.g., Score, Tries, Meters Run, Offloads, Turnovers Conceded) and relative (e.g., success rates for rucks, mauls, scrums, lineouts, tackles) indicators were recorded for winning and losing teams. Statistical methods included descriptive statistics, Mann–Whitney U test, Cohen’s d effect size, and linear regression analysis to identify significant differences and trends. Results revealed that scoring actions (Score, Tries, Conversions) were the most significant indicators consistently differentiating winning from losing teams over the eight seasons, demonstrating high statistical significance and large effect sizes (Cohen’s d = 1.0–1.6). Meters Run was also consistently higher for winning teams (significant in 7/8 seasons), while Turnovers Conceded were consistently higher for losing teams (significant in 6/8 seasons). Notably, a statistically significant increasing trend in the difference for Offloads between winning and losing teams was observed over the analyzed period ($R^2=0.71$, $p<0.05$). Some indicators, like Total Lineouts, showed no consistent differences across all seasons. This study identified both stable and evolving performance indicators that differentiate winning and losing teams in elite rugby over an extended period. The findings offer practical value for coaches, analysts, and sports scientists in strategic planning and highlight the dynamic evolution of the game, particularly the increasing importance of offloads, underscoring the need for continuous updates in training methods and performance monitoring systems.

Key Words: trends, rugby, performance analysis, team, English Premiership

Introduction.

In modern sport, particularly in team sports, the role of scientific analysis is becoming increasingly important. It serves as a key tool for enhancing the effectiveness of the training process, developing tactical models, and optimising managerial decisions (Bompa & Buzzichelli, 2015; Latyshev et al., 2017). Performance analysis enables coaches, analysts, and managers to make evidence-based decisions, thereby contributing to the improved competitiveness of teams (Korobeynikov et al., 2020). In sports games, where results depend on a wide range of interacting factors, performance analysis plays a vital role in both pre-match preparation and post-match review. This analytical approach is beneficial not only for immediate competitive performance but also for long-term strategic planning, the development of player pathways, and injury prevention strategies, as it facilitates a deeper understanding of game-specific demands (Fröhlich et al., 2009; Chéradame et al., 2024).

In recent years, performance analysis in sports games has advanced significantly due to the integration of digital technologies, automated data collection, and machine learning (Hughes & Bartlett, 2002; Kvasnytsya et al., 2024). These developments have enabled broader and deeper insights into team and player performance, including spatio-temporal patterns, decision-making processes, and player interactions (McGarry, 2009). Researchers have increasingly focused on comparing performances indicators between winning and losing teams (Korobeynikov et al., 2025). This line of analysis enables the identification of key performance metrics and the

main factors influencing match outcomes. Furthermore, this approach enables researchers not only to investigate cause-and-effect relationships between team actions and match outcomes but also to develop predictive models for future competitions (Bunker & Susnjak, 2022; Pastor et al., 2023). Such comparative analyses are essential for identifying the key determinants of success, providing clearer insights into the specific actions and strategies that consistently distinguish winning teams from losing ones (Brodani et al., 2023).

Previous research in rugby has mostly focused on individual tournaments or specific time periods. In particular, studies have often examined specific championships, such as the Six Nations or the English Premiership, without exploring the longitudinal changes in key indicators or identifying broader trends among winning and losing teams over an extended period (Ortega et al., 2009; Schoeman & Schall, 2019; Colomer et al., 2020). Although such focused analyses yield valuable insights into performance within specific contexts, they may fail to fully reflect the evolutionary dynamics of the sport, including shifts in tactical paradigms and the changing significance of particular skills across multiple seasons. Some works have concentrated on the performance indicators of a single team or have analysed only isolated matches, which limits the generalisability of the findings (Parmar et al., 2018; Scott et al., 2023).

Despite the availability of research on performance analysis in rugby, there remains a lack of systematic studies exploring long-term changes in team performance. Comparing performance indicators between winning and losing teams over multiple seasons enables the identification of stable indicators of success and provides insight into how these indicators evolve over time in response to shifts in playing strategies and tactical trends. A longitudinal perspective is essential for developing robust performance models that consider the evolving nature of the sport and support the formulation of more adaptive and future-oriented coaching strategies (Wallace & Norton, 2014; Colomer et al., 2020). In related sports such as football and basketball, similar longitudinal and inter-tournament studies have already been conducted, revealing consistent predictors of team success (Wallace & Norton, 2014; Wunderlich & Memmert, 2021). Such a time-based approach offers a more comprehensive understanding of the factors that contribute to victory. Therefore, the relevance of this study lies in the need to examine the dynamics of performance in qualified rugby union (rugby-15) teams by comparing the indicators of winning and losing teams over the course of several competitive seasons.

The aim of this study is to analyze the trends in performance indicators of winning and losing teams in the English Premiership Rugby across multiple seasons

Material and methods

Data Performance indicator data for English Premiership Rugby teams were collected across eight full seasons, from 2016–17 to 2023–24. The dataset was compiled using web scraping techniques in Python from publicly available sources, including the official league websites (www.espn.com and www.premiershiprugby.com). A total of 1,001 matches were analyzed, representing 97.9% of all games played during this period. Twenty-one matches were excluded from the analysis due to draws, which prevented classification of teams into winners and losers.

The dataset includes performance indicators reflecting various aspects of match performance (Hopkins et al., 1999), such as scoring, attacking play, set-pieces, and defensive actions, recorded separately for winning and losing teams. The following indicators were analyzed: Score, Tries, Conversions, Meters Run, Passes, Clean Breaks, Offloads, Total Rucks, Total Mauls, Turnovers Conceded, Total Scrums, Total Lineouts, Total Tackles. All of these indicators are measured as the absolute number of actions performed by the team during a match. Additionally, five indicators were analyzed as percentages, reflecting the proportion of successful actions out of total attempts: Ruck Success Rate, Maul Success Rate, Scrum Success Rate, Lineout Success Rate, and Tackle Success Rate.

Data Analysis Procedures Descriptive statistics were calculated to compare the mean values of each performance indicator between winning and losing teams within each individual season. Both absolute and relative (percentage) differences were calculated to determine the magnitude of variation. To test the statistical significance of the differences in means, the Mann–Whitney U test was applied. The critical level of significance was set at $p < 0.05$. Additionally, Cohen's d effect size was computed to assess the magnitude of the observed differences. This allowed for the evaluation not only of statistical significance but also of the level of the differences. The interpretation of Cohen's d values followed established thresholds: < 0.2 – small effect, $0.2–0.5$ – moderate effect, and > 0.8 – large effect (Fröhlich et al., 2009).

To identify statistically significant variations across seasons in the differences between the performance indicators of winning and losing teams, a one-way analysis of variance (ANOVA) was conducted. This method enabled the detection of seasonal variability in performance differences. Furthermore, to examine long-term trends in the dynamics of performance indicators, linear regression analysis was employed. For each key indicator, a regression model was developed to estimate changes across the analysed seasons. Model quality was evaluated using the coefficient of determination (R^2), slope values, and statistical significance (p).

Data analysis and visualisation were conducted using Python (version 3.12.7). The following libraries were used: Pandas, NumPy, SciPy, Matplotlib, and Seaborn.

Results

The match outcome is determined by the number of points scored by the teams, making it the most essential performance indicator. Figure 1 illustrates the total points scored and the linear regression lines for the winning team, the losing team, and the difference between these values.

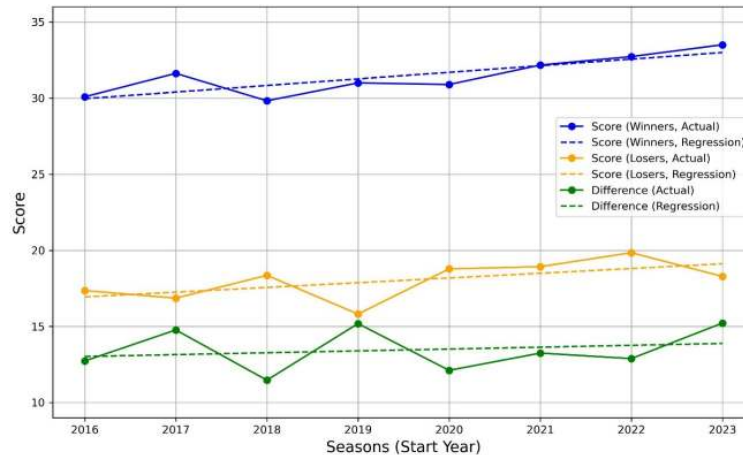


Fig.1. Match Score Trends and Linear Regression Lines for Winning and Losing Teams.

The conducted analysis revealed a statistically significant difference ($p < 0.05$) in the number of points scored between the winning and losing teams in each season (Table 1). The seasonal average difference in scores between the two teams ranged from 62.5% to 96.0%. However, no statistically significant variation in this difference across seasons was found ($p = 0.09$). Table 1 summarizes the analysis of key scoring and attacking performance indicators for both winning and losing teams across eight seasons.

Table 1. Scoring and Attacking Performance Indicators in Rugby Union

Indicators	Metric	Seasons								ANOVA (p)
		2016-17	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23	2023-24	
Score	A. D.	12.7	14.8	11.5	15.2	12.1	13.2	12.9	15.2	p=0.09
	P. D.	73.3	87.6	62.5	96.0	64.5	70.0	64.9	83.2	
	C. d	1.4	1.5	1.3	1.6	1.2	1.4	1.3	1.3	
	p	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	
Tries	A. D.	1.5	1.9	1.6	2.0	1.7	1.8	1.7	2.2	p=0.13
	P. D.	81.6	98.1	76.8	116.2	76.5	72.8	62.5	91.3	
	C. d	1.0	1.2	1.0	1.3	1.0	1.1	1.0	1.2	
	p	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	
Conversion	A. D.	1.4	1.6	1.3	1.6	1.4	1.4	1.4	1.6	p=0.48
	P. D.	101.2	126.3	85.6	137.2	87.4	84.6	74.6	100.7	
	C. d	1.0	1.2	0.9	1.2	1.0	1.0	1.0	1.1	
	p	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05	
Meters Run	A. D.	47.7	63.7	42.3	70.7	59.9	25.5	37.6	98.9	p<0.05
	P. D.	12.6	15.9	10.9	22.3	17.2	6.5	9.6	26.1	
	C. d	0.4	0.5	0.4	0.6	0.5	0.2	0.3	0.7	
	p	<0.05	<0.05	<0.05	<0.05	<0.05	0.26	<0.05	<0.05	
Passes	A. D.	-4.9	1.8	-7.4	4.9	-2.4	-11.5	-5.8	-2.1	p=0.44
	P. D.	-3.3	1.1	-4.6	3.7	-1.7	-7.9	-4.0	-1.4	
	C. d	-0.1	0.0	-0.2	0.1	-0.1	-0.3	-0.1	0.0	
	p	0.36	0.46	0.14	0.51	0.49	<0.05	0.17	0.44	
Clean Breaks	A. D.	1.8	2.4	2.1	2.1	1.7	1.5	1.2	2.2	p=0.71
	P. D.	25.3	28.7	25.8	32.1	21.0	32.3	28.3	46.8	
	C. d	0.4	0.5	0.5	0.4	0.3	0.5	0.5	0.7	
	p	<0.05	<0.05	<0.05	<0.05	0.06	<0.05	<0.05	<0.05	
Offload	A. D.	-0.2	-0.1	-0.4	0.8	0.6	0.2	1.1	1.6	p=0.12
	P. D.	-1.9	-1.4	-5.2	12.7	8.1	2.7	17.3	25.2	
	C. d	0.0	0.0	-0.1	0.2	0.1	0.0	0.3	0.4	
	p	0.87	0.88	0.37	0.15	0.18	0.68	0.06	0.05	

Note. A.D. – Absolute Difference; P.D. – Percentage Difference; C.d – Cohen's d (effect size); p – p-value from Mann-Whitney U test for each season; final p-value (right column) – result of one-way ANOVA across seasons.

The summarized results presented in Table 1 reveal a consistent and statistically significant advantage for winning teams in key scoring indicators, such as Score, Tries, and Conversion Goals, with large effect sizes (Cohen's $d = 1.0$ – 1.6) observed across most seasons. The Meters Run indicator also consistently favored winning teams, although it showed a moderate effect size (Cohen's $d = 0.2$ – 0.7) and only periodic statistical significance, suggesting variability in its impact. In contrast, the Passes and Offload indicators demonstrated lower stability in both the direction and magnitude of differences. Notably, Passes occasionally showed negative differences in certain seasons, indicating an ambiguous relationship between the number of passing and match outcome. The Clean Breaks indicator exhibited a generally positive trend with moderate effect sizes, while Offload showed a tendency toward increasing differences in the final seasons, potentially indicating its growing role in attacking play.

Table 2 presents a comparative analysis of team performance indicators in rugby union related to lineouts, scrums, mauls, rucks, and defensive actions (tackles and turnovers). The data cover eight seasons (2016–2024) and include average differences between winning and losing teams across these set-piece and defensive performance variables.

Table 2. Set-Piece and Defensive Performance Indicators in Rugby Union

Indicators	Metric	Seasons								ANOVA (p)
		2016-17	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23	2023-24	
Total Rucks	A. D.	-1.2	3.1	-3.7	2.6	1.7	-7.0	-4.6	-1.0	p=0.21
	P. D.	-1.3	3.2	-3.8	3.1	2.0	-8.0	-5.1	-1.1	
	C. d	-0.1	0.1	-0.2	0.1	0.1	-0.3	-0.2	-0.1	
	p	0.45	0.31	0.37	0.31	0.48	<0.05	0.06	0.74	
Total Mauls	A. D.	0.6	1.3	0.8	0.7	1.1	0.9	0.1	0.9	p=0.48
	P. D.	17.2	29.8	19.4	13.7	19.5	15.4	2.2	18.0	
	C. d	0.2	0.5	0.3	0.3	0.4	0.3	0.0	0.3	
	p	0.41	<0.05	<0.05	<0.05	<0.05	<0.05	0.61	0.07	
Total Scrums	A. D.	0.5	0.3	0.5	0.2	-0.1	1.1	0.7	0.3	p=0.31
	P. D.	8.8	4.3	7.3	3.5	-1.3	18.0	11.5	4.6	
	C. d	0.2	0.1	0.2	0.1	0.0	0.4	0.2	0.1	
	p	<0.05	0.33	0.07	0.38	0.73	<0.05	0.16	0.36	
Total Lineouts	A. D.	0.17	0.66	0.27	0.27	0.31	0.59	-0.22	-0.31	p=0.90
	P. D.	1.25	5.29	2.25	2.02	2.25	4.33	-1.54	-2.15	
	C. d	0.04	0.17	0.08	0.06	0.08	0.15	-0.06	-0.08	
	p	0.99	0.19	0.53	0.71	0.53	0.14	0.41	0.57	
Total Tackles	A. D.	-3.1	-9.3	3.3	-9.6	-6.4	10.7	8.0	0.3	p=0.06
	P. D.	-2.2	-5.4	2.0	-6.2	-4.1	7.4	5.2	0.2	
	C. d	-0.1	-0.2	0.1	-0.2	-0.2	0.3	0.2	0.0	
	p	0.59	0.07	0.79	<0.05	0.08	<0.05	<0.05	0.70	
Turnovers Conceded	A. D.	-1.1	-1.4	-0.8	-1.4	-0.7	-1.3	-1.2	-1.5	p=0.89
	P. D.	-7.7	-9.4	-5.4	-10.0	-5.4	-9.1	-8.6	-10.5	
	C. d	-0.3	-0.4	-0.2	-0.4	-0.2	-0.4	-0.3	-0.4	
	p	<0.05	<0.05	0.09	<0.05	0.23	<0.05	<0.05	<0.05	

Note. A.D. – Absolute Difference; P.D. – Percentage Difference; C.d – Cohen's d (effect size); p – p-value from Mann–Whitney U test for each season; final p-value (right column) – result of one-way ANOVA across seasons.

Across all analyzed seasons, a advantage of winning teams was observed in most indicators related to set-piece play. Specifically, the number of total mauls, lineouts, and scrums demonstrated a consistently positive absolute difference in the majority of seasons, highlighting the effective use of these elements for gaining competitive advantage. At the same time, certain defensive indicators, such as Total Tackles, were higher in losing teams during several seasons. A similar pattern was observed for Total Rucks, where the advantage between winning and losing teams fluctuated across seasons. Additionally, Turnovers Conceded emerged as a consistently unfavorable indicator for losing teams: the number of lost possessions was steadily higher among the teams that were defeated.

Table 3. Success Rates in Rugby Union

Indicators	Metric	Seasons								ANOVA (p)
		2016-17	2017-18	2018-19	2019-20	2020-21	2021-22	2022-23	2023-24	
Win Rucks	A. D.	-0.99	3.69	-3.39	2.99	1.80	-6.10	-4.23	-1.11	p=0.22
	P. D.	-1.15	3.92	-3.59	3.73	2.18	-7.28	-4.91	-1.34	
	C. d	-0.04	0.15	-0.15	0.15	0.09	-0.29	-0.20	-0.06	
	p	0.53	0.21	0.42	0.24	0.45	<0.05	0.06	0.70	
Win Mauls	A. D.	0.5	1.2	0.6	0.8	1.3	1.0	0.4	1.1	p=0.51
	P. D.	17.5	31.0	16.2	18.9	26.3	19.2	6.2	23.3	
	C. d	0.1	0.5	0.3	0.3	0.5	0.3	0.1	0.4	
	p	0.4	<0.05	0.1	<0.05	<0.05	<0.05	0.3	<0.05	
Win Scrum	A. D.	0.66	0.28	0.46	0.29	0.20	1.03	0.83	0.59	p=0.44
	P. D.	12.85	4.47	7.53	4.76	3.51	21.02	17.30	12.33	
	C. d	0.29	0.11	0.18	0.12	0.08	0.47	0.33	0.26	
	p	<0.05	0.36	0.07	0.27	0.57	<0.05	<0.05	0.11	
Win Lineouts	A. D.	0.48	1.07	0.75	0.65	0.67	0.52	0.10	0.15	p=0.90
	P. D.	4.08	9.86	7.26	5.70	5.55	4.31	0.78	1.25	
	C. d	0.14	0.30	0.22	0.17	0.18	0.15	0.03	0.05	
	p	0.47	<0.05	0.07	0.19	0.13	0.11	0.99	0.76	
Successful Tackles	A. D.	-0.44	-6.02	4.68	-6.53	-3.51	10.85	8.99	4.10	p=0.08
	P. D.	-0.36	-4.09	3.26	-4.87	-2.65	8.73	6.90	3.12	
	C. d	-0.01	-0.15	0.12	-0.19	-0.11	0.30	0.25	0.12	
	p	0.92	0.22	0.54	0.13	0.19	<0.05	<0.05	0.32	

Note. A.D. – Absolute Difference; P.D. – Percentage Difference; C.d – Cohen’s d (effect size); p – p-value from Mann–Whitney U test for each season; final p-value (right column) – result of one-way ANOVA across seasons.

Over the eight analyzed seasons, winning teams consistently demonstrated an advantage in the percentage of set-pieces won, including mauls, scrums, and lineouts. The most notable difference was observed in the percentage of mauls won (Win Mauls). Statistically significant differences ($p < 0.05$) were found in the majority of seasons, with effect sizes (Cohen’s d) ranging from small to moderate (0.3–0.5), indicating the practical relevance of this indicator.

The percentage of scrums won was also consistently higher for the winning teams, with a notable advantage, particularly in the 2021–22 and 2022–23 seasons (Cohen’s d = 0.47 and 0.33, respectively). The Win Lineouts indicator was likewise more frequently in favor of the winning teams, although the differences were less pronounced. In most seasons, the effect size was small (Cohen’s d < 0.3), and a statistically significant difference was observed only in the 2017–18 season.

It is worth noting that the percentage of rucks won did not show a consistent advantage for the winning teams. In some seasons, losing teams even achieved better results, particularly in 2018–19, 2021–22, and 2022–23.

Discussion.

A comparative analysis of performance indicators between winning and losing rugby teams represents a key direction in applied research within the field of sports analytics. Such studies help identify the indicators that most significantly influence match outcomes and overall competition results, providing a foundation for strategic planning in team preparation. A number of scholarly works (Jones et al., 2004; Ortega et al., 2009; Hughes et al., 2017) have analyzed large datasets from high-level competitions in order to determine statistically significant differences between winning and losing teams. These authors employed both general descriptive statistical approaches and more specific methods, depending on the aims of the research. In their systematic review, Colomer et al. (2020) emphasized that in order to draw valid conclusions, researchers should focus on the stability of effects rather than results from isolated tournaments.

The most critical indicator that clearly differentiates teams is the number of points scored, which ultimately determines the match outcome. Over the course of eight seasons (2016/17 – 2023/24), there was a consistent and statistically significant difference ($p < 0.05$) between winning and losing teams, with a high level of significance (Cohen’s d > 1.2). The relative difference ranged between 62% and 96%. Similar conclusions were reported in studies by Moolman et al. (2021) and Kvasnytsya et al. (2024), which also confirmed the substantial importance of the Score. At the same time, some authors (e.g., Hughes et al., 2017) have noted that

evaluating performance solely based on points scored may be limited without considering the context of gameplay and accompanying performances indicators.

Significant attention in the research has also been devoted to the number of Tries and successful Conversion Goals. The analysis revealed consistently significant differences between winning and losing teams in all analyzed seasons. The effect sizes were large (Cohen's $d \approx 1.0-1.3$), indicating the consistent impact of these components of attacking play. Ortega et al. (2009) identified the number of tries as a decisive factor in international matches, while Hughes et al. (2017) emphasized the importance of successful conversions following tries. Therefore, based on our analysis and previous studies, it can be argued that Tries and Conversion Goals form the foundation of a high-level team's scoring strategy, directly influencing the final outcome.

One of the indicators that showed high consistency in differentiating between wins and losses was Meters Run – the total distance a team covers while carrying the ball. In our study, this indicator showed a statistically significant difference in 7 out of 8 seasons ($p < 0.05$), highlighting its substantial contribution to game performance. As an indicator of a team's territorial advancement, Meters Run is closely associated with dominance in play. In the study by Hughes et al. (2017), a similar trend was observed among elite men's teams, where the distance covered correlated with attacking effectiveness. Vaz et al. (2019), analyzing matches, also identified this metric as decisive in structuring attacking phases. Similar conclusions were presented in the systematic review by Colomer et al. (2020), which noted that Meters Run has strong predictive power; however, its effectiveness increases when combined with other indicators – such as the number of Line Breaks and Tackles Won. Thus, our findings support the existing scientific consensus regarding the importance of this metric as a key element of strategic advantage in matches.

Clean Breaks and Turnovers Conceded also demonstrated high discriminative potential. Over the analyzed period, Clean Breaks showed statistically significant differences in 7 out of 8 seasons, while Turnovers Conceded were significantly different in 6 out of 8 seasons, indicating the consistent role of both indicators in distinguishing between winning and losing teams. Clean Breaks reflect a team's ability to effectively penetrate the opposition's defense and create numerical superiority, often leading to try-scoring opportunities. In the study by Moolman et al. (2021), this indicator was identified as one of the most relevant predictors of success in rugby sevens. Similarly, Ortega et al. (2009) highlighted its importance as a predictor of successful attacks. As for Turnovers Conceded, numerous authors, including Kvasnytsya et al. (2024), have emphasized its importance for match outcomes. A reduction in turnovers is directly associated with a higher likelihood of winning, as it allows teams to avoid prolonged defensive phases and maintain possession in advantageous areas.

Interestingly, during the 2020/21 season, when the Clean Breaks indicator did not show a statistically significant difference (although the p -value = 0.06 was close to the threshold), other variables – Total Rucks, Win Rucks, and Passes – were found to be statistically significant. In this season, these three indicators became decisive for the first (and only) time over the eight-season period, which may suggest a shift in tactical emphasis. In certain studies (Bennett et al., 2020), Total Rucks, Win Rucks, and Passes are also considered important metrics that influence match outcomes. However, in most analyses, these indicators tend to have a less pronounced effect compared to those previously discussed (Colomer et al., 2020).

The indicators Total Mauls, Total Tackles, and Total Scrums showed statistically significant differences between winning and losing teams in only two out of eight seasons. This inconsistency suggests their limited discriminative potential in terms of influencing match outcomes at the elite competition level. Although these elements are integral parts of rugby's game structure, their impact on final results does not appear to be systematic (Colomer et al., 2020; Bunker & Spencer, 2020). A similar trend is observed for the relative indicators of won contests (Win Mauls, Win Tackles, Win Scrums), which demonstrated statistically significant differences only in individual seasons, without forming a clear pattern.

No statistically significant differences were observed across all seasons for the indicators Total Lineouts and Offload. The Win Lineouts indicator showed statistically significant differences in only one season, indicating its limited influence within the overall structure of a winning game. However, Offload revealed an interesting feature in the context of trend analysis: it was the only indicator for which a statistically significant increasing trend in the difference between winning and losing teams was recorded ($p < 0.05$). Over the eight seasons, the average difference increased by 1.8 units, the slope of the linear regression was 0.24, and the coefficient of determination was $R^2 = 0.71$. This may indicate a gradual rise in the importance of this indicator within the game model of successful teams. Considering that Offload enables the continuation of attack without entering a ruck phase, the increasing relevance of this indicator aligns well with the modern dynamic style of play.

Conclusion.

The analysis of technical and tactical performance indicators in rugby over eight seasons revealed consistent differences between teams that won and lost matches. The most significant indicators of victory were scoring actions – points scored, tries, and conversions – which demonstrated high statistical significance and a strong effect size (Cohen's $d = 1.0-1.6$). The Meters Run indicator also had a notable impact on match

outcomes, although with a slightly lower effect size. In contrast, certain actions – such as the number of passes – showed weak associations with game success. The results obtained have practical value for coaches, analysts, and sports scientists, as they highlight key performance indicators for game analysis and strategic planning. The identified trends, particularly the gradual rise in the importance of offloads, point to the dynamic evolution of the game, underscoring the need for continuous updates in training methods and performance monitoring systems.

Future research will focus on analyzing the trends of team performance indicators across different rugby championships to identify common patterns and optimize training strategies based on long-term competitive dynamics.

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