

# Do Rugby Union Teams Win Because They Run More? Total Distance and High-Speed Running Don't Predict Pro D2 Competition Points (2023–2025)

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## Headline

**P**redicting success in invasion game sports is notoriously complex. When investigating the association between match outcomes and running activity, a fundamental flaw emerges: success is built on performing sport-specific actions effectively, all of which naturally produce running as a byproduct (Diez et al., 2021, Bradley et al., 2018). Running itself should not be seen as a strategic objective but rather a consequence of game actions (Carling, 2013; Mandorino et al., 2025). Unfortunately, sports science has often prioritized what can be measured over what is truly impactful, leading to a misplaced focus on running as a key performance indicator (KPI) (Mandorino et al., 2025).

Growing evidence suggests that running metrics have little to no direct association with match outcomes in team sports as soccer (Buchheit et al., 2018; Hoppe et al., 2015; Oliva-Lozano et al., 2023; Teixeira et al., 2021) and rugby league (Hulin et al., 2015). These findings align with the notion that match running performance is primarily influenced by tactical decisions, opposition behavior, and evolving game dynamics (Bradley et al., 2011; Paul et al., 2015; Ju et al., 2023). These multifactorial situations, within a constantly variable game context, make running a questionable predictor of success. Carling et al. (2010) showed an increase in running activity following the occurrence of a red card, indicating that teams playing with a numerical disadvantage tend to exhibit higher physical outputs. Furthermore, changes in physical capacities have not been shown to systematically predict changes in match running performance (Buchheit & Mendez-Villanueva, 2014; Byrkjedal et al., 2024). In rugby union, total distance (TD) and high-speed running (HSR) metrics are routinely monitored and sometimes treated as indicators for team training prescription. (Duthie, 2006; Higham et al., 2012). While these metrics provide valuable information about match demands and load exposure (Dubois et al., 2017, Cunningham et al., 2018), their relationship to match outcomes, particularly when expressed as competition points, remains poorly understood or unexplored. Unlike football's simple win/draw/loss outcomes, rugby employs a nuanced points system: win (4 points), draw (2 points), loss (0 points), plus defensive bonus points (+1) for losing by  $\leq 7$  or 5 points and offensive bonus (varies by competition).

## Aim

This study aimed to test whether team total distance and high-speed running distance discriminate between rugby match out-

comes when expressed as competition points bands (0 / 1-2 / 4+ points) in French Pro D2 across the 2023-2025 seasons.

## Methods

### Subjects

This retrospective observational study analyzed 60 Pro D2 (French second-tier professional rugby union competition) regular season matches from the 2023/2024 & 2024/2025 seasons under the same coaching staff with a similar game plan, resulting in 29 wins, 2 draws, and 29 losses. All data were generated through routine GPS monitoring processes. The dataset contained only team-level aggregated data with no directly identifiable athlete information. Therefore, formal ethical approval was not required (Winter & Maughan, 2009). The study was conducted in accordance with the Declaration of Helsinki.

### Outcome Variable: Competition Points Bands

Match outcomes were first coded using standard rugby scoring (win = 4 points, draw = 2 points, loss = 0 points, defensive bonus = +1 point when losing by  $\leq 5$  points in this dataset). Competition points were then grouped into three ordered outcome bands. The 0 points band (n=21) represented losses without defensive bonus. The 1-2 points band (n=10) captured defensive bonus losses (1) or draws (2). The 4+ points band (n=29) represented wins (4 points). To avoid over-complicating the analysis, the offensive bonus point (obtained when scoring at least three more tries than the opponent in Top14 & ProD2) was ignored.

### Running Metrics

Two team-level running metrics were analyzed. Total distance (TD) was defined as total meters covered by the team across the match, summed across all players. High-speed running distance (HSR) was defined as cumulative distance above 18 km.h<sup>-1</sup>, consistent with commonly used absolute thresholds in rugby union GPS research (Reardon et al., 2015). Both metrics were extracted from routine GPS monitoring data collected during all matches.

Ball-in-play (BiP) time represents the effective duration in which players are exposed to locomotor and contact demands and is typically substantially lower than total match duration in elite rugby union (Pollard et al., 2018). Because ball-in-play time can influence match pace and total running volume

in rugby union, we also computed normalized variables (TD per minute of ball-in-play and HSR per minute of ball-in-play).

**Statistical Analysis**

Distributions of TD and HSR across competition points bands were visualized using box plots. Discrimination of points bands was first tested using multinomial logistic regression with a three-class outcome (0 / 1-2 / 4+ points), predictors standardized within cross-validation folds (z-score transformation), balanced class weighting to account for class imbalance, and 5-fold stratified cross-validation. To account for potential nonlinear relationships and interactions between running metrics and competition points, two additional tree-based ensemble methods were implemented: random forests and histogram-based gradient boosting, both using TD and HSR as predictors.

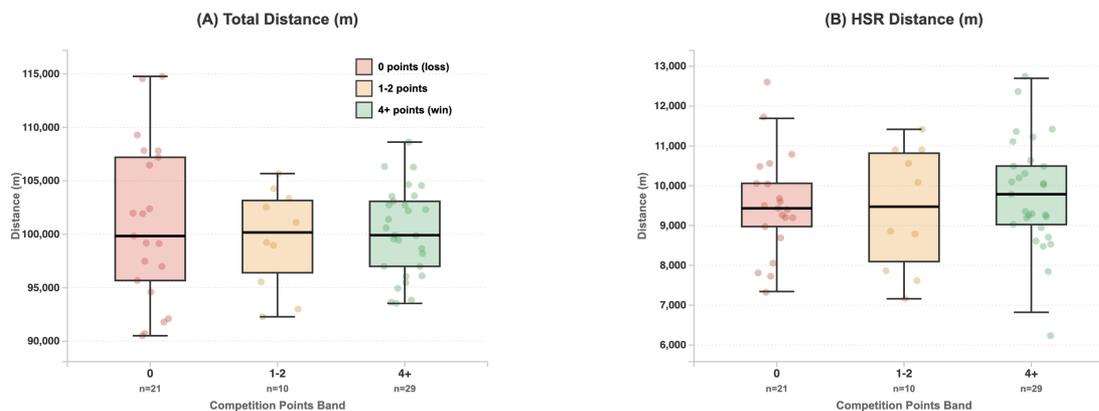
Across all model families, three sets of predictors were considered where applicable: total distance only, HSR distance only, and total distance + HSR distance combined. Performance was assessed using cross-validated accuracy, macro-F1 (macro-averaged F1 score), and log-loss (primary metric eval-

uating probability quality, with lower values indicating better calibrated probability predictions). A baseline model predicting only observed class proportions (no predictors) was computed to provide a minimal performance benchmark. All analyses were conducted in Python 3.9 using scikit-learn and pandas. Confusion matrices were aggregated across all cross-validation folds.

**Results**

Box plots revealed substantial overlap in both TD and HSR distance across the three competition points bands (Figure 1). Neither metric showed a consistent monotonic increase or decrease across points bands. The 1-2 points band showed particularly high variability and overlap with both 0 points and 4+ points outcomes, providing no clear running signature.

Like Figure 1, **Figure 2 shows substantial overlap in both TD & HSR z-scores across the three competition points bands**, with high match-to-match variability and no consistent pattern of higher (or lower) running outputs aligning with better point outcomes, suggesting **no clear running “signature” of match result**.



**Fig. 1.** Box plots of team (A) total distance and (B) high-speed running distance (distance accumulated above 18km/h, aggregated to team totals) across competition points bands (0 / 1-2 / 4+). Both metrics show substantial overlap across points bands with no consistent monotonic pattern. Individual match data points are shown with jittering to reduce overplotting.

The baseline model using only class proportions produced a log-loss of 1.017. Across all model families, none of the running-based models outperformed this baseline in terms of log-loss (Table 1). For the multinomial logistic regression models, the total distance only model produced accuracy = 0.18 (SD = 0.17), macro-F1 = 0.17, and log-loss = 1.144; the HSR distance only model produced accuracy = 0.38 (SD = 0.08), macro-F1 = 0.33, and log-loss = 1.117; and the total distance + HSR distance model produced accuracy = 0.30 (SD = 0.06), macro-F1 = 0.25, and log-loss = 1.160. When TD and HSR were entered together into nonlinear ensemble models, the random forest achieved higher discrimination (accuracy = 0.38 (SD = 0.14), macro-F1 = 0.31, log-loss = 1.212) than the multinomial model, while the HistGradientBoosting model reached accuracy = 0.43 (SD = 0.13), macro-F1 = 0.27, and log-loss = 1.179. However, the log-loss values for all running-based models remained higher than the baseline, indicating poorer probability calibration and limited practical predictive value.

Because the competition-points bands were imbalanced (0 points n=21, 1-2 points n=10, 4+ points n=29), raw accuracy should not be interpreted against a “33.3% chance” reference.

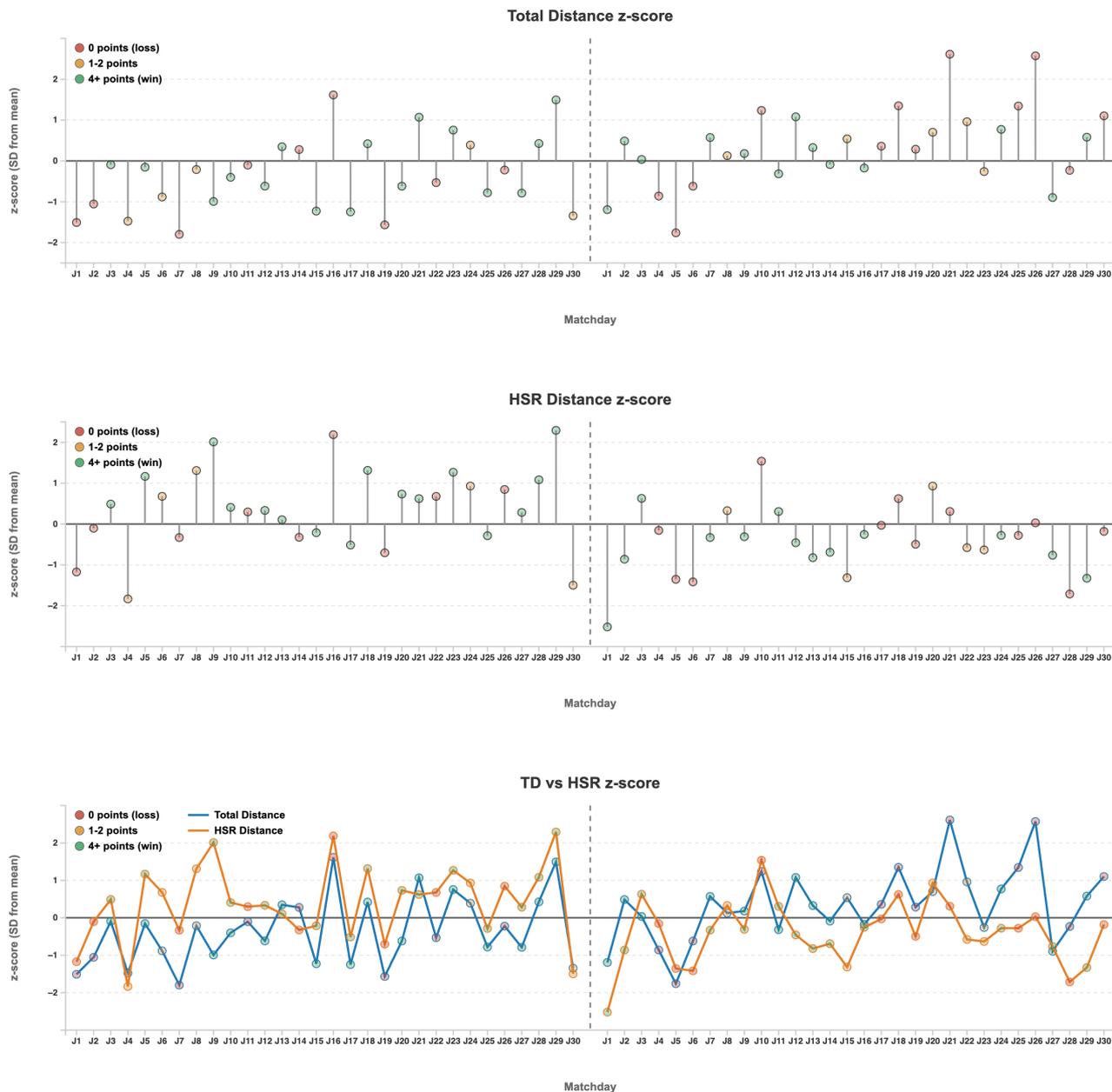
A naïve majority-class classifier that always predicts the most frequent outcome (4+ points) would achieve 29/60 = 0.48 accuracy in this sample. Accordingly, we emphasize log-loss as the primary indicator of practical predictive value and probability calibration; on this criterion, all running-based models produced higher log-loss than the class-proportion baseline (Table 1), indicating that TD/HSR did not improve calibrated prediction of competition points.

Aggregated confusion matrices (Figure 3) highlighted that misclassification was most pronounced for the 1-2 points band, with frequent confusion in both directions (toward 0 points and toward 4+ points). Practically, this suggests that match running volume and HSR exposure do not reliably separate tight outcomes (defensive bonus losses/draws) from either clear losses or wins, limiting the usefulness of TD/HSR as stand-alone indicators of competition-points performance.

Consistent with previous work showing that the BiP structure meaningfully shapes running intensity profiles and justifies expressing running demands relative to BiP (Pollard et al., 2018), these BiP-normalized metrics improved classification-based scores (accuracy and macro-F1), particularly for HSR/BiP. However, they did not improve proba-

bility quality, as cross-validated log-loss remained worse than the baseline model based on class proportions. Therefore, BIP normalization did not change the study’s main conclusion that

running metrics provide limited practical predictive value for competition points outcomes; for readability, we only present and discuss absolute TD and HSR in the main text.



**Fig. 2.** Match-by-match standardized running outputs (z-scores) for Total Distance (TD) (top) and High-Speed Running distance (middle) across the season, with each matchday plotted relative to the squad’s mean (0 line). Points are color-coded by competition points band, and the vertical dashed line indicates the split between the two competition blocks/halves of the season. The bottom panel overlays TD vs HSR z-scores, highlighting that the two metrics sometimes rise and fall together but also frequently diverge on the same matchday.

**Table 1. Cross-validated model performance for predicting competition points bands.**

Model	Predictors	CV Accuracy (SD)	CV Macro-F1	CV Log-loss
Baseline (class proportions)				1.017
Multinomial logistic	TD	0.18 (0.17)	0.17	1.144
Multinomial logistic	HSR	0.38 (0.08)	0.33	1.117
Multinomial logistic	TD & HSR	0.30 (0.06)	0.25	1.160
Random forest	TD & HSR	0.38 (0.14)	0.31	1.212
Hist Gradient Boosting	TD & HSR	0.43 (0.13)	0.27	1.179



**Fig. 3. Confusion matrices for multinomial logistic regression models predicting competition points bands from running metrics (5-fold cross-validation, aggregated across folds). Rows represent true class, columns represent predicted class. (A) Total distance only, (B) HSR distance only, (C) Total distance + HSR distance combined. All models showed poor discrimination, with particularly high misclassification rates for the 1–2 points band.**

### Discussion & Conclusion

This study examined whether team total distance and high-speed running distance discriminate rugby match outcomes when expressed as competition points bands. The key finding is unambiguous: running metrics failed to provide meaningful discrimination. Across model families, models using TD, HSR, or both combined did not improve probability calibration, with all running-based models producing higher log-loss than the no-information baseline that predicts class proportions.

### Running as Consequence, Not Cause

These results align with recent work demonstrating that match running outputs are strongly context-dependent and should not be treated as success KPIs without deeper tactical and performance context (Carling, 2013; Mandorino et al., 2025). Mandorino and colleagues (2025) demonstrated in professional football that running is better understood as a consequence of match demands than a direct determinant of success, and that observed relationships between running and outcomes should be interpreted as associative rather than causal. The present findings suggest this logic applies equally to rugby union competition points.

Teams may accumulate high running volumes for numerous reasons that do not predict success: defending extensively, chasing the game when trailing. None guarantees points. Conversely, teams may achieve victory through set-piece dominance or clinical finishing with controlled running outputs. The inability of HSR distance to explain competition points, even when using an individualized (relative) definition (Gabbett et al., 2015; Scott et al., 2018), reinforces this interpretation. Although this paper focuses on an absolute HSR threshold, we repeated the analyses with a relative threshold ( $\geq 70\%$  of individual top speed) led to the same conclusions. This sug-

gests that contextual and rugby-specific actions that generate running likely dominate the points story.

### Model Behaviour And Practical Predictability

While tree-based ensemble models (random forests, histogram-based gradient boosting) achieved higher accuracy and macro-F1 than multinomial logistic regression, their log-loss values remained above baseline. This pattern indicates that TD and HSR contain only weak, unstable structure related to competition points outcomes: models can exploit this structure to classify slightly better than chance in-sample, but cannot generate well-calibrated, practically useful predictions for applied decision-making. From a performance science perspective, running metrics therefore appear insufficient as stand-alone predictors of success, even when analysed with more sophisticated machine learning techniques.

### The 1-2 Points Problem

The weakness of running metrics for discriminating the 1-2 points band is practically important. This band captures tight outcomes (draws and defensive bonus losses) that are often season-critical in professional rugby competitions like Pro D2. Teams separated by 1-2 points across a season may finish on opposite sides of playoff qualification or relegation battles. Yet neither total distance nor HSR distance provided a reliable signature of whether teams earned 0 points, 1-2 points, or 4+ points in a given match. The substantial overlap shown in Figure 1 and the failure of models to beat baseline on probability quality indicate that running volume and HSR exposure do not provide stable, generalizable information about these crucial tight match outcomes.

### Running Metrics as Demand Descriptors

The present findings do not suggest that running metrics lack value. On the contrary, total distance and HSR distance re-

main essential for describing match demands, quantifying load exposure, managing player welfare, and informing recovery protocols (Dubois et al., 2017; Gabbett et al., 2012). However, their value lies in describing what happened rather than explaining why the team won or lost or predicting whether the team will earn competition points. This distinction is crucial for applied practice. As Mandorino and colleagues emphasize (2025), sports science has often prioritized what can be measured over what is truly impactful, leading to misplaced focus on convenient metrics rather than meaningful performance determinants. The current results support repositioning running metrics within KPI frameworks: valuable as demand descriptors and load management tools, but inappropriate as primary indicators of match success or team performance quality.

### Limitations and Future Directions

This study has several important limitations. First, the sample comes from a single professional club over two seasons, which may restrict generalizability to other teams, competitions, or playing styles. Validation across multiple teams and competition levels would strengthen conclusions. Second, the analysis focused specifically on running metrics to test their discriminative value for points outcomes, but did not incorporate other factors known to influence match success in rugby, such as possession quality, territory, set-piece performance, tactical efficiency, or opponent strength. Variables such as team strength (e.g., ELO ranking), fixture congestion, and squad rotation (Settembre et al., 2024) were not included in the model. Future research should adopt more comprehensive models incorporating rugby-specific performance determinants to better capture the complexity of match outcomes.

Beyond isolated running variables, future work should apply multivariate techniques (e.g., principal component analysis) to a broader set of rugby-specific physical outputs, with the aim of identifying latent physical profiles more tightly linked to match KPIs and, ultimately, match outcomes (Cunningham et al., 2018). Candidate variables might include kick-chase peak speed, acceleration during defensive line rushes, and “back-in-the-game” time after tackles (time to regain effective involvement in play), derived from integrated GPS–video workflows and anchored in established KPI frameworks that emphasise ball-carrying effectiveness, collision dominance, and gainline success (Cunningham et al., 2018; Wedding et al., 2020). Building on recent work that reviews how physical qualities underpin key rugby performance actions and ball-carrying capability, such rugby-specific physical components could then be tested, alone and alongside technical–tactical indicators, to determine whether they offer superior explanatory or predictive value for competition points compared with traditional distance-based running metrics (Cunningham et al., 2018; Wedding et al., 2020; Mandorino et al., 2025). Future work should also integrate mechanical work metrics (Buchheit et al., 2026) to quantify the energetic cost of directional changes, decelerations, and re-accelerations that distance-based running metrics inherently miss.

### Take-Home Messages

- **Team TD/HSR are poor standalone predictors of Pro D2 competition points.** Models using these metrics underperformed a no-information baseline on probability calibration (log-loss), despite some tree-based methods achieving above-chance accuracy.
- **Running reflects match context more than it drives outcomes.** High running volumes often result from de-

fending, chasing games, or tactical demands rather than superior physical preparation or execution leading to points.

- **Tight matches (Draw Or Defensive Bonus) lack a running signature.** These season-critical outcomes showed the highest variability and overlap in TD/HSR, reinforcing that generic running capacity does not discriminate close contests.
- **Use running metrics as demand descriptors, not performance KPIs.** TD and HSR remain essential for quantifying match exposure, prescribing training loads, and managing recovery, but should not serve as primary indicators of match success.
- **Richer models require rugby-specific and contextual integration.** Future work should combine running data with technical-tactical KPIs (possession, territory, set pieces), opponent strength, and match state for meaningful performance prediction.

### Conflicts of Interest

The authors declare no conflicts of interest relevant to this work.

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