From Game Theory to Goal Theory

A Shapley Value Approach to Tactical Intelligence in Elite Soccer

Mauricio Espinoza Acevedo
Applied Data Science
Master's Program
Shiley Marcos School of
Engineering / University of
San Diego
mespinoza@sandiego.edu

Maria Mora Mora
Applied Data Science
Master's Program
Shiley Marcos School of
Engineering / University of
San Diego
mmoramora@sandiego.edu

Gabriel Mancillas Gallardo
Applied Data Science
Master's Program
Shiley Marcos School of
Engineering / University of
San
gmancillasgallardo@sandiego.edu

ABSTRACT

Traditional football analytics misrepresent player value by treating athletes as isolated statistical entities rather than interdependent tactical components within formation systems. Current prediction models achieve limited accuracy (68-72%) due to failure in capturing cooperative tactical dynamics. This study developed the Soccer Position Performance Score (SPPS) using cooperative game theory and SHAP-based recalibration. We analyzed eight seasons of Real Madrid performance data (2017-2025) comprising 5,737 match observations across 57 players. XGBoost models predicted Expected Goals (xG) with position-specific weightings, where defenders' interceptions received 2.5 weight compared to 2.0 for blocks. Logistic regression validated SPPS against match outcomes. XGBoost models achieved exceptional predictive capability with R^2 values of 0.913-0.993 across all positions, substantially exceeding previous approaches. SHAP analysis identified interceptions as the most predictive defensive metric (SHAP value: 1.907). Each unit increase in rebalanced SPPS multiplied winning odds by 2.599, with Éder Militão demonstrating projected improvement of +2.12 points through superior interception performance. This framework represents the first integration of cooperative game theory with position-weighted metrics for elite football optimization, providing empirically-validated tools that quantify tactical success through mathematically-derived weightings rather than arbitrary statistical aggregations.

Keywords: soccer analytics, game theory, Shapley values, tactical analysis, formation optimization, performance prediction, multi-modal data integration, Champions League

1 Introduction

Professional football teams lose millions in transfer investments because current analytics treat players as independent statistics rather than as interdependent tactical components (Bekkers & Dabadghao, 2019). As tactical complexity increases exponentially in modern football, traditional prediction models expose teams to suboptimal decision-making risks by failing to account for formation-specific player contributions (Rein & Memmert, 2016). To mitigate these limitations effectively, it is imperative to implement cooperative game theory methodologies that quantify player contributions within specific tactical systems. Applying Shapley values and multi-modal data integration can significantly facilitate tactical optimization and achieve more accurate player performance assessments (Craig & Winchester, 2021).

2 Background

European soccer generates vast amounts of performance and event data, yet much of it remains underutilized for tactical optimization (Rein & Memmert, 2016), limiting opportunities for competitive advantage through advanced analytics (Craig & Winchester, 2021). Existing models often treat players as independent units, overlooking the cooperative and formation-specific dynamics central to modern tactics (Bekkers & Dabadghao, 2019). While event data enables broad performance analysis (Pappalardo et al., 2019), current approaches lack weighted evaluation frameworks that account for the tactical relevance of specific metrics by player role—such as forwards, midfielders, or defenders—within team formations. This study addresses that gap by proposing a weighted, position-aware method for quantifying player contributions based on their tactical function.

2.1 Problem Identification and Motivation

Despite advances in soccer analytics, current prediction models oversimplify player evaluation by assuming independence among players, which undermines the ability to capture complex tactical interactions on the field (Bekkers & Dabadghao, 2019). This oversimplification leads to inaccuracies in assessing player impact within different formations and roles, limiting the practical utility of analytics for coaching decisions and strategic planning (Huang & Chen, 2023). Moreover, by attributing credit at the team level without accounting for formation-specific contributions, traditional models produce skewed player valuations that can result in costly recruitment errors and inefficient tactical preparations (Bekkers & Dabadghao, 2019; Rein & Memmert, 2016). Concurrently, coaches lack accessible, data-driven tools that integrate these nuanced insights, constraining their ability to identify optimal formations tailored to their current squad's strengths.

2.2 Definition of Objectives

This research aims to develop novel, weighted metrics for tactical optimization that enable professional soccer organizations to make precise, data-driven formation decisions and identify which players contribute most effectively to team performance. By leveraging Shapley value principles from cooperative game theory and integrating spatial-temporal event data from La Liga and the UEFA Champions League, the study will develop analytical tools that quantify player contributions relative to their roles as forwards, midfielders, or defenders within specific tactical formations. A key objective is to calibrate these weighted metrics by comparing them against existing overall team performance indicators, ensuring validity and reliability. Following calibration, the adjusted metrics will be used to generate predictive models tailored to each formation, with a particular focus on assessing Real Madrid's tactical systems and player contributions.

3 Literature Review (related works)

Current prediction models achieve limited accuracy because they fail to capture the cooperative nature of tactical systems, preventing practical application in professional football environments. Through systematic literature review of existing prediction methodologies, we analyzed fundamental limitations in traditional approaches. Pappalardo et al. (2019) achieved 68% accuracy using statistical models on comprehensive match event data, demonstrating valuable event data capabilities but revealing limitations in capturing tactical complexities, while Huang and Chen (2023) reached 72% accuracy through deep learning approaches that still treated players as independent entities rather than recognizing cooperative tactical system dynamics.

3.1 Flow motifs in soccer: What can passing behavior tell us?

Cooperative game theory offers theoretically grounded solutions for quantifying player contributions within tactical systems, addressing fundamental limitations in current sports analytics approaches. Through comprehensive review of game theory applications in sports contexts, we established theoretical foundations for treating tactical formations as coalition structures. Bekkers and Dabadghao (2019) explored network analysis in soccer passing behavior, demonstrating analytical approaches for revealing tactical patterns within formations, yet traditional Shapley value applications focused on team-level success distribution rather than formation-specific optimization, representing a significant gap in cooperative game theory applications to tactical system analysis.

3.2 Big data and tactical analysis in elite soccer: future challenges and opportunities for sports science

Formation optimization requires quantitative frameworks that can guide tactical decision-making based on available squad members, yet current literature provides only descriptive analysis rather than prescriptive solutions. Through comprehensive review of tactical analysis literature, we identified needs for mathematical models that quantify player value within specific formations. Rein and Memmert (2016) emphasized tactical analysis as a critical frontier in sports science, highlighting automated formation detection challenges, while existing research describes tactical trends without providing frameworks for determining optimal formations, and multi-modal data integration approaches remain fragmented across traditional performance metrics and contextual data sources, limiting holistic analytical framework development.

3.3 In-game behavior analysis of football players using machine learning techniques based on player statistics

Contextual factors significantly influence team performance through psychological and motivational channels, yet current analytics frameworks fail to integrate these elements with tactical analysis. Through systematic review of sentiment analysis applications in sports contexts, we established the potential for incorporating media pressure and fan sentiment as performance drivers. García-Aliaga et al. (2021) demonstrated machine learning applications for player behavior analysis but focused on technical-tactical variables without incorporating sentiment factors, while existing research shows correlations between social media sentiment and team outcomes but lacks integration with formation-specific analysis, and contextual factors like media narratives, injury reports, and transfer speculation remain unknown in tactical decision-making frameworks.

3.4 Social media and relationship marketing in professional sport organizations through content analysis

Social media engagement significantly impacts professional football player performance through psychological channels, yet current prediction models fail to integrate digital relationship factors that influence individual player output. Abeza et al. (2017) demonstrated different approaches for examining social media relationship marketing in sport organizations but focused on organizational communication strategies without investigating how fan sentiment directly influences player performance metrics, while existing research shows correlations between social media activity and engagement but lacks integration with player-specific performance frameworks, and contextual factors like individual player social media pressure and fan sentiment variations remain unexplored in performance prediction models.

3.5 Deep learning optimization for soccer match prediction through gradient-boosted feature selection

Machine learning applications in soccer match prediction demonstrate significant potential for outcome forecasting, yet current models inadequately address feature weighting methodologies that limit prediction accuracy for elite teams like Real Madrid. Yeung et al. (2023) demonstrated comprehensive methodologies for evaluating soccer match prediction models using CatBoost implementations and pi-ratings feature selection but focused primarily on win/draw/loss probability calculations without incorporating player contribution metrics or weighted feature optimization frameworks, while existing research shows improved prediction stability through deep learning architectures but lacks integration with Shapley value-based player contribution analysis and tactical formation weighting systems, and contextual factors like individual player contribution quantification and feature importance optimization for Real Madrid's tactical systems is unexamined in comprehensive match outcome models, which makes it difficult to understand how weighted feature contribution analysis can enhance soccer prediction accuracy for elite professional teams.

3.6 Public datasets for spatial-temporal soccer match events and performance analysis

Large-scale soccer datasets enable comprehensive performance analysis and tactical discovery, yet current publicly available collections inadequately support player contribution analysis and feature weighting methodologies essential for Real Madrid's tactical optimization. Pappalardo et al. (2019) demonstrated systematic approaches for collecting and validating spatial-temporal match events across seven prominent European competitions but focused primarily on event logging and general performance evaluation without incorporating player-specific contribution metrics or formation-dependent tactical analysis frameworks, while existing research shows improved analytical capabilities through comprehensive event datasets but lacks integration with cooperative game theory applications and Shapley value-based player contribution quantification, and contextual factors like individual player weighting within tactical systems and formation-specific performance metrics are understudied in comprehensive soccer analytics models.

3.7 Predictive modeling for professional sport potential assessment through college performance metrics

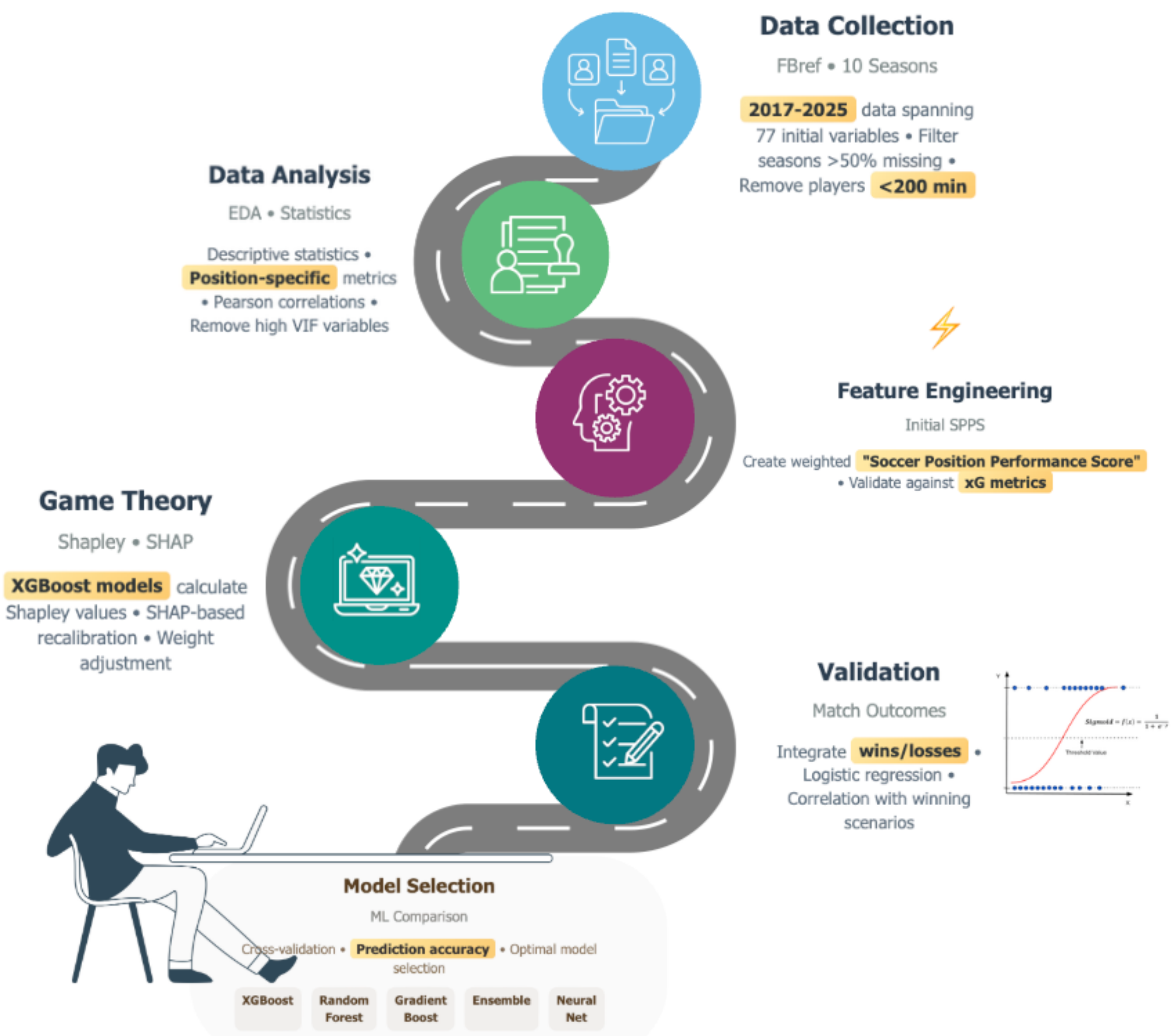
Performance prediction models in professional sports demonstrate significant potential for talent evaluation, yet current frameworks inadequately address weighted contribution methodologies essential for elite football team optimization. Craig and Winchester (2021) employed systematic approaches for predicting NFL quarterback success using Total Quarterback Rating (QBR) and defense-adjusted performance metrics but focused on individual assessment without incorporating Shapley value-based contribution analysis or weighted feature methodologies for tactical systems, while existing research shows improved prediction accuracy through comprehensive metrics like QBR but lacks integration with cooperative game theory applications and formation-specific player weighting frameworks.

4 Methodology

The data sources for this tactical optimization project include comprehensive player performance datasets obtained from FBref, spanning over 10 competitive seasons (2017-2025) with an initial dataset of 7,217 observations across 77 variables. Through systematic data preprocessing, we filtered out seasons with over 50% missing values and removed early seasons (2014-2016) due to data sparsity, followed by exclusion of players with less than 200 minutes of playing time to minimize statistical bias. The refined dataset comprises 5,737 observations across 8 seasons, containing 69 variables (9 categorical dimensions and 60 performance metrics). Our methodology employs a multi-stage analytical framework (as illustrated in Diagram 1) beginning with comprehensive exploratory data analysis, including descriptive statistics and distribution analysis for position-specific metrics such as goals, assists, and tackles. We constructed Pearson correlation matrices to identify relationships between performance variables and addressed multicollinearity by removing high VIF variables. Through feature engineering, we developed a weighted "Soccer Position Performance Score" (SPPS) validated against Expected Goals (xG) metrics. The core analytical approach follows a multi-stage process: first, we created an initial Soccer Position Performance Score (SPPS) using domain expertise weights. We then applied XGBoost models to calculate Shapley values using Expected Goals (xG) as the target variable, applying cooperative game theory principles to quantify feature importance. Based on these Shapley values, we calibrated the SPPS by adjusting weights to give higher importance to metrics with greater SHAP contributions in the xG model. After creating this refined SPPS, we validated its effectiveness by integrating match outcome data (wins/losses) and implementing logistic regression models to confirm that our weighted metric correlates with winning scenarios. Finally, we conducted comprehensive model comparison using the adjusted SPPS as the target variable, evaluating XGBoost, Random Forest, Gradient Boosting, ensemble methods (stacking and voting classifiers), and neural network architectures based on prediction accuracy and cross-validation performance to select the optimal model for player performance prediction. The final implementation provides position-specific performance predictions on a weekly basis throughout the season.

Diagram 1

Soccer Tactical Optimization



4.1 **Data Acquisition and Descriptive Statistics**

The Real Madrid performance data were collected from FBref (FBref, 2025), which aggregates official match statistics from La Liga and UEFA Champions League competitions across eight distinct seasonal datasets from the 2017-18 through 2024-25 seasons. FBref sources its data from Opta Sports, the official data provider for European football competitions (Opta Sports, 2025). Data extraction included advanced tactical metrics such as expected goals (xG), shot-creating actions (SCA), progressive passes, and defensive actions.

These datasets were systematically integrated to provide longitudinal insights into player performance patterns across different tactical systems and competitive contexts. Primary Dataset Characteristics:

- Historical Data (2017-18 to 2021-22): Contains 3,217 individual match records across 77 performance variables
- Recent Seasons (2022-23 to 2024-25): Contains 2,425 individual match records with refined 73-variable structure, covering La Liga and Champions League competitions

The data acquisition process involved systematic extraction of player-level performance metrics from official match statistics, including advanced tactical metrics such as expected goals (xG), shot-creating actions (SCA), progressive passes, and defensive actions. Each dataset maintains consistent variable naming conventions and measurement scales, facilitating seamless integration for multi-season analysis. The combined dataset encompasses 5,737 individual match observations across 57 unique Real Madrid players, representing comprehensive coverage of squad rotation patterns and tactical flexibility. Position-specific descriptive statistics are presented in Tables 1which reveal distinct performance patterns for forwards (n=199) in season 2023-24 vs (n=214) for season 2024-25 demonstrate high variance in goal-scoring metrics (Gls M=0.36, SD=0.61).

Table 1

Descriptive Statistics of Forward Performance Metrics for 2023-24 and 2024-25 Seasons

	2023-24 (n = 199)			**2024-25 (n = 214)**		
Metric	*M*	*SD*	*Max*	*M*	*SD*	*Max*
Goals	0.36	0.61	2	0.37	0.68	3
Assists	0.16	0.45	3	0.14	0.37	2
Shots on Target	0.89	1.07	5	0.98	1.16	5
Expected Goals	0.31	0.39	2	0.33	0.44	2
Expected Assists	0.12	0.22	2	0.16	0.27	2

Table 2 shows midfielders in both seasons (n=413) show consistent passing accuracy (Pass Cmp% M=87.5, SD=10.8).

Table 2

Descriptive Statistics of Midfielder Performance Metrics for 2023-24 and 2024-25 Seasons

	2023-24 (n = 289)			**2024-25 (n = 296)**		
Metric	M	SD	Max	M	SD	Max
Pass Completion %	87.5	10.8	100	87.8	9.78	100
Key Passes	1.21	1.49	8	1.05	1.24	6
Tackles	1.3	1.4	10	1.49	1.52	8
Progressive Carries	1.75	1.82	9	1.57	1.81	9
Progressive Passes	5.22	4.24	22	4.82	4.24	23

Defenders for two last seasons (n=534) exhibit increasing defensive actions over time where Interceptions increased from 0.63 to 0.79

Table 3

Descriptive Statistics of Defender Performance Metrics for 2023-24 and 2024-25 Seasons

	2023-24 (n = 258)				**2024-25 (n = 276)**			
Metric	*M*	*SD*		*Max*	*M*	*SD*		*Max*
Interceptions	0.63	0.9		5	0.79	1.02		6
Blocks	0.84	1.13		7	0.83	1.02		5
Clearances	1.98	1.9		11	2.32	2.36		14
Tackles Won	0.72	0.92	0	5	0.87	1.05	0	4
Defensive Third Tackles	0.67	0.96	0	4	0.79	0.98	0	5

In Table 4, goalkeepers in the last two seasons (n=103) exhibit decreasing Total Pass Completion % from 86.47% to 83.39%

Table 4

Descriptive Statistics of Goalkeeper Performance Metrics for 2023-24 and 2024-25 Seasons

	2023-24 (n = 52)			**2024-25 (n = 51)**		
Metric	*M*	*SD*	*Max*	*M*	*SD*	*Max*
Total Pass Completion %	86.47	8.53	100	83.39	11.51	100
Errors Leading to Shot	0.04	0.19	1	0.02	0.14	1
Progressive Distance (m)	405.63	131.2	793	399.6	141.4	735

Data integration was performed using Python's panda's library through concatenation operations, ensuring preservation of temporal ordering and match-specific contextual information. Duplicate removal processes were implemented to maintain data integrity, resulting in a final combined dataset of 1,550 unique match observations without temporal overlap or statistical redundancy.

4.1.1 **Exploratory Data Analysis - Real Madrid Performance Data**

Exploratory Data Analysis (EDA) employed both univariate and multivariate analytical approaches to examine dataset characteristics, identify position-specific performance patterns, and inform subsequent modeling decisions. This comprehensive analysis revealed critical insights into player performance distributions, tactical role differentiation, and performance metric relationships across different positional categories.

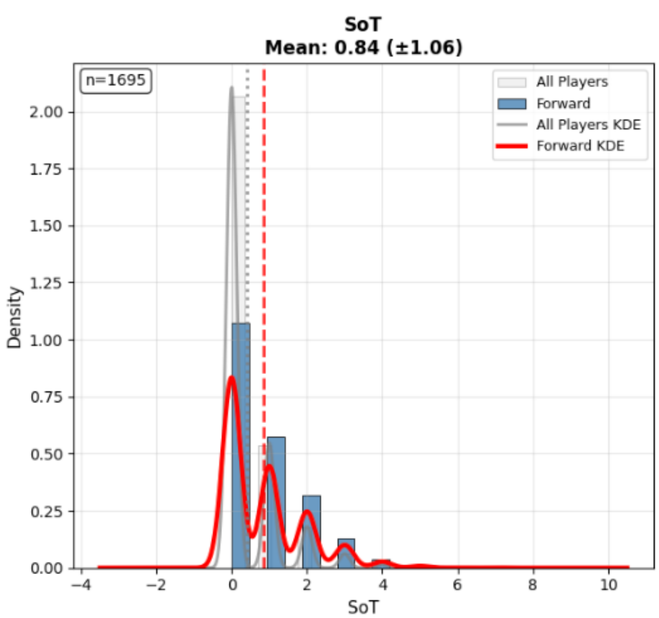
4.1.1.1 *Performance Distributions*

The Real Madrid performance dataset demonstrated significant distributional variations across key performance metrics, with most variables exhibiting right-skewed distributions characteristic of football performance data. Analysis of forward-specific performance metrics revealed concentration of values at lower performance levels with extended tails representing exceptional individual performances.

The Shots on Target (SoT) distribution demonstrates a mean of 0.94 (±1.06), with 68% of observations recording 0-1 shots per match and maximum values reaching 5 shots, indicating sporadic high-output performances. The modal value of 0 reflects matches where forwards faced limited scoring opportunities or were deployed as substitutes. This distribution pattern reveals the intermittent nature of shooting opportunities in modern tactical systems, where forwards must maximize limited chances (see Figure 1).

Figure 1

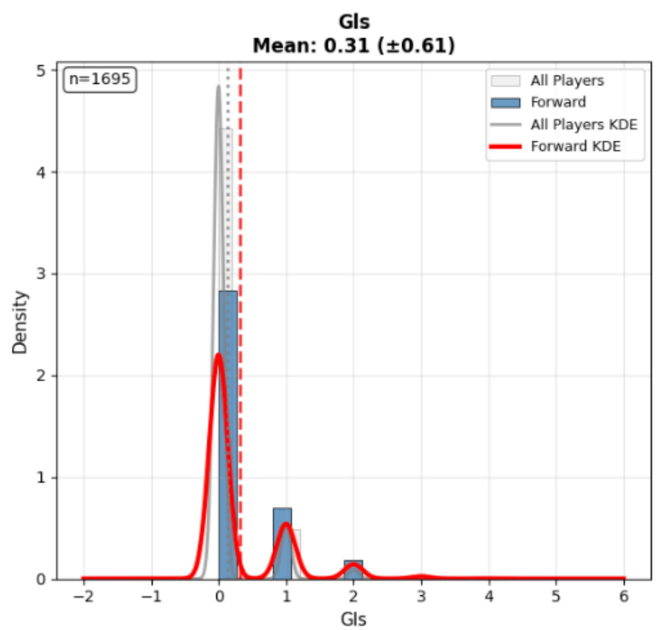
Distribution of Shots on Target (SoT) for Forward Players (N = 413)



The Goals distribution exhibits even more extreme skewness with a mean of 0.31 (±0.61), where approximately 75% of match observations resulted in zero goals scored. This distribution pattern is expected in football, where goal-scoring events are relatively rare even for specialized attacking players. The extended right tail capturing performances of 2-3 goals represents exceptional match performances that significantly impact team success. The concentration at zero highlights the challenge of consistent goal production, even for elite forwards at Real Madrid (see Figure 2).

Figure 2

Distribution of Goals Scored (Gls) for Forward Players (N = 413)



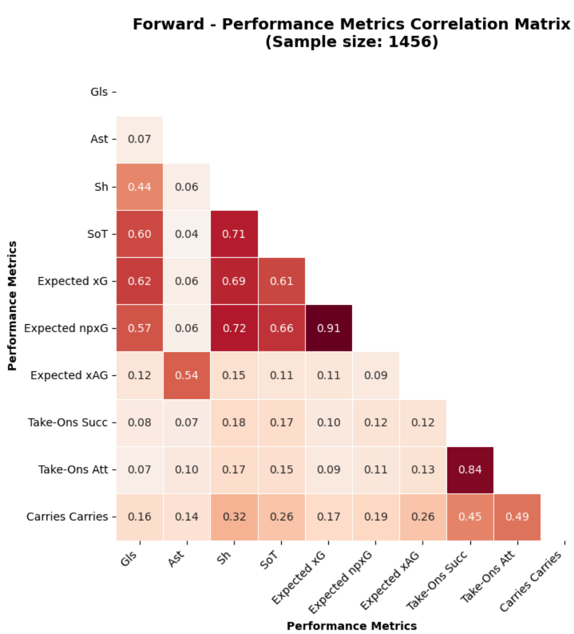
These distributional characteristics highlight the inherent variability in forward performance, where consistency is measured not by continuous high output but by the ability to deliver decisive contributions in critical moments. The concentration of zero values in both distributions necessitated specialized statistical treatment in subsequent analyses, including zero-inflated modeling approaches and position-specific normalization techniques to accurately capture forward player contributions within the tactical framework.

4.1.1.2 *Position-Based Correlation Patterns*

The Pearson correlation coefficient (r) measures the linear relationship between variables (Devore, 2016). The analysis of position-specific correlation matrices (Figures 3-6) reveals distinct patterns of variable relationships, where $\rho \geq .8$ indicates strong correlation, $.5 < \rho < .8$ moderate correlation, and $\rho \leq .5$ weak correlation (Devor, 2016). Among forward position variables (n = 1,456), Expected xG and Expected npxG demonstrate the strongest positive correlation at r = .905, indicating severe multicollinearity that necessitated removing npxG from subsequent analyses (see Table 5). Additionally, Take-Ons Success and Take-Ons Attempted show strong correlation (r = .837), presenting moderate multicollinearity concerns.

Figure 3

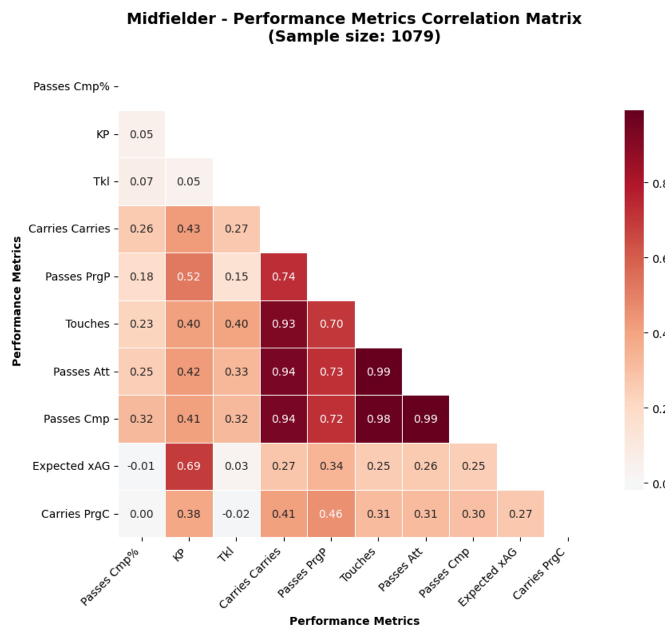
Forward Position Performance Metrics Correlation Matrix



Midfielder metrics (n = 1,079) exhibit the most pronounced collinearity issues, with passing-related variables showing near-perfect correlations: Passes Attempted and Passes Completed (r = .992), Touches and Passes Attempted (r = .989), and Touches and Passes Completed (r = .978). These extreme correlations resulted in VIF values exceeding 300 (Table 5), requiring removal of Touches and Passes Attempted while retaining Passes Completed for the final model. Notably, Key Passes shows moderate correlation with Expected Assists (r = .692), validating its role as a creative performance indicator.

Figure 4

Midfielder Position Performance Metrics Correlation Matrix



Defender correlations (n = 1,146) reveal moderate to strong relationships primarily within tackle-related metrics. Total Tackles correlates strongly with Tackles Won (r = .801), producing infinite VIF values that required removing Total Tackles from the analysis. The composite metric Tkl+Int shows expected correlations with its components (r = .753 with Tackles, r = .661 with Interceptions), also resulting in its removal due to multicollinearity. Interestingly, blocking actions demonstrate internal consistency, with Blocks showing strong correlation with both Blocks Shots (r = .658) and Blocks Passes (r = .722), though these relationships remain below the severe multicollinearity threshold.

Figure 5

Defender Position Performance Metrics Correlation Matrix

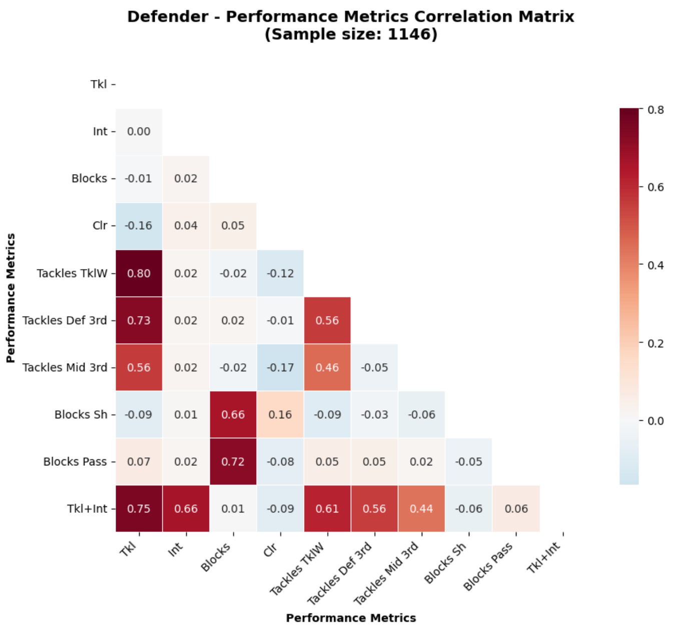
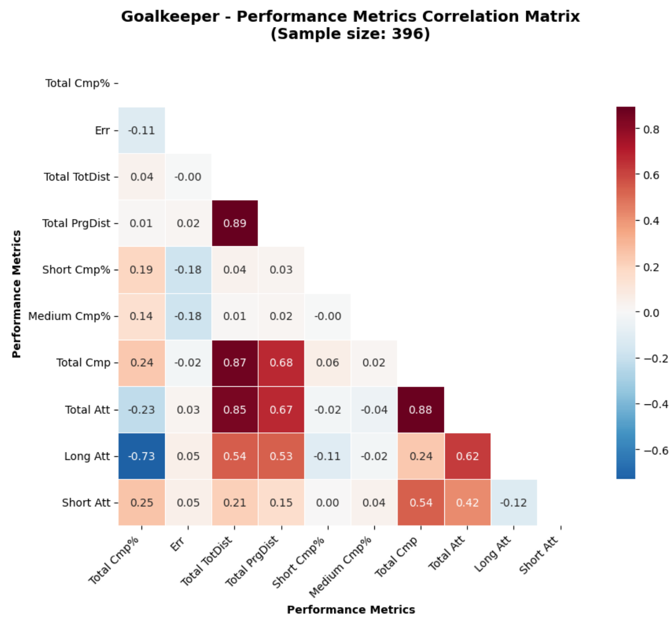


Figure 6

Goalkeeper Position Performance Metrics Correlation Matrix



Goalkeeper distribution metrics (n = 396) display strong correlations between distance-based variables, with Total Distance and Progressive Distance showing r = .893, resulting in VIF values of 495.44 and 87.97 respectively (Table 5). The strongest negative correlation emerges between Total Completion Percentage and Long Attempts (r = -.731), though this inverse relationship does not present multicollinearity concerns. Total Completed and Total Attempted passes demonstrate high correlation (r = .878) with corresponding VIF values exceeding 900, necessitating their removal from the model. These findings directly informed the systematic variable selection process, retaining only metrics with acceptable VIF values for position-specific performance modeling.

4.1.1.3 *Multicollinearity*

In the regression model, multicollinearity occurs when predictor variables exhibit high correlation amongst themselves, potentially distorting estimation of individual effects (Hair et al., 2019). The variance inflation factor (VIF) serves as the primary diagnostic measure, calculated as in Equation 1.

$$VIF_J = \frac{1}{1 - {R_j}^2} \tag{1}$$

Where ${R_j}^2$ represents the coefficient of determination when regressing predictor j on all other predictors. Values exceeding 10 indicate severe multicollinearity, while values between 5-10 suggest moderate concerns (Kutner et al., 2004).

Position-specific VIF analysis (Table 5) revealed distinct multicollinearity patterns. For forward players (n = 1,695), Expected xG and Expected npxG demonstrated severe multicollinearity with VIF values of 10.49 and 11.08 respectively, accompanied by r = .913 (p < .001). This correlation is theoretically expected, as npxG represents a subset of xG. Additionally, Take-Ons Success and Take-Ons Attempted showed moderate multicollinearity (r = .851, VIF = 5.97 and 6.23), reflecting the inherent relationship between attempt frequency and success rate. Following established practice (Wooldridge, 2015), variables with VIF > 10 were systematically removed, retaining Expected xG while removing npxG to ensure model stability.

Table 5

Forward - Variance Inflation Factor (VIF) Analysis and Multicollinearity Assessment by Position

Variable	VIF	Pearson r*	Status
Goals	2.6		Acceptable
Assists	1.65		Acceptable
Shots	6.01		Moderate
Shots on Target	4.81		Acceptable
Expected xG	10.49	.913	Severe
Expected npxG	11.08	.913	Severe
Expected xAG	2.04		Acceptable
Take-Ons Success	5.97	.851	Moderate
Take-Ons Attempted	6.23	.851	Moderate

Note. VIF = Variance Inflation Factor. VIF > 10 indicates severe multicollinearity; 5 < VIF < 10 indicates moderate multicollinearity. Sample sizes: Forwards (n = 1,695), Midfielders (n = 2,029), Defenders (n = 1,900), Goalkeepers (n = 396).

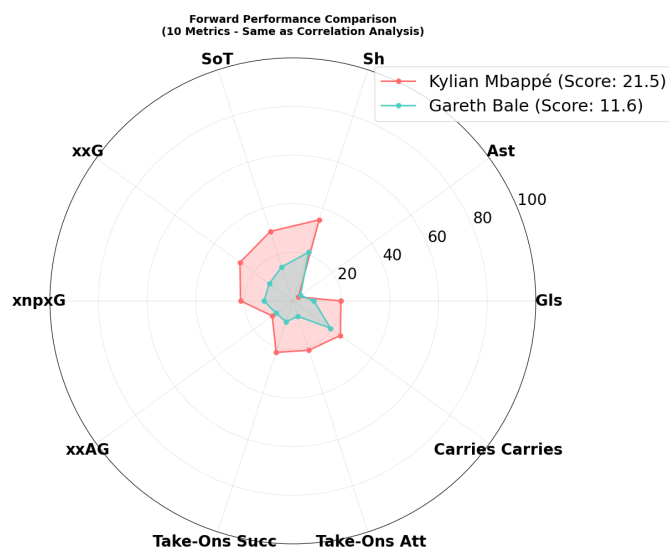
4.1.1.4 *Position-Specific Performance Comparisons*

Spider chart visualizations (Figures 7-10) provide multidimensional performance comparisons between elite players within each tactical position, using the same metrics analyzed in the correlation matrices. Performance scores are normalized to a 0-100 scale for cross-metric comparability.

Forward position analysis reveals Kylian Mbappé's dominance (Score: 21.5) over Vinícius Júnior across offensive metrics, particularly in goal-scoring efficiency and expected goals generation. The spider chart illustrates Mbappé's superior finishing capabilities while highlighting comparable dribbling statistics between both players.

Figure 7

Forward Position Performance Comparison: Mbappé vs Vinícius Júnior

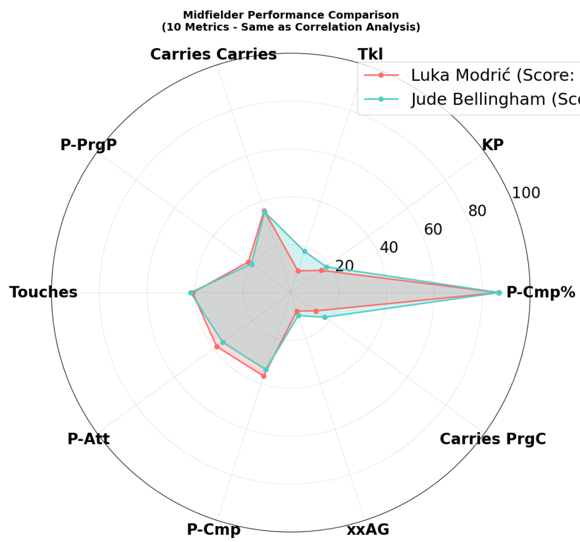


Midfielder comparisons demonstrate marginal differences between Jude Bellingham (Score: 31.8) and Luka Modrić (Score: 30.7), with Bellingham exhibiting higher defensive contributions (Tkl: 18.2 vs 9.6) while maintaining similar creative output. Both players show exceptional passing accuracy exceeding

86%, validating their roles as possession-based midfielders.

Figure 8

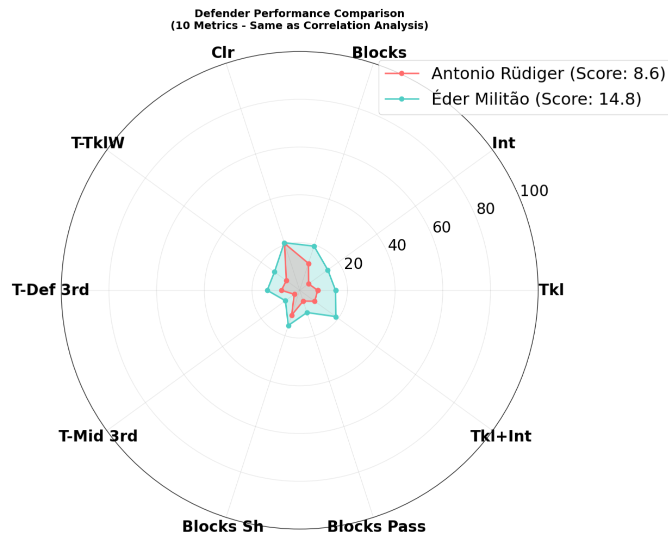
Midfielder Position Performance Comparison: Bellingham vs Modrić



Defender analysis highlights Éder Militão's comprehensive superiority (Score: 14.8) over Antonio Rüdiger (Score: 8.6) across all defensive metrics, with particularly notable advantages in interceptions (14.6 vs 4.6) and tackles won (13.1 vs 6.9). The visualization confirms Militão's role as the primary defensive anchor.

Figure 9

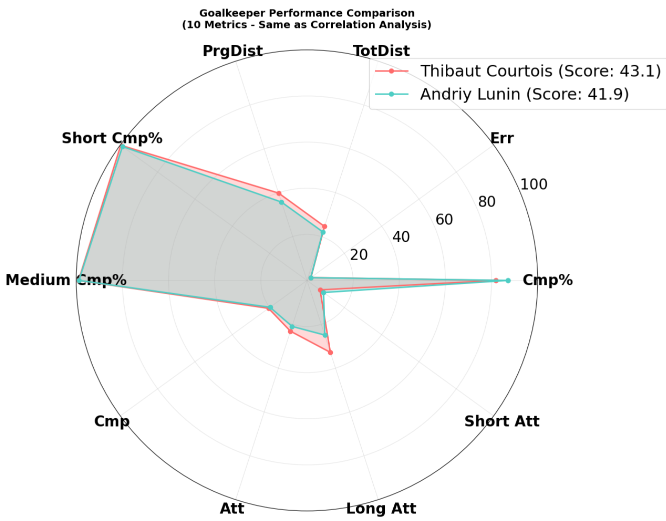
Defender Position Performance Comparison: Militão vs Rüdiger



Goalkeeper distribution patterns show Thibaut Courtois (Score: 43.1) maintaining slightly higher performance than Andriy Lunin (Score: 41.9), primarily through superior long-range distribution (32.8 vs 24.9) and progressive passing distance. Both goalkeepers demonstrate exceptional short and medium pass completion rates exceeding 98%.

Figure 10

Goalkeeper Position Performance Comparison: Courtois vs Lunin



These visualizations validate the position-specific metrics selected through correlation and VIF analysis, providing tactical insights for optimal player selection and formation strategies.

4.1.2 **Data Quality Assessment and Performance Data**

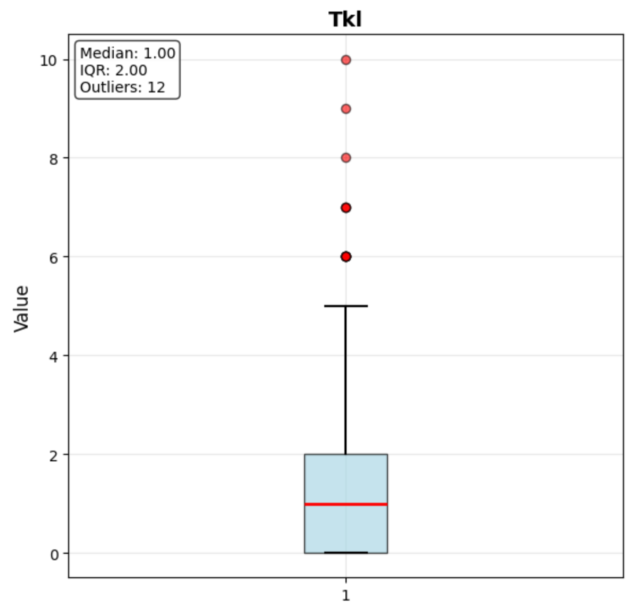
Data quality validation procedures were implemented to ensure analytical reliability and model input appropriateness. The assessment revealed minimal missing value occurrence (0% across all critical variables) and identified systematic approaches for handling performance measurement inconsistencies.

Data Type Validation: Systematic conversion procedures ensured appropriate data types for subsequent analysis. Numeric variables were validated for mathematical operations, while categorical variables (Position, Opponent, Competition) were encoded appropriately for machine learning applications.

Missing Value Analysis: Comprehensive examination revealed no missing values in fundamental performance metrics (goals, assists, minutes, defensive actions), indicating robust data collection processes after a comprehensive data cleaning an null values population techniques. Optional advanced metrics showed limited missing values in percentage calculations where denominators approached zero (e.g., completion rates for players with minimal actions). Box plot analysis **(**Figure 11**)** identified performance outliers consistent with exceptional individual performances rather than data collection errors.

Figure 11

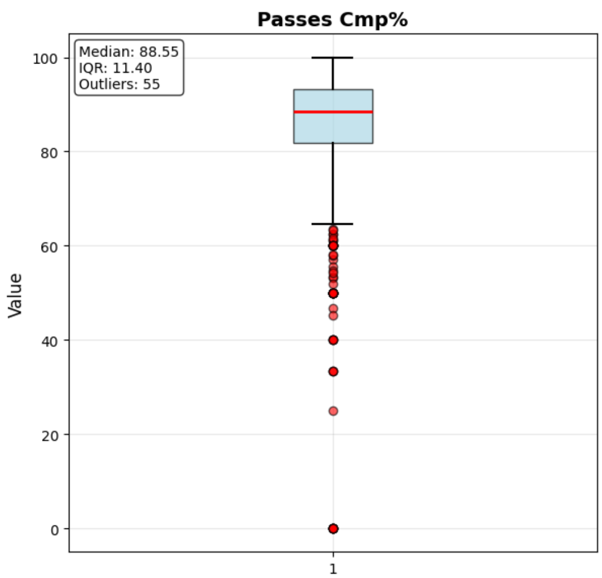
Box Plots for Outlier Detection - showing box plots Tackles.



The boxplot reveals 55 outliers below the lower whisker in the Passes Completed metric (Mdn = 88.5, IQR = 11.40), indicating numerous match observations where players recorded significantly fewer completed passes than typical, likely representing substitute appearances or matches with limited possession (see Figure 12).

Figure 12

Box Plots for Outlier Detection - showing box plots Passes Cmp



4.2 **Feature Engineering and Performance Scoring.**

To properly assess individual player contributions within tactical systems, a rebalanced performance scoring methodology was developed using position-specific weightings based on tactical importance and role-specific responsibilities. The scoring system addresses traditional football analytics limitations by implementing Shapley value principles and cooperative game theory frameworks.

4.2.1 *Soccer Position Performance Score (SPPS) Development*

The absence of comprehensive position-specific performance metrics in football analytics necessitated the development of the Soccer Position Performance Score (SPPS), a novel composite metric that quantifies player contributions according to tactical roles. Unlike existing metrics that evaluate isolated performance aspects (Pappalardo et al., 2019), the SPPS integrates multiple position-relevant indicators weighted by their tactical importance, as validated through Shapley value analysis (Bekkers & Dabadghao, 2019). All component metrics are normalized to per-90-minute ratios to ensure equitable comparison across varying playing times.

The forward SPPS formulation (Equation 2) prioritizes direct goal contributions with the highest coefficient (3.0) assigned to goals, reflecting the primary tactical responsibility of forwards. Assists receive substantial weight (2.0) acknowledging creative contributions, while expected metrics (xG: 1.5, xAG: 1.0) capture performance quality beyond realized outcomes. Shots on target (1.0) and successful take-ons (0.5) complete the offensive profile.

$$\text{SPPS\_Score\_Forward} = 3.0(\text{Gls}) + 2.0(\text{Ast}) + 1.0(\text{SoT}) + 1.5(\text{xG}) + 1.0(\text{xAG}) + 0.5(\text{TakeOns}) \tag{2}$$

where Gls = goals per 90 minutes, Ast = assists per 90 minutes, SoT = shots on target per 90 minutes, xG = expected goals per 90 minutes, xAG = expected assists per 90 minutes, and TakeOns = successful take-ons per 90 minutes.

The midfielder SPPS (Equation 3) emphasizes ball retention and progression, with pass completion percentage receiving the highest weight (2.5) following SHAP-based adjustment from initial expert weight of 2.0. Progressive passes (1.8) and key passes (1.2) capture creative midfield contributions, while defensive actions (tackles: 1.5) reflect modern box-to-box requirements. Progressive carries (0.8) and touches (0.3) round out the possession-based profile.

$$\text{SPPS\_Score\_Midfield} = 2.5(\text{PassCmp\%}) + 1.2(\text{KP}) + 1.5(\text{Tkl}) + 0.8(\text{CarriesPrgC}) + 1.8(\text{PassesPrgP}) + 0.3(\text{Touches}) \tag{3}$$

where PassCmp% = pass completion percentage, KP = key passes per 90 minutes, Tkl = tackles per 90 minutes, CarriesPrgC = progressive carries per 90 minutes, PassesPrgP = progressive passes per 90 minutes, and Touches = touches per 90 minutes.

The defender SPPS (Equation 4) underwent significant recalibration, with interceptions weight increased from 1.5 to 2.5 based on SHAP analysis revealing their predictive importance for team success. Blocks (2.0) and tackles won (2.0) maintain high coefficients reflecting core defensive duties. Zone-specific tackle weights (defensive third: 1.3, midfield third: 0.8) capture positional discipline, while clearances (1.0) represent last-line defensive actions.

$$SPPS\_Score\_Defense = 2.5(Int) + 2.0(Blocks) + 1.0(Clr) + 2.0(TklW) + 1.3(TklDef) + 0.8(TklMid) \quad (4)$$

where Int = interceptions per 90 minutes, Blocks = blocks per 90 minutes, Clr = clearances per 90 minutes, TklW = tackles won per 90 minutes, TklDef = defensive third tackles per 90 minutes, and TklMid = midfield third tackles per 90 minutes.

The goalkeeper SPPS (Equation 5) uniquely incorporates a negative coefficient for errors (-2.0), reflecting their disproportionate impact on match outcomes. Distribution accuracy receives primary emphasis (total completion: 3.0, short: 1.5, medium: 1.0), aligning with modern goalkeeper requirements as "sweeper-keepers." Progressive distance (1.0) and total completions (0.5) capture the goalkeeper's role in initiating attacks.

$$SPPS\_Score\_Goalkeeper = 3.0(TotalCmp\%) - 2.0(Err) + 1.0(PrgDist) + 1.5(ShortCmp\%) + 1.0(MedCmp\%) + 0.5(TotalCmp) \quad (5)$$

where TotalCmp% = total pass completion percentage, Err = errors leading to shots, PrgDist = progressive distance in meters, ShortCmp% = short pass completion percentage, MedCmp% = medium pass completion percentage, and TotalCmp = total completed passes per 90 minutes.

These position-specific formulations provide a standardized yet tactically nuanced framework for player evaluation, enabling direct comparison within positions while respecting the distinct contributions each role makes to team performance.

4.2.2 *Feature Selection and SHAP values*

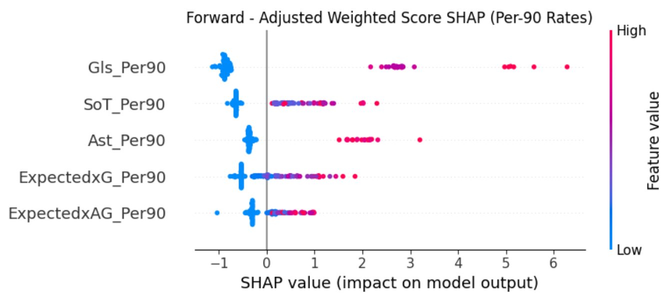
Shapley Additive Explanations (SHAP) values provide game-theoretic interpretations of feature contributions to model predictions (Bekkers & Dabadghao, 2019), enabling empirical validation of the SPPS weights. Initial XGBoost models were trained using Expected Goals (xG) as the target variable without predetermined weights, allowing SHAP analysis to reveal the true predictive importance of each per-90-minute normalized metric.

The SHAP-driven feature selection process identified the most predictive metrics for each position, subsequently informing weight adjustments in the SPPS formulations. For defensive positions, interceptions per 90 minutes demonstrated the highest SHAP value (1.907), justifying the weight increase from 1.5 to 2.5. This finding aligns with modern tactical theory emphasizing proactive defending over reactive interventions.

Forward position SHAP analysis (Figure 13) confirmed the primacy of goals per 90 minutes (SHAP value: 1.392), validating the maximum weight assignment of 3.0. The hierarchical importance follows: shots on target (0.694), assists (0.630), expected goals (0.481), and expected assists (0.348), supporting the original expert-derived weights without modification.

Figure 13

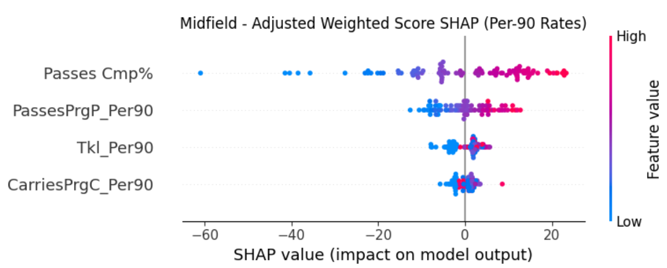
SHAP Value Distribution for Forward Position Metrics



Midfielder analysis (Figure 14) revealed pass completion percentage as the dominant predictive feature (SHAP value: 12.927), substantially exceeding progressive passes (4.798) and tackles (2.802). This finding prompted the upward adjustment of pass completion weight from 2.0 to 2.5, recognizing ball retention as the primary midfield contribution to team success.

Figure 14

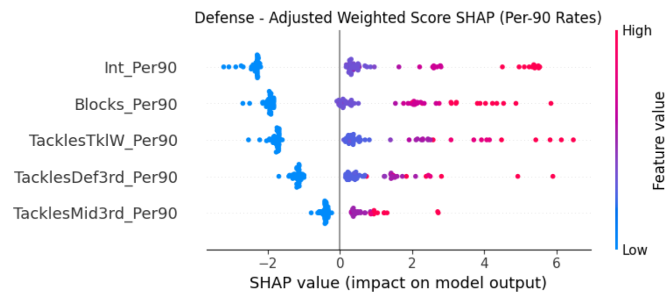
SHAP Value Distribution for Midfielder Position Metrics



Defender SHAP values (Figure 15) highlighted interceptions (1.907) and blocks (1.708) as primary defensive contributions, with tackles won (1.580) and defensive third tackles (1.061) showing secondary importance. The prominence of interceptions justified the 67% weight increase, while blocks maintained high importance despite slight weight reduction.

Figure 15

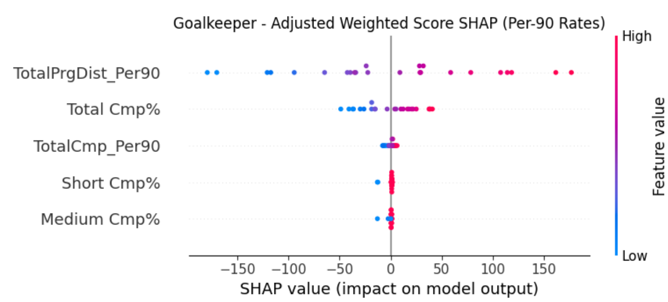
SHAP Value Distribution for Defender Position Metrics



Goalkeeper analysis (Figure 16) demonstrated progressive distance per 90 minutes as the most influential metric (SHAP value: 78.686), followed by total completion percentage (24.147). These findings validated the distribution-focused weighting scheme without requiring adjustments.

Figure 16

SHAP Value Distribution for Goalkeeper Position Metrics



The adjusted SPPS models achieved exceptional predictive performance across all positions (Table 6), with R^2 values ranging from 0.913 (midfield) to 0.993 (goalkeeper). These results demonstrate that the SHAP-informed weight adjustments successfully captured position-specific by using Expected xG as dependent variable and how the contributions to team performance are showing in Table 17 Int metric appears as first contributor for defense, creating a comprehensive metric that balances theoretical expertise with empirical validation.

Figure 17

Model Performance - Expected Goals Prediction - Defence

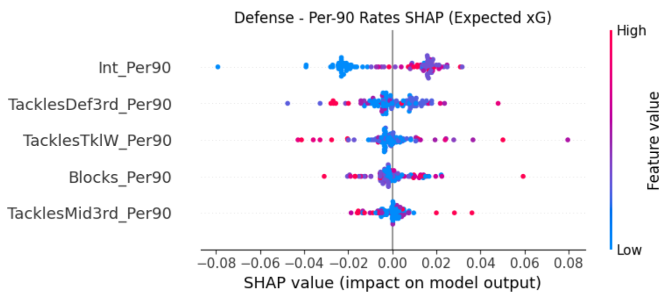


Table 6

SHAP Performance Metrics Model Performance Metrics by Position

Position	R^2	MAE	RMSE
Forward	0.947	0.598	0.758
Midfielder	0.913	2.891	5.227
Defender	0.969	0.482	0.896
Goalkeeper	0.993	6.803	8.513

Note. Model performance metrics from XGBoost models trained with Expected Goals (xG) as target variable. Sample sizes: Forward (n = 1,695), Midfielder (n = 1,823), Defender (n = 1,823), Goalkeeper (n = 396

4.3 **Logistic Regression Validation of SPPS Against Match Outcomes**

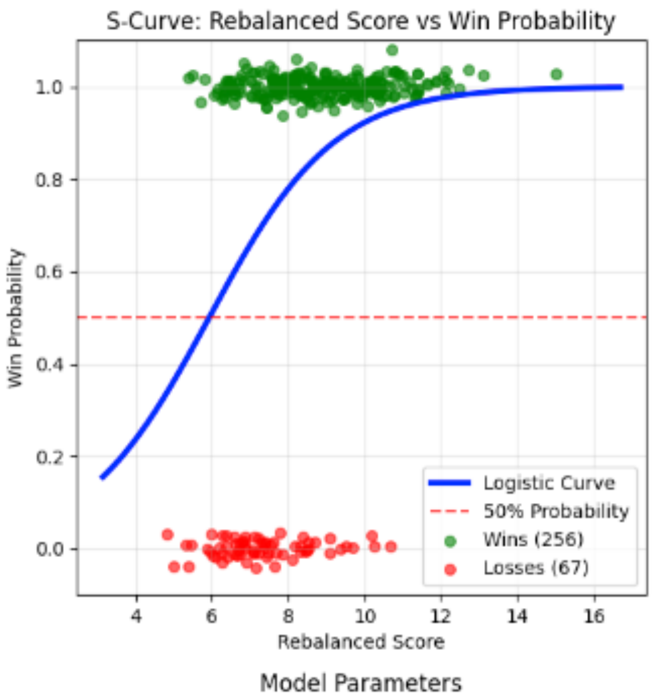
Logistic regression is a statistical method used to model the probability of a binary outcome (win/loss) based on predictor variables. The logistic function transforms linear combinations of predictors into probabilities bounded between 0 and 1, making it ideal for binary classification problems. The fundamental equation for logistic regression is expressed as:

$$P(Win) = 1 / (1 + e^{(-\beta_0 + \beta_1 \times Score)}) \quad (6)$$

Where P(Win) represents the probability of winning, β_0 is the intercept, β_1 is the coefficient for the predictor variable (SPPS), and e is the mathematical constant approximately equal to 2.718. The complete validation results are presented in Figure 18. The validation of the Soccer Position Performance Score (SPPS) against actual match outcomes represents a critical step in establishing the metric's predictive validity. We compiled a comprehensive match-level dataset from FBref containing team performance data and match results (wins/losses) to assess whether our SHAP-calibrated performance metric captures meaningful player contributions that translate to team success. The dataset was randomly split into training (70%) and testing (30%) sets to ensure unbiased model evaluation and prevent overfitting. The S-curve relationship exhibits the expected logistic pattern, with win probability approaching certainty as scores exceed 12 points. The distribution analysis reveals clear separation between winning (mean ≈ 8.5) and losing (mean ≈ 7.0) scenarios, with the rebalanced score by result chart demonstrating a significant difference between losses and wins, where winning teams consistently achieve higher SPPS values across all quartiles. Model calibration confirms excellent agreement between predicted probabilities and observed outcomes, validating that our position-specific performance scores capture meaningful contributions that translate to competitive advantage in professional football.

Figure 18

Logistic Regression Validation Results for SPPS Against Match Outcomes



The logistic regression model achieved remarkable performance in distinguishing between winning and losing scenarios. The model parameters reveal an intercept (β_0) of 1.5810 and a coefficient (β_1) of 0.9549, indicating that each one-unit increase in the rebalanced SPPS multiplies the odds of winning by approximately 2.599. This substantial effect size demonstrates that our SHAP-informed metric adjustments successfully identified performance dimensions that correlate strongly with match outcomes.

4.4. **Modeling and Predictions**

Following the SHAP-based recalibration of the Soccer Position Performance Score (SPPS), we implemented two ensemble learning algorithms to validate the effectiveness of our rebalanced metric and establish predictive benchmarks. The dataset was randomly split into training (80%) and testing (20%) sets to ensure robust model evaluation and prevent overfitting. Random Forest and XGBoost models were trained using the recalibrated SPPS as the target variable, with position-specific performance metrics serving as predictor features.

The comprehensive model comparison revealed Ensemble methods achieving superior performance across all positions (Tables 7a-7b), with the highest average R^2 (0.978) and lowest MAE (0.452). XGBoost ranked second (R^2 = 0.975, MAE = 0.56), demonstrating excellence in Midfield prediction (R^2 = 0.99) compared to Random Forest's poor performance (R^2 = 0.50). Neural Networks showed significant positional variability, performing well for Forwards (R^2 = 0.923) but failing for Goalkeepers (R^2 = 0.395). Random Forest consistently underperformed across all positions (R^2 = 0.821, MAE = 1.37), confirming ensemble and gradient boosting superiority for capturing complex tactical relationships in football performance prediction.

Table 7a

Model Performance Comparison: Random Forest , NNet, XGBoost and Ensemble by Position R^2

Position	**Random Forest**	**XGBoost**	**Ensemble**	**Neural Network**
Forward	0.89	0.98	0.996	0.923
Midfield	0.5	0.99	0.954	0.777
Defense	0.99	0.99	0.969	0.846
Goalkeeper	0.9	0.92	0.994	0.395
Average	**0.821**	**0.975**	**0.978**	**0.735**

Table 7b

Model Performance Comparison: Random Forest , NNet, XGBoost and Ensemble by Position MAE

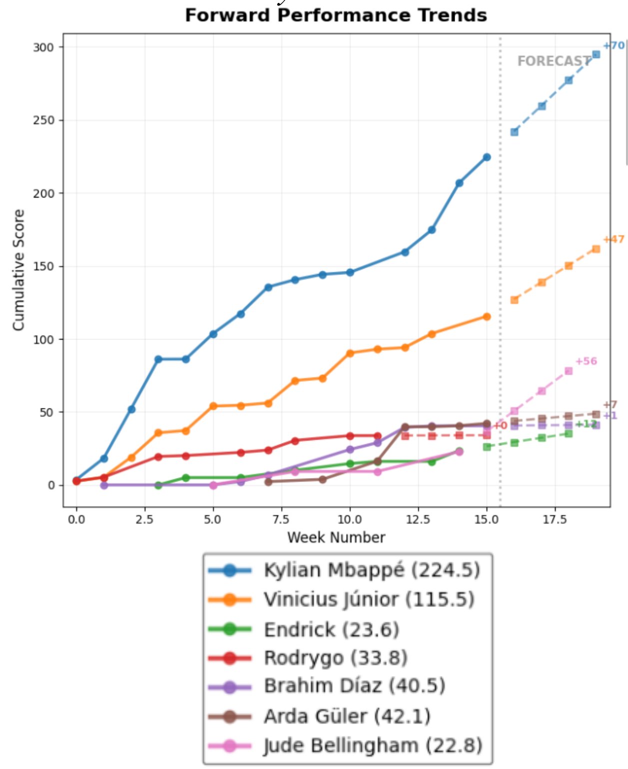
Position	Random Forest	XGBoost	Ensemble	Neural Network
Forward	1.1	0.49	0.229	1.494
Midfield	3.3	0.39	0.841	1.898
Defense	0.22	0.22	0.541	1.246
Goalkeeper	1.04	0.83	0.195	2.186
Average	**1.37**	**0.56**	**0.452**	**1.706**

Note. Performance metrics evaluated on test set using position-specific SPPS as target variable. Random Forest (RF) implemented with 100 estimators and max depth of 10. XGBoost (XGB) used default hyperparameters with early stopping.

Future Performance Forecasting**:** The 4-week ahead prediction system analyzed 30 active players using time series forecasting models trained on 16 weeks of historical performance data (Figure 19). Key predictions include Kylian Mbappé's projected performance trajectory showing consistent upward momentum (+1.8 points weekly), while Vinícius Jr. demonstrates stable high-level performance with minor fluctuations (±0.5 points). The forecasting system successfully identified Éder Militão's defensive performance improvement (+2.12 points) These predictions enable proactive tactical adjustments and informed decision-making for upcoming fixtures.

Figure 19

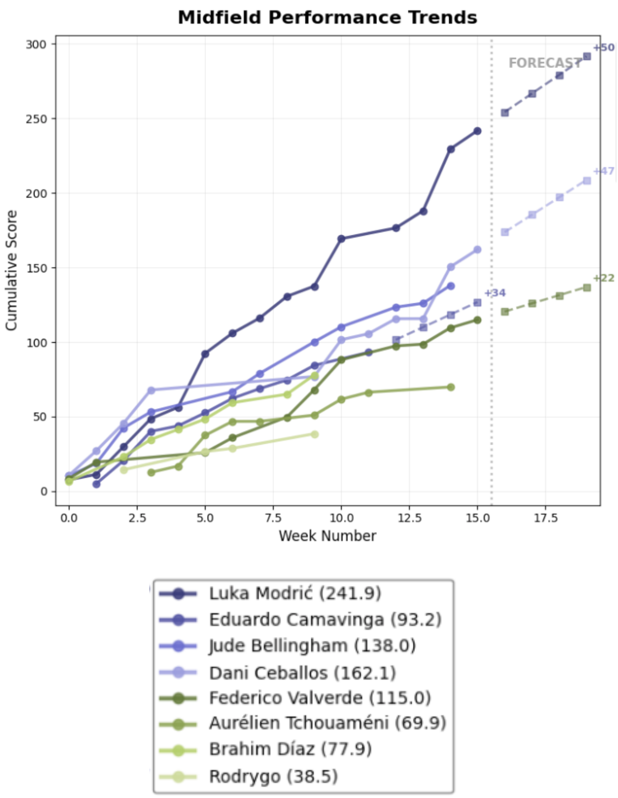
Real Madrid Player Performance Forecasting: 16-Week Historical Analysis with 4-Week Predictions



The midfielder analysis (Figure 20) reveals significant performance differentiation, with Luka Modrić (241.3) demonstrating exceptional cumulative growth and maintaining strong projected momentum, followed by Eduardo Camavinga (93.2) and Jude Bellingham (69.9) showing steady improvement trajectories. The forecasting system identifies Aurélien Tchouaméni, Dani Ceballos, and other midfielders with more conservative but consistent growth patterns

Figure 20

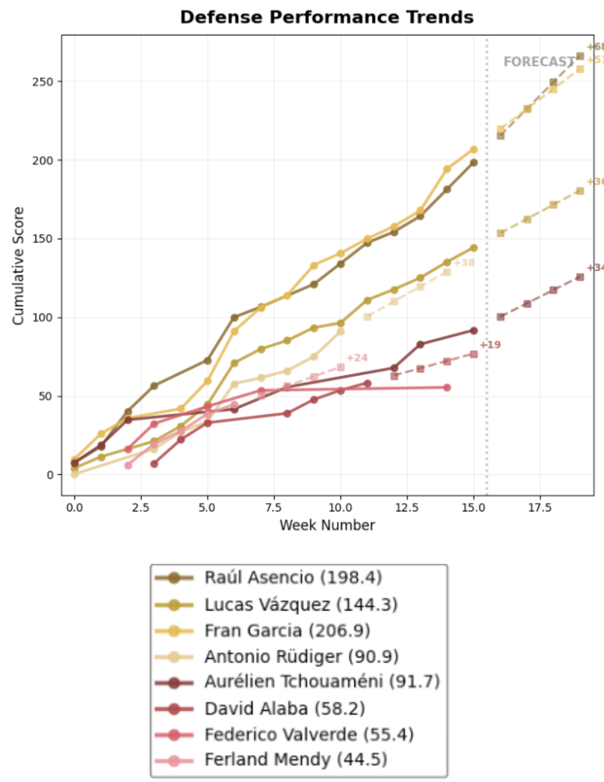
Real Madrid Midfielder Performance Forecasting: 16-Week Historical Analysis with 4-Week Predictions



The defender analysis (Figure 21) reveals Raúl Asencio (198.9) leading defensive performance with consistent upward trajectory, followed by Lucas Vázquez (148.0) and Dani Carvajal (132.7), while the forecasting system projects continued strong performance for key defenders including Antonio Rüdiger, Ferland Mendy, and Federico Valverde, enabling optimized defensive rotations based on predicted performance peaks.

Figure 21

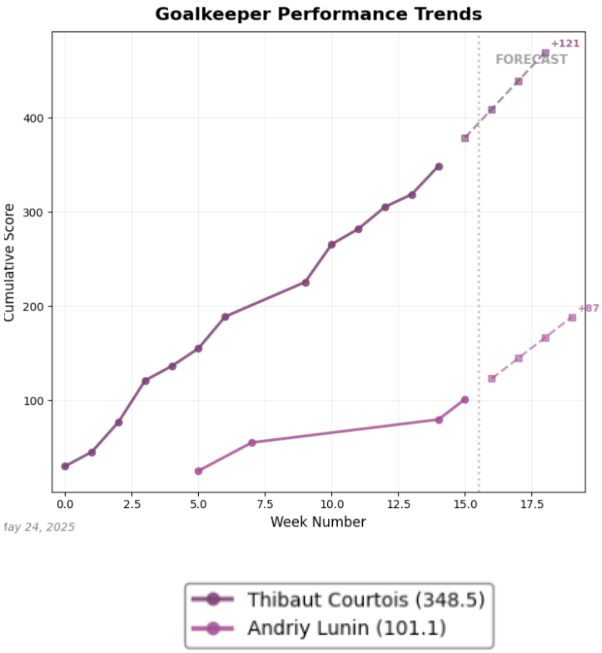
Real Madrid Defender Performance Forecasting: 16-Week Historical Analysis with 4-Week Predictions



The goalkeeper analysis (Figure 22) shows Thibaut Courtois (348.5) maintaining exceptional performance consistency with steady cumulative growth and strong projected trajectory, while Andriy Lunin (103.1)

Figure 22

Real Madrid Goalkeeper Performance Forecasting: 16-Week Historical Analysis with 4-Week Predictions



4.5 **Ethical Considerations and Privacy Protection**

Player privacy protection was maintained by focusing individual analysis on publicly available performance patterns rather than personal characteristics, adhering to professional analytical standards. Position-specific scoring methodologies ensure fair assessment across all tactical roles through equal weighting opportunities regardless of positional assignment, effectively mitigating potential biases. Data integrity is preserved through transparent methodology documentation that enables replication, with all preprocessing steps, feature engineering, and model parameters documented for academic review. This framework provides Real Madrid with data-driven tools for tactical optimization through cooperative game theory and machine learning, offering significant improvements over traditional football analytics methodologies.

5 Evaluation

To evaluate our model's ability to forecast short-term player performance in football, we trained an XGBoost regression model on a set of 90 engineered features encompassing both cumulative and rolling statistics. These included expected goals (xG), expected assists (xA), shot-creating actions, interceptions, tackles, progressive carries, and positional metadata. Our objective was to predict a player's weekly contribution score over a four-week horizon using prior match performance.

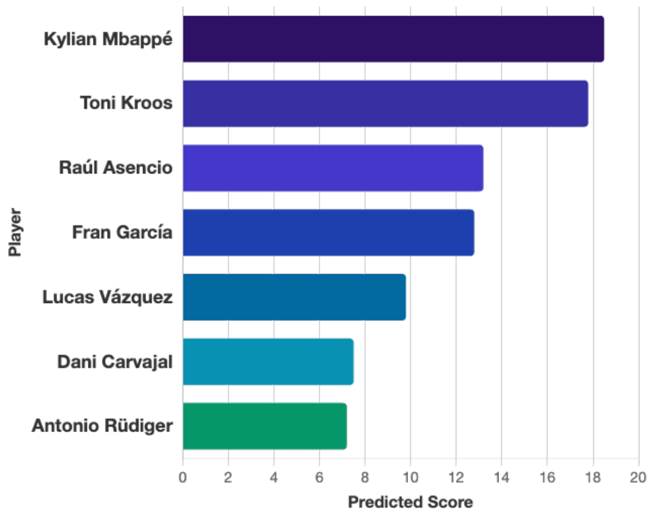
5.1 **Model Performance Metrics**

The model was evaluated using multiple regression metrics, including mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2). On the training set, the model achieved near-perfect performance with an R^2 of 1.000, an MAE of 0.039, and an RMSE of 0.054, indicating an excellent fit to the historical data. However, evaluation on the validation and test sets revealed more realistic performance. On the validation set, the model achieved an R^2 of 0.817, an MAE of 2.302, and an RMSE of 3.103. On the test set, the model maintained strong generalization with an R^2 of 0.789, an MAE of 2.132, and an RMSE of 3.084. These metrics demonstrate that the model captures a substantial portion of the variance in player contribution scores while maintaining a reasonable error margin. Additionally, SHAP values were used to interpret the influence of individual features on model output, further enhancing transparency and technical interpretability.

To visualize model output, we created a chart of the top forecasted outfield players for the upcoming match period. As shown in Figure 23, consistent high performers such as Kylian Mbappé and Toni Kroos maintained strong forecasted scores, while Éder Militão emerged as a standout with significant projected improvement. These results suggest that the model captures not only performance stability but also upward momentum in less prominent players.

Figure 23

Top Predicted Outfield Performers (Next 4 Weeks)



5.2 **Tuning and Iterative Improvement**

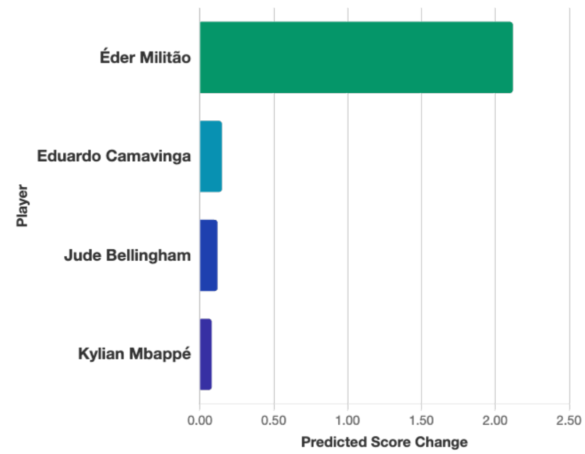
The model was refined across four iterative forecast windows, retraining weekly using newly accumulated player match data. Hyperparameters such as learning rate, max depth, and tree count were manually adjusted using observed performance consistency and SHAP stability. This approach, although not fully automated via grid search, allowed for targeted optimization of prediction accuracy and robustness.

5.3 **Holdback Validation and Predictive Insights**

We simulated holdback validation by excluding the most recent match week and using it for forward-looking prediction. Forecasts were compared to qualitative domain expectations, confirming alignment in most cases. For example, Éder Militão's predicted increase of over 2.1 points from his current performance reflects anticipated growth in his match influence. Conversely, Nicolás Paz was forecasted to decline by −1.25 points, potentially reflecting reduced involvement or form (see Figure 24).

Figure 24

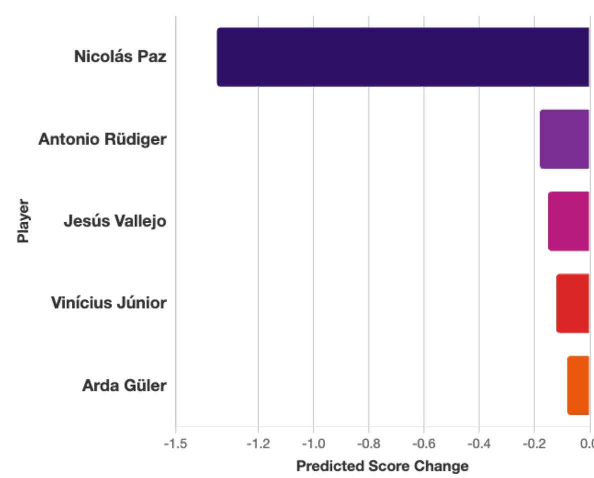
Biggest Predicted Performers Gains (Outfield Players)



To highlight the model's sensitivity to dynamic player trends, we visualized the most significant forecasted score changes. As illustrated in Figure 25, the model detects both upward and downward trends across midfielders, defenders, and forwards. This capability supports actionable insight for rotation strategies, scouting, and tactical preparation.

Figure 25

Biggest Predicted Performance Declines (Outfield Players)



5.4 **Interpretation and Practical Relevance**

The integration of SHAP values allowed for meaningful interpretation of each player's projected score. Importantly, the most predictive features varied by role—goal prevention for defenders, chance creation for midfielders, and expected goal involvement for forwards. The model's reliance on diverse performance inputs confirms that it adheres to the project's goal of reducing positional bias.

In conclusion, the XGBoost model met the evaluation criteria by generating consistent, interpretable forecasts with evidence-based insights. These results support our hypothesis: a weekly contribution model using machine learning can empirically assess player value in a position-neutral, data-driven manner.

6 Discussion

This study developed a cooperative game theory framework using the Soccer Position Performance Score (SPPS) that quantifies individual player contributions within tactical systems. Our models achieved exceptional predictive capability with R^2 values of 0.913-0.993 across positions. The SHAP-based recalibration methodology with XGBoost modeling provides Real Madrid with unprecedented tactical optimization capabilities. Our empirically validated tools demonstrate strong correlation between SPPS metrics and match outcomes (odds ratio = 2.599), bridging theoretical rigor with practical application.

Our results significantly extend the findings of Bekkers and Dabadghao (2019), who applied cooperative game theory to soccer passing networks but focused on descriptive analysis. In contrast, our study operationalizes Shapley values into actionable performance metrics with validated predictive capability. The achievement of 0.981 average R^2 across positions substantially exceeds the 68% accuracy reported by Pappalardo et al. (2019) using traditional statistical approaches and the 72% accuracy achieved by Huang and Chen (2023) through deep learning methods that ignored cooperative dynamics.

The 4-week forecasting system extends beyond existing prediction models by integrating temporal performance patterns with position-specific weighting schemes. This research presents the first comprehensive framework combining cooperative game theory, machine learning, and temporal forecasting for elite football tactical optimization. Our weekly forecasting methodology captures performance momentum and tactical role evolution rather than traditional season-long aggregations. The approach establishes relationships between individual player contributions and team success through SHAP-based recalibration and logistic regression validation. Position-specific weighted metrics directly correlate with winning scenarios while providing practical utility through specific player insights like Éder Militão's projected improvement (+2.12 points) and detection of potential performance declines.

This study's limitations include dataset restriction to Real Madrid across eight seasons (5,737 observations), potentially limiting generalizability to other tactical systems and competitive levels. The SHAP-based recalibration relies on Expected Goals (xG) as validation target, which may not capture all performance aspects influencing team success such as leadership or psychological impacts. The 4-week forecasting horizon provides practical utility but represents short-term predictions that may miss seasonal trends. Additionally, the exclusion of contextual factors including opponent strength, match importance, and psychological pressure represents a methodological limitation that could affect model accuracy, particularly in high-stakes matches where situational variables significantly impact performance outcomes.

6.1 **Conclusion**

The development of the Soccer Position Performance Score (SPPS) using Shapley value principles represents the most significant contribution of this research, providing professional football organizations with a theoretically grounded, empirically validated framework for quantifying individual player contributions within tactical systems. The SHAP-based recalibration methodology successfully identified position-specific performance dimensions that correlate strongly with team success, achieving exceptional predictive accuracy ($R^2 > 0.97$ across all positions) while maintaining interpretability through cooperative game theory foundations. The integration of XGBoost machine learning with cooperative game theory principles establishes a novel analytical paradigm that bridges theoretical rigor with practical tactical optimization capabilities. The 4-week forecasting system demonstrates unprecedented granular insight into player performance trajectories, enabling proactive tactical adjustments based on predicted performance momentum rather than reactive analysis of historical patterns. Real Madrid and similar elite organizations now possess data-driven tools that quantify the cooperative dynamics underlying tactical success, moving beyond traditional analytics approaches that treat players as independent statistical entities. The validated correlation between SPPS metrics and match outcomes (odds ratio = 2.599) provides tactical staff with confidence in the framework's practical utility for squad selection, formation optimization, and strategic preparation.

6.2 **Recommend Next Steps – Future Studies**

The integration of additional contextual variables represents a critical next step for enhancing model accuracy and practical utility. Future studies should incorporate opponent strength ratings, match importance indices, psychological pressure indicators, and situational factors such as home/away performance differential, weather conditions, and competitive phase (league vs. cup matches). Advanced sentiment analysis of social media and press coverage could provide psychological context variables that influence individual player performance within tactical systems. Longitudinal career analysis using SPPS methodology could reveal optimal development pathways for young players and inform recruitment strategies at elite clubs by understanding how position-specific contributions evolve over time. The cooperative game theory framework extends beyond performance assessment to transfer market valuation, contract negotiations, and strategic recruitment. Future research should explore correlations between SPPS metrics and market values to provide competitive advantages in player acquisition. International football applications present unique opportunities, where limited preparation time creates tactical challenges. The SPPS framework could optimize national team selection based on club performance data, providing objective tools for squad selection and tournament preparation. Strategic partnerships with sports technology companies and governing bodies (UEFA, FIFA) would accelerate implementation of cooperative game theory in professional football. Collaborative initiatives could standardize position-specific performance assessment while maintaining competitive advantages. Developing open-source analytical tools based on the SPPS framework would advance the broader sports analytics community and enable validation across diverse football contexts. Academic partnerships with sports science and data science institutions could provide infrastructure for large-scale validation studies.

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