The Open Sports Sciences Journal
DOI: 10.2174/011875399X508299261013132917, 2026, 19, e1875399X508299
ISSN: 1875-399X
1

RESEARCH ARTICLE OPEN ACCESS

Predicting Ranking Trajectories of EPL Derby Teams

Ji-Young Chung[1] and Da-In Lee[2,*]

[1]*Sports Education, Kyung Hee University, Seoul, South Korea*
[2]*Graduate School of Physical Education, Kyung Hee University, Seoul, South Korea*

Abstract:

Introduction: Research on forecasting league rankings during critical stages of the season, particularly in derby contexts, remains limited.

Methods: This study forecasts league rankings for English Premier League derby teams at mid-season (Round 19) and end-of-season (Round 38) using the NeuralProphet time-series forecasting model and historical ranking data from the 1992–1993 to 2024–2025 seasons.

Results: The results indicate that Liverpool is predicted to finish first in both Round 19 and Round 38, while Manchester City and Arsenal are expected to rank third at both stages. Manchester United is forecasted to show a slight improvement from mid-season to the end of the season, whereas Tottenham Hotspur is predicted to experience a modest decline. Everton is projected to remain near the relegation zone throughout the season.

Discussion: These findings suggest that time-series–based league ranking forecasts can provide valuable practical insights for squad management, tactical planning, and mid- to long-term strategic decision-making.

Conclusion: The study also highlights the potential benefits of advancing ranking prediction research through multivariate time-series methods and staged forecasting frameworks.

Keywords: English premier league, NeuralProphet, Timeseries, League ranking, Sports analytics, Football.

© 2026 The Author(s). Published by Bentham Open.
This is an open access article distributed under the terms of the Creative Commons Attribution 4.0 International Public License (CC-BY 4.0), a copy of which is available at: https://creativecommons.org/licenses/by/4.0/legalcode. This license permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

*Address correspondence to this author at the Graduate School of Physical Education, Kyung Hee University, Seoul, South Korea; E-mail: leedi1008@khu.ac.kr

Cite as: Chung J, Lee D-I. Predicting Ranking Trajectories of EPL Derby Teams. Open Sports Sci J, 2026; 19: e1875399X508299. http://dx.doi.org/10.2174/011875399X508299261013132917

Received: May 18, 2026
Revised: August 26, 2026
Accepted: September 11, 2026
Published: October 28, 2026

Send Orders for Reprints to
reprints@benthamscience.net

1. INTRODUCTION

The Premier League comprises 20 clubs, each playing 38 matches over the course of a season. Match outcomes are classified as wins, draws, or losses, which correspond to the allocation of 3, 1, and 0 points, respectively. League standings are determined by the total points accumulated by each team. At the end of the season, the three lowest-ranked teams are relegated to the second-tier Championship division, while the top four teams qualify for the UEFA Champions League [1]. The team finishing in fifth place qualifies for the UEFA Europa League, and those finishing sixth or seventh may qualify for either the Europa League or the UEFA Europa Conference League, depending on the results of domestic cup competitions [2]. This structure highlights the significant influence of league positioning on the strategic planning and operational decisions of clubs for the following season [3].

Seasonal performance is a critical determinant of qualification for European competitions [4]. League results significantly influence squad composition and preparation

for the following season [5]. Consequently, understanding seasonal performance is essential for clubs when developing strategies and long-term plans for subsequent seasons [6].

Within the Premier League, competition is also defined by long-established rivalries between clubs, particularly derby matches. A derby match typically refers to a contest between clubs based in the same city or region [7]. Representative examples include the Manchester Derby between Manchester United and Manchester City, which reflects intra-regional competition among local fan bases [8]; the Merseyside Derby between Liverpool FC and Everton FC [9], widely regarded as one of the most intense rivalries in football; the North London Derby between Arsenal and Tottenham Hotspur, characterized by a long history of fluctuating dominance that has intensified regional rivalry [10]; and the Northwest Derby between Manchester United and Liverpool FC, where inter-city competition has evolved into one of football's most prominent rivalries [11].

Derby matches often exhibit heightened intensity due to their association with local identity and collective behavior [12]. In major cities such as London, Manchester, and Liverpool, long-standing histories and deeply entrenched rivalries generate high levels of engagement among both players and fans [13]. Furthermore, derby results can affect players' confidence and overall league performance, potentially prompting adjustments in managerial tactics and broader club strategies [14]. These characteristics make derby matches a particularly meaningful context for examining league ranking dynamics through predictive analysis.

Unlike most major European leagues that implement a mid-season break from Christmas to early January, the Premier League continues competition throughout the festive period, beginning on Boxing Day [15]. The congested fixture schedule increases the risk of injury and heightens the importance of strategic match management [16]. For instance, Chelsea FC's performance during the 2014–2015 Boxing Day fixtures played a critical role in its championship success [17]. These cases illustrate that mid-season rankings can be as influential as end-of-season standings. Although previous studies have attempted to predict match outcomes or season rankings in football [18-20], limited attention has been given to forecasting rankings specifically related to derby rivalries or mid-season league standings.

This study addresses this gap by conducting a time-series forecasting analysis of league rankings in the world's most widely viewed football league. It focuses on clubs involved in the Manchester Derby, Merseyside Derby, North London Derby, and Northwest Derby-namely Manchester United, Manchester City, Liverpool FC, Everton FC, Tottenham Hotspur, and Arsenal FC-by predicting their rankings at the midpoint of the season (Round 19, immediately following the Boxing Day period) and at the end of the season (Round 38). Through this approach, the study aims to extend football forecasting research from predominantly match-level prediction toward the temporal forecasting of league-ranking trajectories and to examine the expected competitive positions of major EPL rivals at different stages of the season.

2. MATERIALS AND METHODS

2.1. Study Design

The present study employed a time-series forecasting framework using the NeuralProphet model to predict future league standings in the English Premier League (EPL). Time-series forecasting is an analytical approach that estimates future outcomes based on chronologically ordered observations and has been widely applied across disciplines such as economics, healthcare, media studies, and the natural sciences [21]. Earlier forecasting studies primarily relied on statistical methods, including ARIMA and SARIMA models [22]. However, these traditional techniques are limited by assumptions of linearity, reducing their effectiveness in handling the nonlinear and highly dynamic characteristics of modern datasets [23].

To address these methodological limitations, recent forecasting research has increasingly incorporated deep learning architectures capable of modeling nonlinear sequential patterns, such as Long Short-Term Memory (LSTM) networks and NeuralProphet [24]. NeuralProphet, developed by Facebook's Data Science team, extends the traditional Prophet framework by incorporating neural network architectures, enabling improved modeling of nonlinear, nonstationary, and complex temporal patterns. It has demonstrated forecasting improvements ranging from 55% to 92% over Prophet in short- and medium-term prediction scenarios [25].

NeuralProphet preserves interpretable time-series components, such as trend and seasonality, while integrating neural network-based elements that enable flexible modeling of temporal patterns [25]. These features are particularly relevant to EPL rankings, which consist of sequential observations that evolve across seasons and form long-term ranking trajectories. Consequently, NeuralProphet was chosen to capture temporal changes in historical league positions and to extend these patterns for forecasting future rankings.

Within the field of sports analytics, NeuralProphet forecasting has been employed to predict team rankings in the English Premier League [26]. Meanwhile, Lee and Chung [27] applied NeuralProphet to predict lap times in Formula 1, demonstrating the model's robustness for sports-related forecasting tasks. Additionally, Lee *et al*. [28] used NeuralProphet to estimate attendance patterns in the KBO League, further supporting the model's applicability for short-term predictive analyses in sports contexts.

Based on these methodological considerations, this study employed the NeuralProphet framework to forecast EPL derby team rankings using historical league data from the 1992–1993 through 2024–2025 seasons. The analysis specifically focused on clubs involved in four prominent rivalries-the Manchester Derby, Merseyside Derby, North

London Derby, and Northwest Derby-including Manchester United, Manchester City, Liverpool, Everton, Tottenham Hotspur, and Arsenal. Forecasts were generated for two key competitive stages: the post-Boxing Day midpoint of the season (Round 19) and the final league standings at the end of the season (Round 38).

2.2. Configuration and Training of the NeuralProphet Model

The same NeuralProphet modeling procedure and parameter configuration were consistently applied to the historical ranking data of all teams included in the analysis. The analysis was conducted using Python 3.10 and NeuralProphet version 0.9.0. The historical league ranking was specified as the target variable, and all available ranking observations up to and including the 2024–2025 season were used for model fitting. No separate training, validation, or test data splits were applied.

The NeuralProphet model was configured to capture the temporal structure of the EPL ranking data. The rankings were modeled at six-month intervals (`freq='6M'`). Yearly seasonality was enabled to account for recurring annual patterns, while weekly and daily seasonalities were disabled because the ranking data were not structured at weekly or daily intervals. The seasonality component was specified using a multiplicative mode. The learning rate was set to 0.01, and these parameter settings were applied consistently across all team datasets.

Following model fitting, historical fitted values were generated for the observed period. These fitted values were then compared with the corresponding observed rankings to assess the degree of historical model fit. The fitted models were subsequently used to forecast the next two observation points, corresponding to Rounds 19 and 38 of the 2025–2026 season. Since NeuralProphet produces continuous numerical estimates, both the original estimates and their rounded integer values were used in the evaluation.

2.3. Data Collection

To forecast league rankings, data on team positions from Rounds 19 and 38 of each season between 1992–1993 and 2024–2025 were collected from the official Premier League website (https://www.premierleague.com/en/). The dataset comprises 33 seasons with two observations per season, resulting in a total of 66 ranking observations per team. NeuralProphet has been applied in previous research using time-series datasets of a similar scale. For example, Lee and Chung [29] applied NeuralProphet to 72 quarterly observations to forecast financial indicators of K League citizen football clubs. Similarly, the present study utilized 66 ranking observations per team, representing the complete historical period of the Premier League from its inaugural 1992–1993 season through the 2024–2025 season.

Manchester United, Liverpool, Everton, Arsenal, and Tottenham Hotspur have not been relegated since the Premier League's inception in the 1992–1993 season; therefore, no missing values occurred for these five clubs during data collection. In contrast, Manchester City was relegated to lower divisions during the 1996–1997 to 1999–2000 seasons and again in the 2001–2002 season. For these relegated seasons, Manchester City's league position was adjusted to 20th place to maintain continuity in the time-series data.

2.4. Model Performance Evaluation

To assess forecasting performance, this study employed two commonly used error metrics: MAE (Mean Absolute Error) and RMSE (Root Mean Squared Error), as presented in Table **1**. These metrics are widely utilized to evaluate the accuracy of predictive models in time-series research [30]. MAE quantifies the average magnitude of prediction errors regardless of their direction, while RMSE calculates the square root of the mean of squared prediction errors, thereby assigning greater weight to larger deviations [31]. Lower MAE and RMSE values indicate smaller discrepancies between estimated and observed values, with values closer to zero representing lower forecasting errors [32].

In this study, MAE and RMSE were calculated by comparing the historical ranking estimates generated by NeuralProphet with the corresponding observed league rankings at the same time points. Since NeuralProphet produces continuous numerical estimates, whereas EPL rankings are expressed as discrete integer positions, the error metrics were computed for both the original continuous estimates and the values rounded to the nearest integer. Thus, the reported MAE and RMSE values represent the discrepancies between the model-estimated and observed rankings within the historical data used in the analysis. Specifically, MAE indicates the average number of ranking positions by which the estimated rankings differ from the observed rankings, while RMSE reflects the magnitude of these discrepancies with greater sensitivity to larger ranking errors. Accordingly, smaller MAE and RMSE values indicate that the model-generated historical estimates were closer to the actual league rankings.

2.5. Forecasting League Rankings

The NeuralProphet model was used to forecast league rankings for the 2025–2026 season at two time points: Round 19 and Round 38. The model generated predictions as continuous real-valued outputs; however, because actual league rankings are represented as discrete natural numbers, the predicted values were rounded to the nearest integer. Accordingly, ranking outcomes were reported by distinguishing between the original continuous predictions and their rounded integer counterparts to ensure consistency with the league's ranking system.

Table 1. Model's predictive accuracy.

Category	MAE		References	
	Actual Value (Continuous)	Rounded Value (Integer)	Actual Value (Continuous)	Rounded Value (Integer)
Manchester United	1.414	1.394	2.094	2.060
Manchester City	1.794	1.788	2.521	2.486
Liverpool	1.813	1.848	2.296	2.348
Everton	2.777	2.742	3.475	3.466
Arsenal	1.782	1.727	2.392	2.374
Tottenham	2.38	2.318	3.178	3.184

3. RESULTS

3.1. Manchester United

Figures 1 and 2, along with Table 2, present the predicted league standings for Manchester United in the 2025–2026 season. The team was predicted to be in 8th place at Round 19 and to improve to 7th place by Round 38, indicating a positive change in their league position during the latter half of the season.

3.2. Manchester City

Figures 3 and 4, along with Table 3, present the predicted league standings for Manchester City in the 2025–2026 season. The team is predicted to finish in third place at both Round 19 and Round 38.

Table 2. The forecasted league rankings for Manchester United.

Round	Actual Value (Continuous)	Rounded Value (Integer)
19R	8.286336	8
38R	6.761899	7

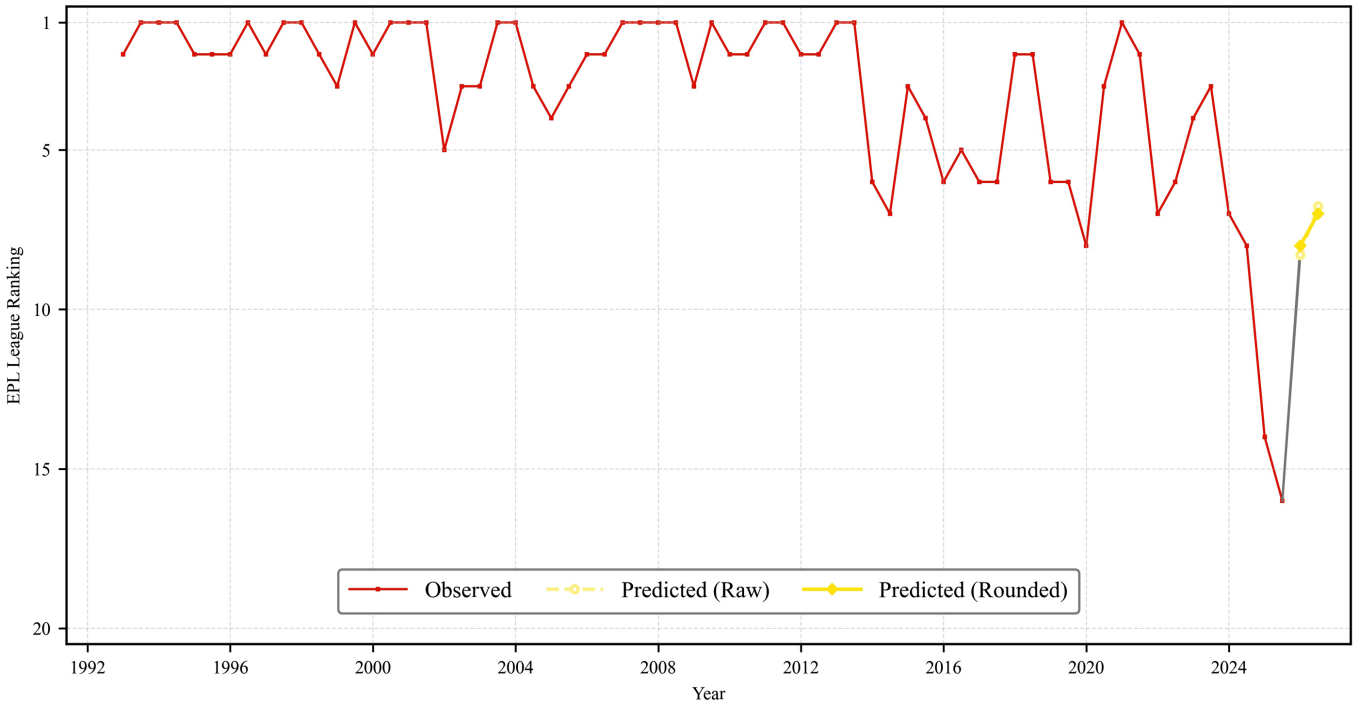

Fig. (1). Historical and forecasted EPL rankings for Manchester United.

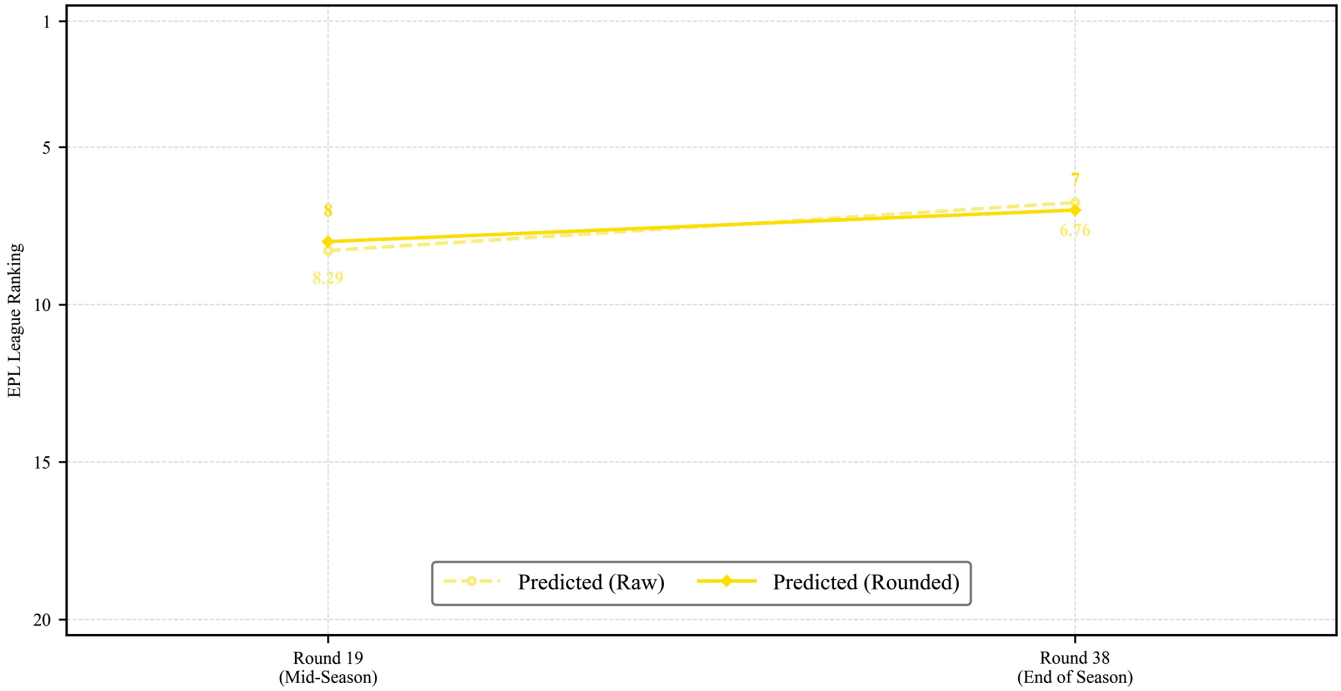

Fig. (2). Detailed forecast of EPL rankings for Manchester United.

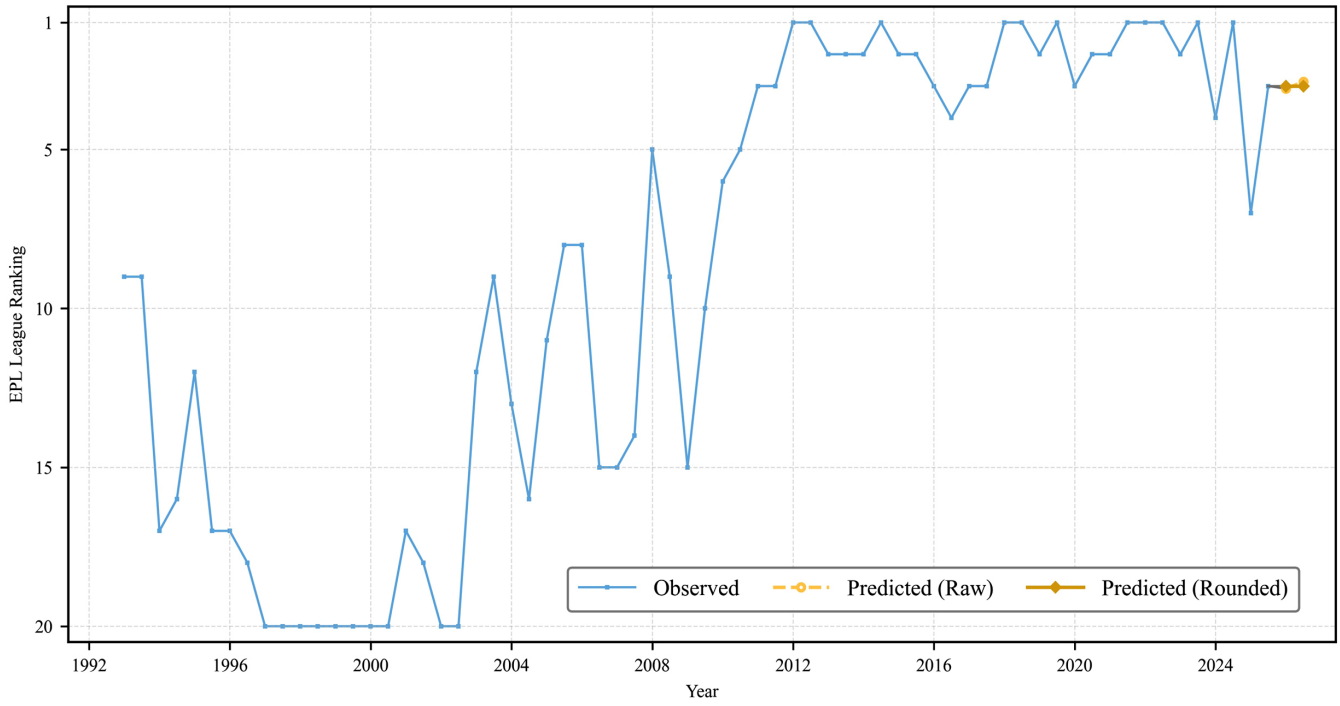

Fig. (3). Historical and forecasted EPL rankings for Manchester city.

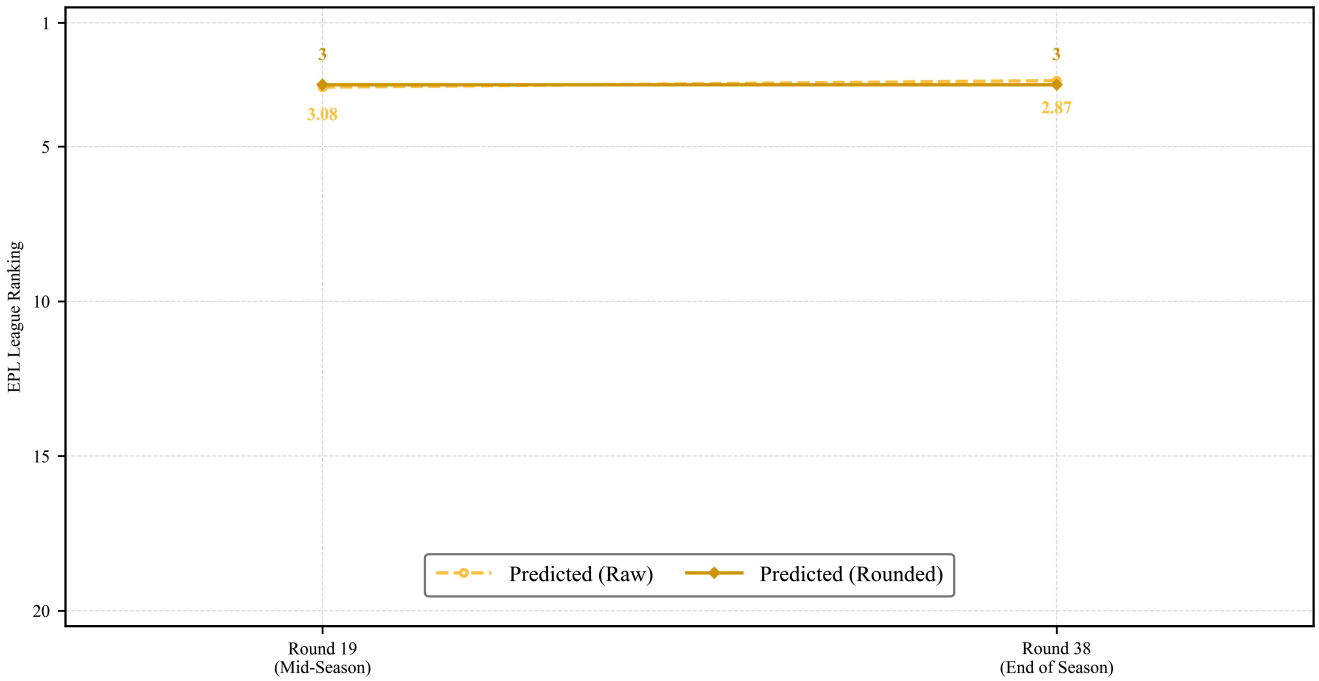

Fig. (4). Detailed forecast of EPL rankings for Manchester city.

Table 3. The forecasted league rankings for Manchester city.

Round	Actual Value (Continuous)	Rounded Value (Integer)
19R	3.080883	3
38R	2.867812	3

3.3. Liverpool

Figures **5** and **6**, along with Table **4**, present the predicted league standings for Liverpool in the 2025–2026 season. The team is predicted to finish in first place at both Round 19 and Round 38.

Table 4. The forecasted league rankings for Liverpool.

Round	Actual Value (Continuous)	Rounded Value (Integer)
19R	1.285766	1
38R	1.091420	1

3.4. Everton

Figures **7** and **8**, along with Table **5**, present the predicted league standings for Everton in the 2025–2026 season. The team is predicted to finish in 17th place at both Round 19 and Round 38.

Table 5. The forecasted league rankings for Everton.

Round	Actual Value (Continuous)	Rounded Value (Integer)
19R	17.121111	17
38R	16.987461	17

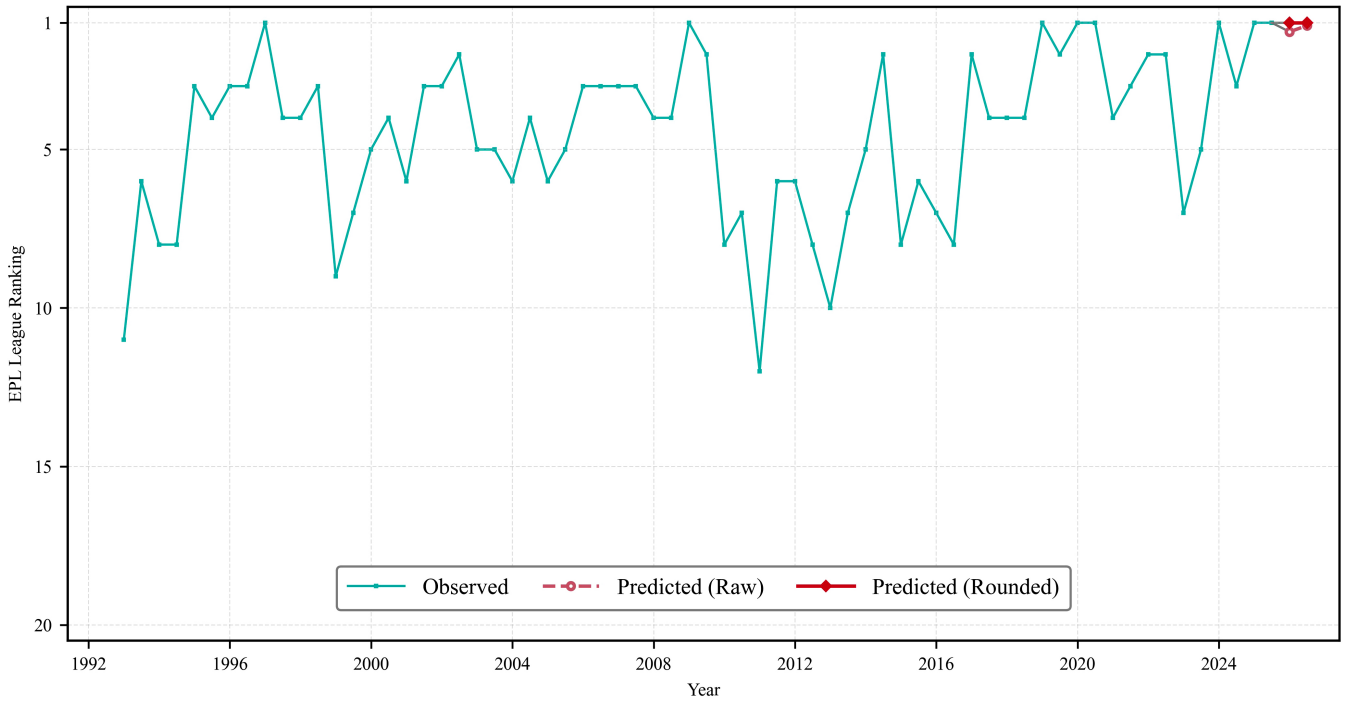

Fig. (5). Historical and forecasted EPL rankings for Liverpool.

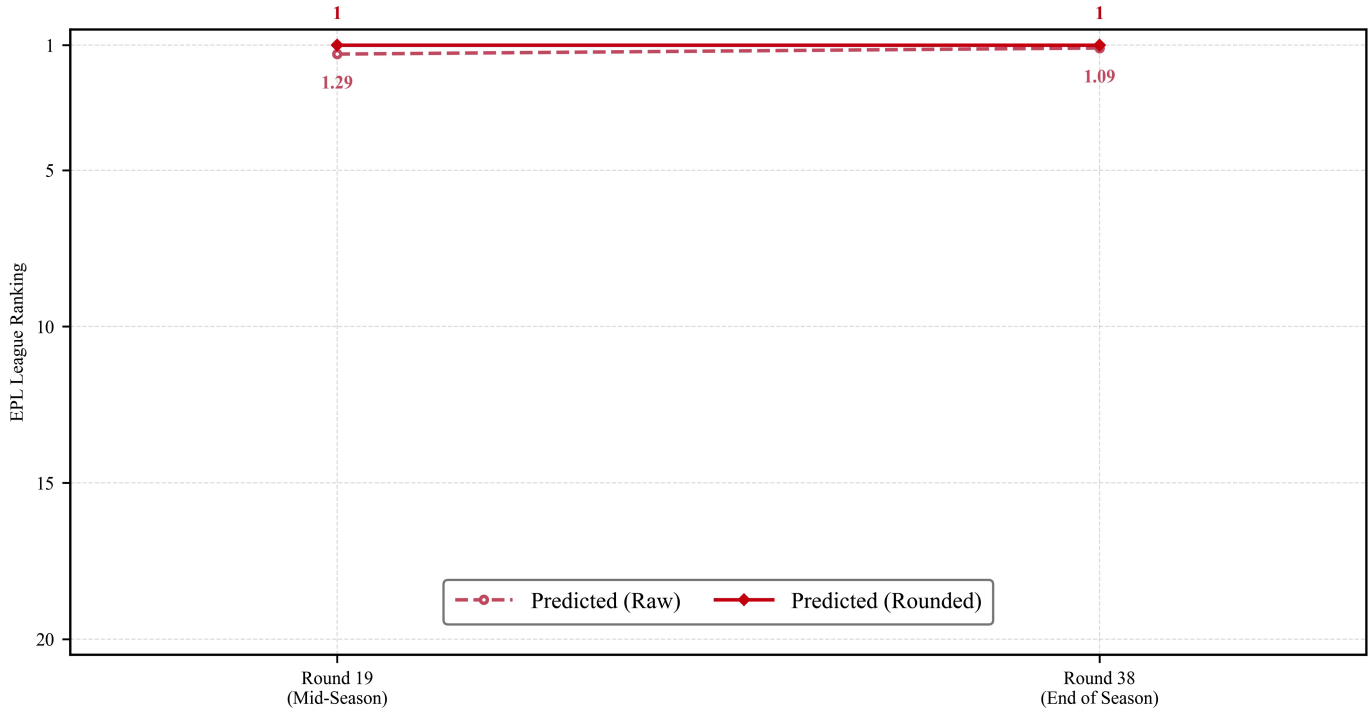

Fig. (6). Detailed forecast of EPL rankings for Liverpool.

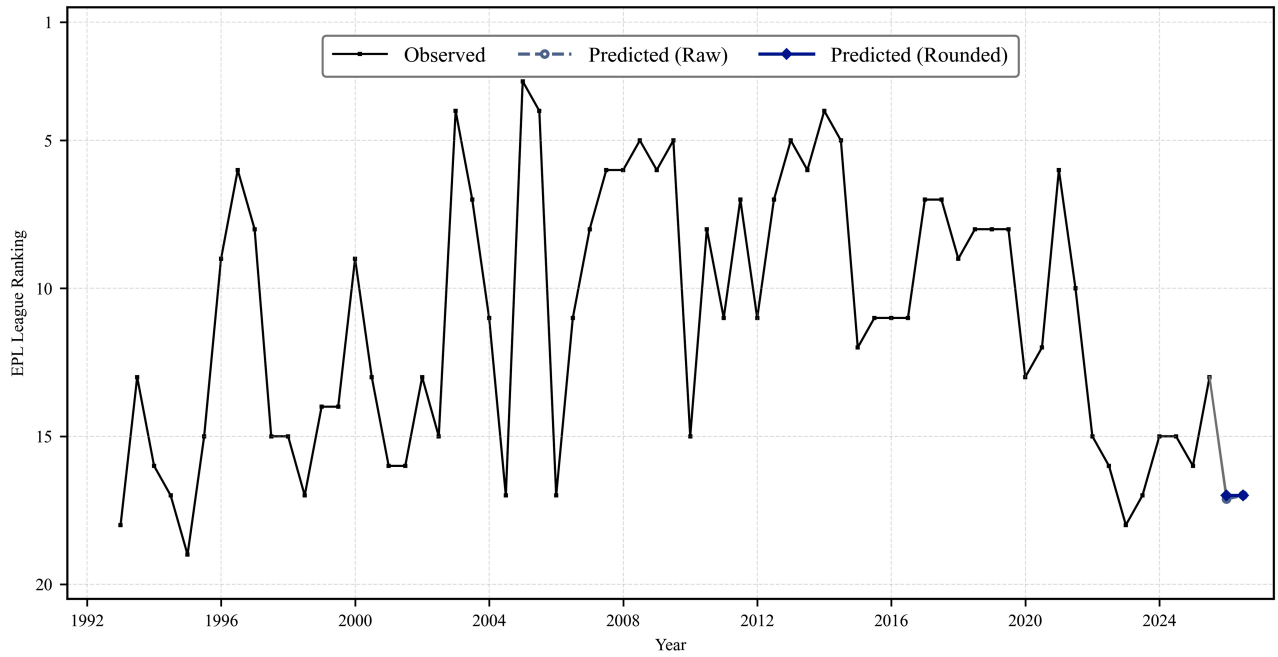

Fig. (7). Historical and forecasted EPL rankings for Everton.

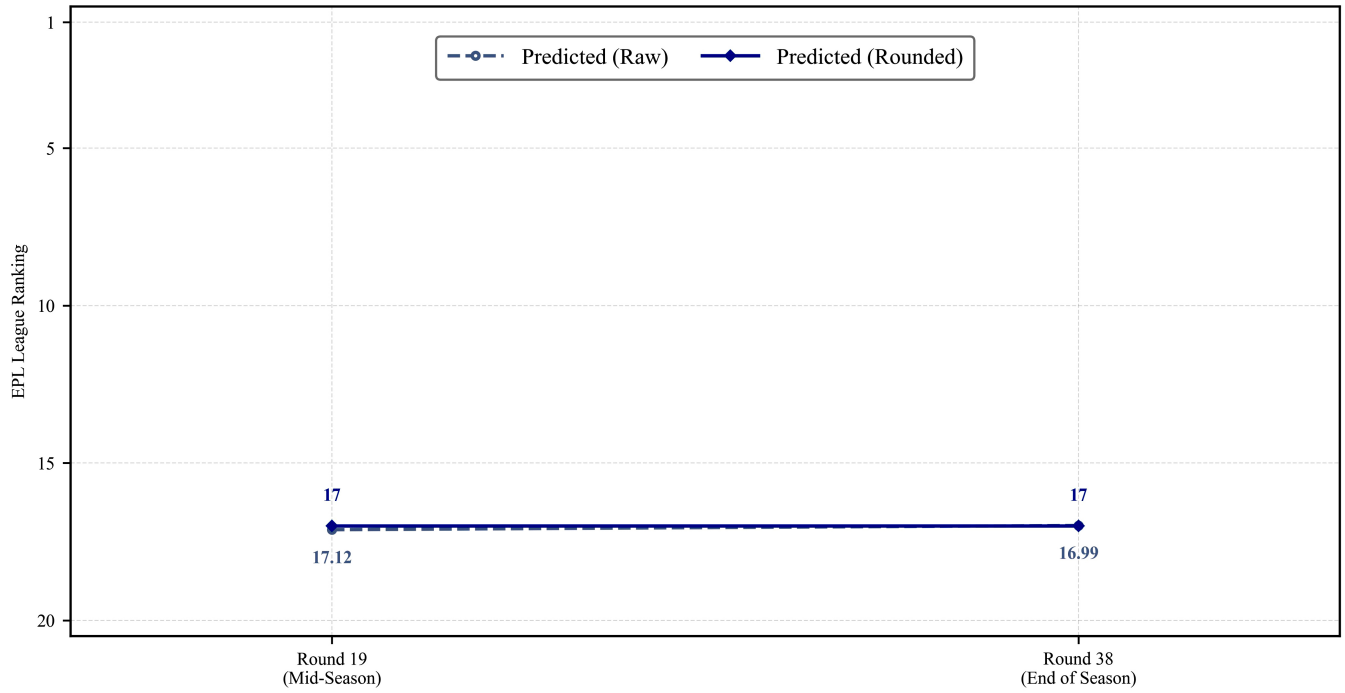

Fig. (8). Detailed forecast of EPL rankings for Everton.

3.5. Arsenal

Figures **9** and **10**, along with Table **6**, present the predicted league standings for Arsenal in the 2025–2026 season. The team is predicted to finish in third place at both Round 19 and Round 38.

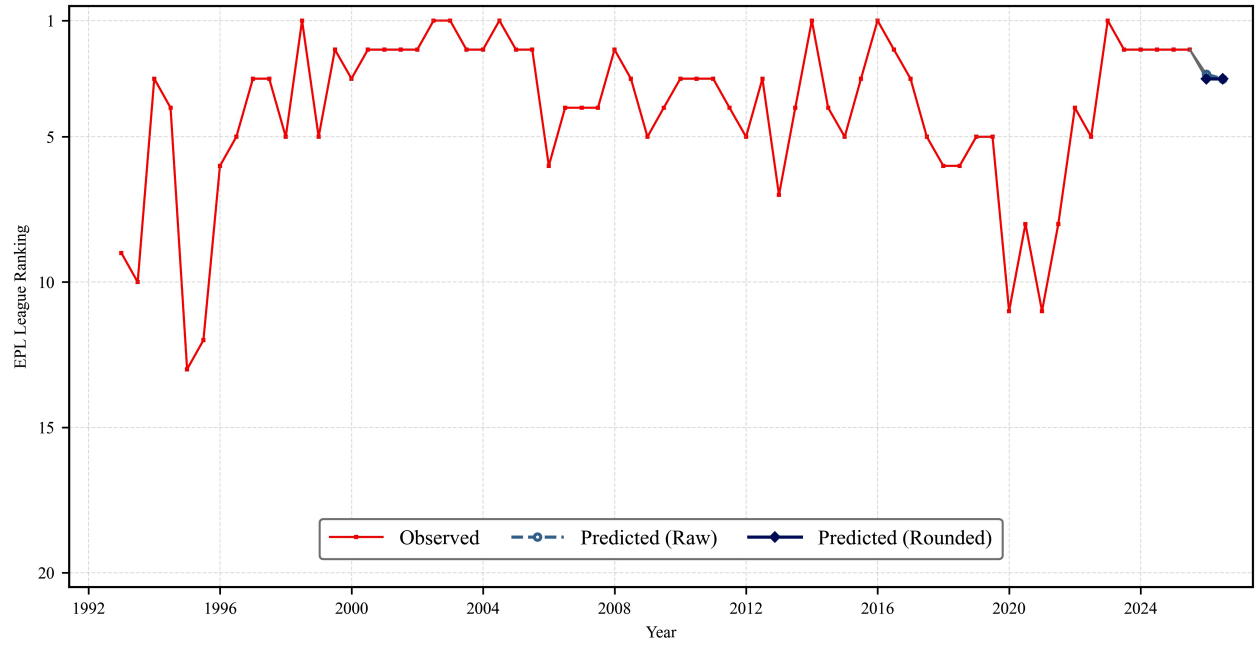

Fig. (9). Historical and forecasted EPL rankings for Arsenal.

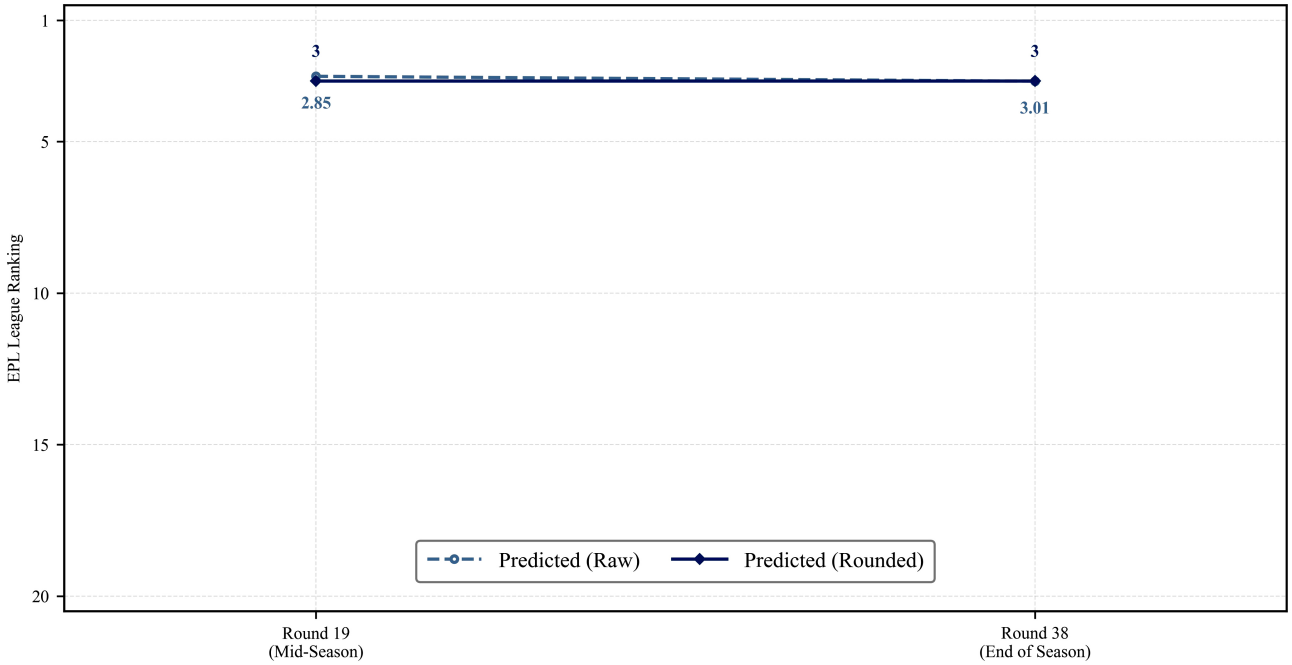

Fig. (10). Detailed forecast of EPL rankings for Arsenal.

Table 6. The forecasted league rankings for Arsenal.

Round	Actual Value (Continuous)	Rounded Value (Integer)
19R	2.847373	3
38R	3.008644	3

3.6. Tottenham

Figures 11 and 12, along with Table 7, present the predicted league standings for Tottenham Hotspur in the 2025–2026 season. The team is predicted to be in 8th place at Round 19, dropping to 9th place by Round 38, indicating a decline in league position during the latter half of the season.

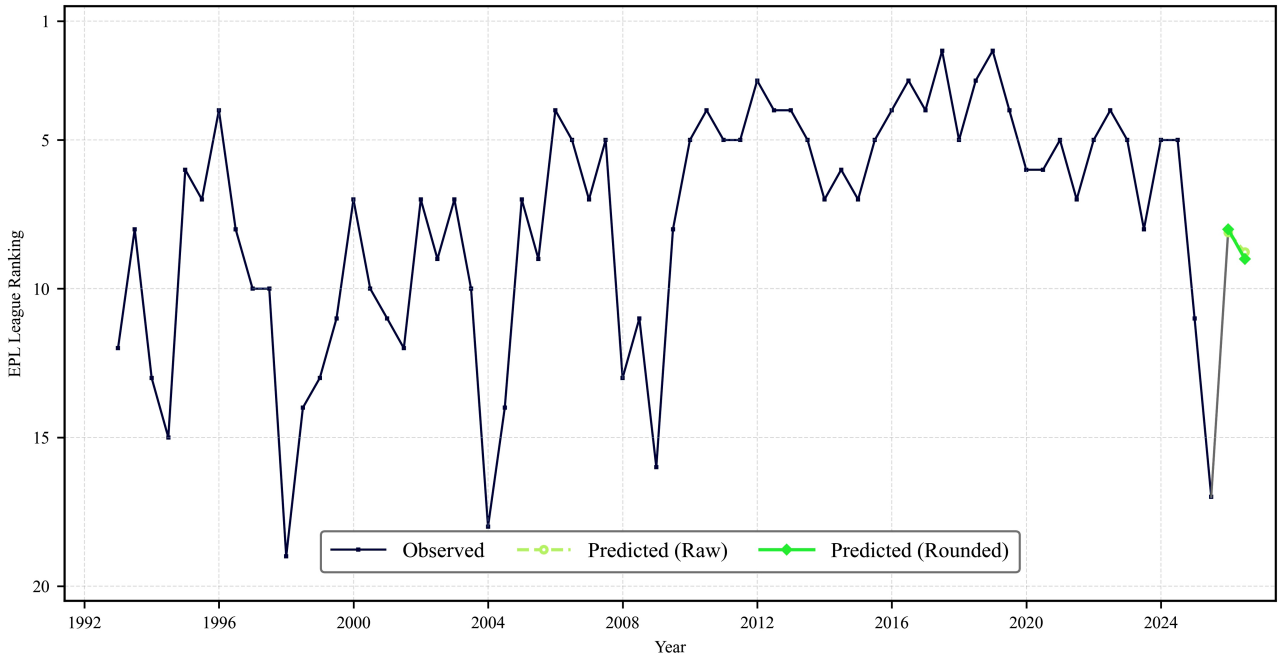

Fig. (11). Historical and forecasted EPL rankings for Tottenham Hotspur.

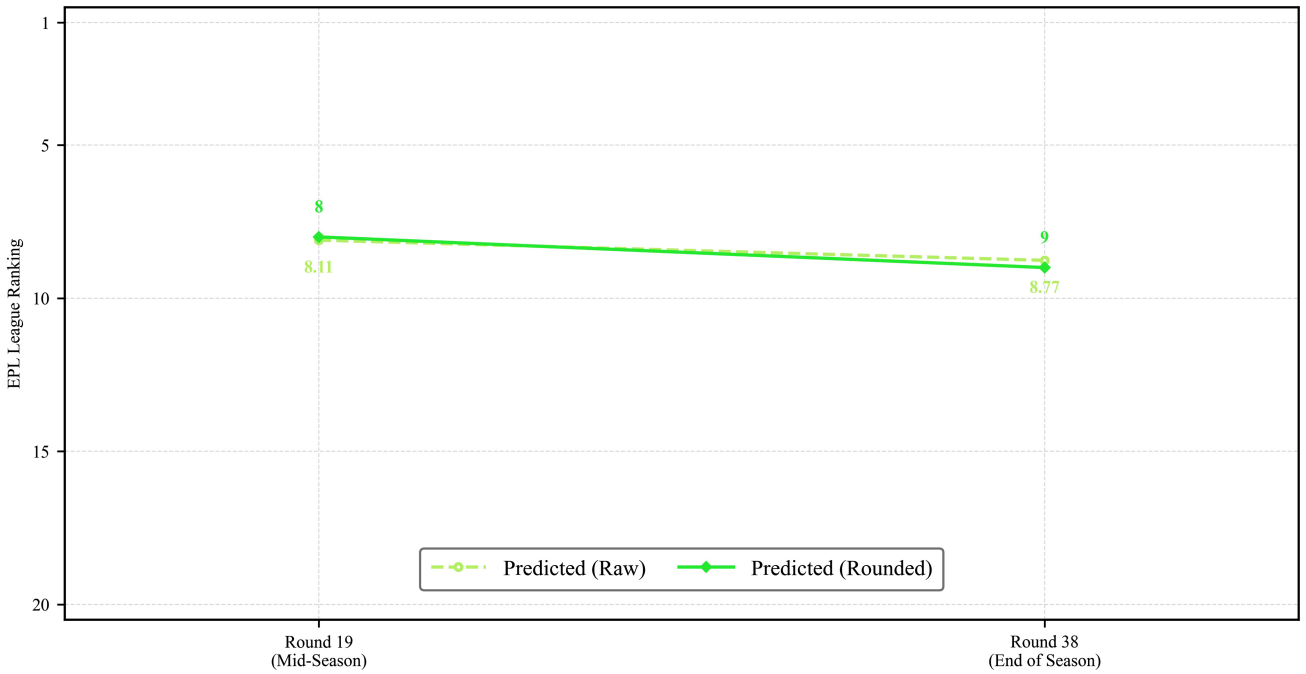

Fig. (12). Detailed forecast of EPL rankings for Tottenham Hotspur.

Table 7. The forecasted league rankings for Tottenham Hotspur.

Round	Actual Value (Continuous)	Rounded Value (Integer)
19R	8.105234	8
38R	8.765211	9

4. DISCUSSION

The present study applied NeuralProphet to historical EPL ranking data to forecast the positions of six clubs involved in major EPL derbies at Rounds 19 and 38. The results indicated relatively minor changes between the two forecast points. Liverpool was predicted to rank first at both Round 19 and Round 38, while Manchester City and Arsenal were forecasted to remain in third place, and Everton in 17th place. Manchester United was expected to improve from eighth to seventh place, whereas Tottenham Hotspur was predicted to decline from eighth to ninth place. Overall, four of the six teams maintained the same rounded ranking between the two forecast points, while the remaining two showed a one-position change.

The predicted ranking patterns can be understood in relation to the characteristics of NeuralProphet and the temporal structure of the data used in this study. NeuralProphet models chronologically ordered observations by representing temporal components such as trend and seasonality. In this study, the historical rankings of each team were arranged sequentially across seasons, and future rankings were estimated based on the temporal patterns identified in these historical observations. The relatively small differences between Round 19 and Round 38 indicate that the temporal patterns extracted from the historical ranking data resulted in largely continuous trajectories across the two forecast points. However, the continuous forecast values exhibited changes even when the rounded league positions remained unchanged. For example, Manchester City's predicted ranking changed from 3.08 at Round 19 to 2.86 at Round 38, whereas Arsenal's changed from 2.85 to 3.00. This demonstrates that the continuous estimates can capture subtle temporal variations in the predicted trajectory that are not apparent when the forecasts are converted into integer league positions.

The one-position changes observed for Manchester United and Tottenham Hotspur further illustrate differences in the ranking trajectories derived from historical data. Manchester United exhibited an upward trajectory, moving from eighth to seventh place, whereas Tottenham experienced a downward trajectory, dropping from eighth to ninth place. In contrast, Liverpool and Everton maintained consistent predicted positions across both forecast points. These patterns indicate that the model generated varying directions and magnitudes of temporal change based on each team's historical ranking series. Therefore, the findings are more appropriately interpreted in terms of the continuity and change in predicted ranking trajectories rather than as indicators of specific changes in team performance or club management.

From a methodological standpoint, this study differs from conventional football forecasting approaches that primarily focus on predicting individual match outcomes or specific performance indicators. Instead of treating each match as an independent prediction target, this study considers league rankings as a longitudinal time-series variable and examines their progression between the mid-season and the end of a future season. This approach allows football forecasting to be viewed from a season-level temporal perspective by emphasizing changes in a team's relative competitive position over time. Consequently, the academic significance of this study lies in extending the application of time-series forecasting from individual outcomes to longitudinal league-ranking trajectories and demonstrating the applicability of NeuralProphet for analyzing temporal changes in EPL standings.

5. STUDY LIMITATIONS

This study has several limitations. First, the forecasting model used league ranking as the sole time-series variable and did not incorporate other performance-related and contextual factors that may influence league standings. EPL rankings are determined by multiple interacting factors, including points, goal difference, goals scored and conceded, player injuries and availability, transfers, managerial changes, and fixture congestion. The exclusion of these variables limits the ability of the forecasts to capture the complex dynamics underlying changes in league position. Future research should develop multivariate forecasting frameworks that incorporate relevant performance and contextual variables to provide a more comprehensive representation of ranking dynamics.

Second, this study did not explicitly model the temporal dependency between mid-season and end-of-season rankings. Although Round 19 and Round 38 were forecasted as two sequential time points, the predicted Round 19 ranking was not used as a conditioning variable for the Round 38 forecast. Therefore, the model did not directly estimate how a team's mid-season position influences its subsequent ranking progression. Future research could address this limitation by developing a staged forecasting framework that incorporates mid-season rankings and related performance data into the prediction of end-of-season standings.

Third, this study focused on applying NeuralProphet to forecast EPL ranking trajectories and did not aim to compare the relative performance of different forecasting algorithms. Future research could extend these findings by comparing NeuralProphet with alternative forecasting methods, such as ARIMA, Prophet, and LSTM, under identical data conditions. Such comparative analyses

would provide valuable insights into the relative strengths and predictive characteristics of various forecasting approaches for league ranking data and contribute to the development of more robust forecasting frameworks in sports analytics.

CONCLUSION

This study applied NeuralProphet to historical EPL ranking data to forecast the positions of selected teams at Rounds 19 and 38 of the 2025–2026 season. The results indicated that the predicted rankings generally aligned with each team's historical ranking patterns, although the magnitude and direction of ranking changes varied among teams. These findings demonstrate the applicability of NeuralProphet to longitudinal professional football ranking data and offer a quantitative method for examining potential shifts in team ranking trajectories. From a practical standpoint, the predicted rankings can serve as supplementary information for monitoring potential changes in team positions and understanding their ranking trajectories throughout the season. The forecasting approach employed in this study can also be applied to other professional football leagues, offering a quantitative framework for analyzing and predicting league ranking trajectories across diverse competitive environments.

AUTHORS' CONTRIBUTIONS

The authors confirm their contributions to the paper as follows: J.Y.C. and D-I.L.: Study conception and design; J.Y.C.: Data collection, Draft manuscript, Methodology; D-I.L.: Conceptualization. All authors reviewed the results and approved the final version of the manuscript.

LIST OF ABBREVIATIONS

UEFA	=	Union of European Football Associations
EPL	=	English Premier League
ARIMA	=	Autoregressive Integrated Moving Average
SARIMA	=	Seasonal Autoregressive Integrated Moving Average
LSTM	=	Long Short-Term Memory
MAE	=	Mean Absolute Error
RMSE	=	Root Mean Squared Error

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The original data used in this study were obtained from the Tables section of the official English Premier League (EPL) website (https://www.premierleague.com/en). Specifically, league standings were collected by selecting the relevant seasons and match weeks in the Tables section to identify each team's ranking at the 19th and 38th match weeks of each season. The processed and reorganized dataset generated and analyzed during this study is available from the corresponding author [D-I.L.] upon reasonable request.

FUNDING

None.

CONFLICT OF INTEREST

The author(s) declare no conflict of interest, financial or otherwise.

ACKNOWLEDGEMENTS

Declared none.

REFERENCES

[1] League P. Premier League Handbook 2025/26. London: Premier League 2025. Available from: https://resources.premierleague.pulselive.com/premierleague/document/2025/10/22/c03ebde8-8b59-4822-9f3b-bd42ed587f92/PL_Handbook_25-26_07.10.pdf [Accessed date: 16 October 2026]

[2] League P. How Premier League clubs qualify for European competitions. 2025. Available from: https://www.premierleague.com/en/european-qualification-explained [Accessed date: 18 May 2026]

[3] Kim DM, Choi HJ. The cluster Analysis of performance by official record of the English Premier League. Korean J Sport Sci 2019; 28(2): 1237-45. http://dx.doi.org/10.35159/kjss.2019.04.28.2.1237

[4] Green C, Lozano F, Simmons R. Rank-order tournaments, probability of winning and investing in talent: Evidence from champions' league qualifying rules. Natl Inst Econ Rev 2015; 232(1): R30-40. http://dx.doi.org/10.1177/002795011523200104

[5] Lee DI, Chung JY. Predicting final standings of the Korean professional basketball regular season using machine learning: a sports analytics perspective. Korean J Measurem Evaluat Sport 2023; 25(2): 103-15. http://dx.doi.org/10.21797/ksme.2023.25.2.008

[6] Cordes O, Lamb PF, Lames M. Concepts and methods for strategy building and tactical adherence: a case study in football. Int J Sports Sci Coaching 2012; 7(2): 241-54. http://dx.doi.org/10.1260/1747-9541.7.2.241

[7] Barros CP, Leach S. Performance evaluation of the English Premier Football League with data envelopment analysis. Appl Econ 2006; 38(12): 1449-58. http://dx.doi.org/10.1080/00036840500396574

[8] Wang D, Muto Y. Study on competition and strategy in professional football clubs: A case study of Manchester United and Manchester City. Supotsu Sangyogaku Kenkyu 2024; 34(4): 4_353-76. http://dx.doi.org/10.5997/sposun.34.4_353

[9] Doran J, Jordan D. The effect of geographical proximity and rivalry on performance: Evidence from the English Football League. Reg Stud 2018; 52(11): 1559-69. http://dx.doi.org/10.1080/00343404.2017.1414177

[10] Pranata EC, Supatmi S. Analisis kinerja keuangan pada klub sepak bola (studi kasus pada Arsenal, Tottenham Hotspur dan Everton). Jurnal Ekonomi dan Bisnis 2016; 17(2): 41-70. http://dx.doi.org/10.24914/jeb.v17i2.268

[11] Warner S. 'You only sing when you're winning': Football factions and rock rivalries in Manchester and Liverpool. Soccer Soc 2011; 12(1): 58-73. http://dx.doi.org/10.1080/14660970.2011.530468

[12] Birajdar P, Charles N. Application of probabilistic methods to predict derby matches in the English Premier League(EPL). 2014. Available from: https://www.academia.edu/9746576/Application_of_Probabilistic_Methods_to_Predict_Derby_Matches_in_the_English_Premier_League_EPL_ [Accessed date: 16 October 2026]

[13] Tyler BD, Cobbs JB. Rival conceptions of rivalry: Why some

competitions mean more than others. Eur Sport Manag Q 2015; 15(2): 227-48.
http://dx.doi.org/10.1080/16184742.2015.1010558

[14] Milstein N, Striet Y, Lavidor M, Anaki D, Gordon I. Rivalry and performance: A systematic review and meta-analysis. Organ Psychol Rev 2022; 12(3): 332-61.
http://dx.doi.org/10.1177/20413866221082128

[15] Allen T, Taberner M, Zhilkin M, Green M. Evolving running load demands and fixture congestion in the English Premier League: A decade of insights from 2015/2016 to 2024/2025. Br J Sports Med 2025; 59(23): 1643-54.
http://dx.doi.org/10.1136/bjsports-2025-110430 PMID: 41419309

[16] Page RM, Field A, Langley B, Harper LD, Julian R. The effects of fixture congestion on injury in professional male soccer: A systematic review. Sports Med 2023; 53(3): 667-85.
http://dx.doi.org/10.1007/s40279-022-01799-5 PMID: 36527592

[17] Wunderlich F, Seck A, Memmert D. The influence of randomness on goals in football decreases over time. An empirical analysis of randomness involved in goal scoring in the English Premier League. J Sports Sci 2021; 39(20): 2322-37.
http://dx.doi.org/10.1080/02640414.2021.1930685 PMID: 34024249

[18] Divekar C, Deb S, Roy R. Real-time forecasting within soccer matches through a Bayesian lens. J R Stat Soc Ser A Stat Soc 2024; 187(2): 513-40.
http://dx.doi.org/10.1093/jrsssa/qnad136

[19] Wong A, Li E, Le H, Bhangu G, Bhatia S. A predictive analytics framework for forecasting soccer match outcomes using machine learning models. Decis Analyt J 2025; 14: 100537.
http://dx.doi.org/10.1016/j.dajour.2024.100537

[20] Wang T, Zhang Z. Machine learning-based football match prediction system. Appl Computat Engineer 2024; 92(1): 181-6.
http://dx.doi.org/10.54254/2755-2721/92/20241749

[21] Lim B, Zohren S. Time-series forecasting with deep learning: a survey. Phil Trans R Soc A 2021; 379(2194): 20200209.
http://dx.doi.org/10.1098/rsta.2020.0209

[22] Park KH, Jung GH, Ahn HC. A Time Series Forecasting Model with the Option to Choose between Global and Clustered Local Models for Hotel Demand Forecasting. Korea J BigData 2024; 9(1): 31-47.
http://dx.doi.org/10.36498/kbigdt.2024.9.1.31

[23] Wang S, Li C, Lim A. Why are the ARIMA and SARIMA not sufficient. arXiv 2021. Available from: https://arxiv.org/abs/1904.07632
http://dx.doi.org/10.48550/arXiv.1904.07632

[24] Yu Z, Niu K, Chen X, Guo Z, Li D. A hybrid model based on NeuralProphet and long short-term memory for time series forecasting. 2022 IEEE International Conference on Big Data (Big Data). December 17-20, 2022; Osaka, Japan. 2022.
http://dx.doi.org/10.1109/BigData55660.2022.10020471

[25] Triebe O, Hewamalage H, Pilyugina P, Laptev N, Bergmeir C, Rajagopal R. NeuralProphet: Explainable forecasting at scale. arXiv 2021. Available from: https://arxiv.org/abs/2111.15397
http://dx.doi.org/10.48550/arXiv.2111.15397

[26] Lee DI, Chung JY. Predicting english premier league derby team rankings. Asia-Pacific J Converg Res Interchange 2026; 12(2): 535-45.
http://dx.doi.org/10.47116/apjcri.2026.02.36

[27] Lee DI, Chung JY. Formula 1 lap time prediction *via* time series analysis: focusing on the Monaco and Italian Grand Prix. Korean J Sport Sci 2025; 34(1): 274-92. Available from: https://www.kci.go.kr/kciportal/ci/sereArticleSearch/ciSereArtiView.kci?sereArticleSearchBean.artiId=ART003179547
http://dx.doi.org/10.35159/kjss.2025.2.34.1.274

[28] Lee DI, Heo DH, Chung JY. Prediction of team-specific attendance in the KBO League through time series analysis. Korean J Sport Sci 2025; 34(1): 161-76.
http://dx.doi.org/10.35159/kjss.2025.2.34.1.161

[29] Lee DI, Chung JY. Predicting quarterly financial statements of citizen football clubs in the K league. Asia-pacific J Converg Res Interch 2025; 11(11): 639-54.
http://dx.doi.org/10.47116/apjcri.2025.11.44

[30] Choi SC, Suh T. Study on forecasting the price of oyster mushrooms: Application of SARIMA, LSTM, and NeuralProphet. J Korean Instit Informat Technol 2024; 22(8): 21-30.
http://dx.doi.org/10.14801/jkiit.2024.22.8.21

[31] Hyndman RJ, Koehler AB. Another look at measures of forecast accuracy. Int J Forecast 2006; 22(4): 679-88.
http://dx.doi.org/10.1016/j.ijforecast.2006.03.001

[32] Kusumaningtyas MA, Hadi MZS, Sa'Adah N. Cloud-based weather prediction for agricultural land using NeuralProphet. 2024 International Electronics Symposium (IES). August 6-8, 2024; Denpasar, Indonesia. 2024. Available from: https://ieeexplore.ieee.org/document/10665868
http://dx.doi.org/10.1109/IES63037.2024.10665868