https://doi.org/10.5817/StS2024-2-5

Uncovering Determinants of Victory and Defeat in Men's UEFA Champions League: An Analytical Exploration Using Logistic Regression

Debajit Karmakar[1], Sohom Saha[2], Masilamani Elayaraja[3], Anindita Das[1], Arnav Sharma[1], Poli Borah[4], Lakshyajit Gogoi[4], Hemantajit Gogoi[4], Karuppasamy Govindasamy[5]

[1]Department of Physical Education Pedagogy, Lakshmibai National Institute of Physical Education, Gwalior, Madhya Pradesh, India

[2]Department of Sport Psychology, Lakshmibai National Institute of Physical Education, Gwalior, Madhya Pradesh, India

[3]Department of Physical Education and Sports, Pondicherry University, Puducherry, India

[4]Department of Physical Education, Faculty of Physical Education and Sport Sciences, Rajiv Gandhi University, Arunachal Pradesh, India

[5]Department of Physical Education and Sports Sciences, College of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur – 603 203, Tamil Nadu, India.

ABSTRACT

This study aimed to explore the factors influencing outcomes in men's UEFA Champions League matches. The sample comprised 201 UEFA Champions League face offs, and the primary objective was to identify key components significantly associated with success in the UEFA Champions League through logistic regression analysis. The game outcome was treated as the dependent variable in a Binary Logistic Regression (Forward: LR Method). Logistic regression analysis identified six significant variables in establishing the model for match-winning: Ball Possession ($p = .042$), Passes Attempted ($p = .001$), Passes Completed ($p = .001$), Ball Recovered ($p < .001$), Clearance Completed ($p = .002$), and Goals ($p = 001$). The study highlights a significant correlation between crucial variables and success in UEFA Champions League matches. Players and coaches can gain valuable insights into essential elements contributing to victory in this prestigious tournament.

Keywords: UEFA Champions League; Factors Determining Outcomes; Logistical Regression Analysis; Winning and Losing Determinants; Prediction

INTRODUCTION

Sports require the use of statistics on a regular basis (Willoughby, 2002). It has been suggested recently to focus on developing the performance indicators. In team sports, match analysis can deliver an impartial, legitimate, and objective record of team actions, which makes it helpful for evaluating and monitoring team performances (Higham et al., 2014). Coaches and performance analysts search for the vital elements of performance in order to diagnose and explain previous accomplishments (i.e., what was incorrect and why) as well as to forecast and indicate potential behaviours (i.e., what will occur and what should we do). In-game coaches can utilise data to guide their assessments on which performance statistics to focus on in order to achieve an optimal result (Wheatcroft, 2021). Goal scoring is crucial in professional football, as it determines success or failure, unlike other sports where scores are minimal or non-existent. Football performance analysis research focuses on describing match behaviours and activities, with less exploration on using data to forecast future performances, but could provide valuable insights for performance enhancement (Carling et al., 2013). Coaches and performance analysts search for the vital elements of performance in order to diagnose and explain previous accomplishments (i.e., what was incorrect and why) as well as to forecast and indicate potential behaviours (i.e., what will occur and what should we do). In-game, coaches can utilise data to guide or assess the players, in which performance statistics will play a major role to achieve an optimal result (Moura et al., 2014). Data normalisation and regression analysis were used in earlier studies that focused on predictive modelling to investigate the likelihood of goal scoring (Tim McGarry et al., 2002). Performance indicators describes the an action elements that discuss components of a successful performance. (Hughes & Bartlett, 2002). Logistic Regression Analysis is a useful tool in team sports for reporting and assessing performance indicators related to competition outcome from a strategic and tactical standpoint. (Castellano et al., 2012).

Regression is a statistical method used in football shot analysis, first used by Pollard and Reep in 1997. It helps researchers examine variables influencing a shot‘s or goal’s success probability. Quantifying the chance of scoring, measuring the effectiveness can provide the space to improve scoring probability by practicing (Reilly et al., 2005). Data scientists created a system that uses classification in data mining to predict team’s success probability based on their performances (Igiri, Chinwe Peace & ; Nwachukwu, Enoch Okechukwu, 2014). When making decisions in team sports in the past, decision-makers frequently relied on their intuition and prior experiences, especially when attempting to link team strategies and play styles to sport outcomes in terms of the outcomes of matches (Ievoli et al., 2021). In general, football team results can be described in terms of results, goals scored, goal differentials, or likelihood of winning (Clemente et al., 2020) we analyzed (a. Therefore, football results can be predicted using statistical techniques to identify determinants. Some strategies view ball possession as the key outcome variable (Ievoli et al., 2021). Another strategy involves using machine learning tools to forecast match results while attempting to account for various features that may affect match outcomes (Opsahl & Panzarasa, 2009). It might be worthwhile to use data based knowledge (often based on objective judgements) acquired from subject-matter specialists in the field to forecast match outcomes. Data Scientists use this framework (Karanfil, 2017), Such techniques offer accurate outcomes that are encouraging.

Currently, with the development of the statistical concept, information technology is used extensively in sports training. Numerous academics have built numerous assessment models and conducted extensive research on sports performance assessment models (Zheng & Man, 2022). Today, analysts, fans, and team managers engage in the anticipation of match outcomes by making predictions about potential winners. The landscape of football match predictions has evolved, with various statistical measures playing a pivotal role in forecasting results. These predictions draw upon a wealth of data encompassing team statistics, player performances, historical trends, and other relevant factors. Team managers and club directors rely on this multifaceted data to make informed decisions, deciphering not only who will emerge victorious but also the strategic requirements for success in a given game. Therefore, this study aims to delve into the intricate web of factors influencing football match outcomes, particularly in the context of the Men's UEFA Champions League. By employing a logistical regression approach, we seek to identify and analyze the key determinants that contribute significantly to winning or losing in this elite competition. Through a comprehensive examination of the data, we aim to provide valuable insights for analysts, team managers, and football enthusiasts, contributing to a deeper understanding of the dynamics that shape success on the pitch in one of the most prestigious football tournaments worldwide.

METHOD

Leading clubs compete in the esteemed UEFA Champions League each year, this is managed by UEFA, the Union of European Football Associations. This study looked at the matches from the UEFA Champions League (Men) competitions in 2020–21 and 2021–22 in order to uncover the characteristics that affect a football team's ability to win. The study variables selected to analyse were the Goal, Ball Possession, Passing Accuracy, Passes Attempted, Passes Completed, Total Attempts, Attempts on Target, Corner Taken, Offside, Ball Recovered, Tackles, Blocks, Clearance Completed (Table 1). Only the matches with final outcomes has been selected for this study and matches with no outcomes has been excluded from the study.

Table 1. Description of selected variables for the analysis

Factors	Description
Goal	*When the ball goes through the goal posts and completely crosses the goal line, the goal is scored.*
Ball Possession (%)	Physical control of the ball or other plaything by one team is known as possession, and it usually results in a scoring opportunity for that team.
Passing accuracy (%)	*The ability of a team to complete the passes successfully, without any interruption.*
Passes attempted	total number of chance to make the passes
Passes completed	total number of chance to make the passes
Total attempts	Total number of trials to score a goal.
Attempts on target	Total number of trials to score a goal, on the target.
Corners taken	When a goal is not scored and the ball crosses the goal line, touches a player of the defending team, or is in the air, a corner kick is given.
Offside	When the ball is played forward to an opponent who is behind the final defender, it is considered an offside.

Ball recovered	Recovered ball from opponents after losing the possession
Tackles	the act of a defender coming to meet an opponent who is in possession of the ball, engaging him, and then legally using a foot to take the ball away
Blocks	Block is when a player obstructs a shot initialize by an opponent player.
Clearances completed	Successful clearing the ball from goal area, during an attack.

Participants

The study sample was of a total 201 matches of the 2020-21 (a total of 105 matches have been selected, distributed across various stages of the competition as follows: 69 matches from the group stages, 16 matches from the Round of 16 first leg, 9 matches from the Round of 16 second leg, 4 matches from the quarter-final first leg, 3 matches from the quarter-final second leg, 1 match from the semi-final first leg, 2 matches from the semi-final second leg, and the final match) & 2021–22 (a total of 96 matches, comprising 75 group stage matches, 4 first-leg matches from the round of 16, 7 second-leg matches from the round of 16, 4 first-leg matches from the quarter-finals, 1 second-leg match from the quarter-finals, 2 first-leg matches from the semi-finals, 2 second-leg matches from the semi-finals, and the final match) UEFA Champions League Tournament. To predict the winning and losing factors, matches with a final outcome (win/lose) has been taken and the matches which had drawn has been excluded as the final outcome was not in winning or loosing. In both the session 2020–21 and 2021–22, there were 8 groups and each group consists of 4 teams. With this there were total 32 teams in each sessions. The information used in this study was taken from the official UEFA Champions League website. (UEFA.com, n.d.).

Procedure

IBM SPSS (version 26.0.0) was used for all statistical analyses. The outcome of the game was used as the dependent variable and the predictor factors used as covariates in an analysis of the data using Binary Logistic Regression (Forward: LR Method).

Statistical Analysis

β, standard error β, Wald's χ^2 were calculated in the logistic regression model. Model evaluation was conducted using the likelihood ratio test, Cox & Snell (R^2) and Nagelkerke (R^2) tests. The goodness of fit test for the models was conducted using the Hosmer & Lemeshow test. In addition, observed and predicted frequencies by the regression model were also calculated with a cut-off of 0.50. The statistical level of significance was set at $p \leq 0.05$.

RESULTS

A total of 201 observations were analysed. The following variables were identified by the logistic regression analysis as being important in establishing the model for match winning: Ball Possession, Passes Attempted, Passes Completed, Ball Recovered, Clearance Completed, Goals. Predicted logit of Winning = -15.256 + 0.85·(Possession) + (-0.017)·(Passes Attempted) + 0.015·(Passes Completed) + 0.091·(Ball recovered) + 0.1·(Clearance Completed) + 2.703·(Goals). The Likelihood ratio test of the model resulted in χ^2 value of 221.543 with $p < 0.001$. In addition, the Cox and Snell resulted in R^2 value of 0.566 and Nagelkerke resulted in R^2 value of 0.755. The model's overall correct predicted percentage was discovered to be 87.3%. The logistic regression analysis found that some variables from the study was insignificant to determine the model for winning of matches: Passing Accuracy, Total Attempts, Attempts on Target, Corners Taken, Offsides, Tackles and Blocks.

Table 2. Total number of cases

Cases	N
Included in Analysis	402
Missing Cases	0
Total	402

Total matches analysed from the tournaments were 201, so the teams faced in each matches were 2, hence the statistical cases were 402 (Table no 2).

Table 3. The classification table provide a summary of the correctness of this logistic regression model**.**

Classification Table*				
Observed		Predicted Result		
				Percentage Correct
		lose	win	
Result	lose	175	26	87.1
	win	25	176	87.6
Overall Percentage				87.3
*** The cut value is 0.50**				

In this classification table the correctness of the table is 87.3% (Table no 3). The probability threshold used in logistic regression to categorise observations as either positive or negative is known as the cut value. For example, an observation will be categorised as positive if the anticipated probability is greater than 0.5, and as negative if the predicted probability is less than 0.5.

Table 4. Variables that are taken in the study

Variables in the Equation						
Factors	**β**	**S.E.**	**Wald χ^2**	**df**	**Sig*.**	**Exp(B).**
Possession	.085	.042	4.118	1	.042	1.089
Passing_accuracy	.067	.043	2.458	1	.117	1.069
Passes_attempted	-.017	.005	11.093	1	.001	.983
Passes_completed	.015	.004	11.318	1	.001	1.015
Total_attempts	-.023	.062	.139	1	.709	.977
Attempts_on_target	-.072	.116	.388	1	.533	.930
Corners_taken	.064	.078	.669	1	.413	1.066
Offsides	-.150	.091	2.724	1	.099	.861
Balls recovered	.091	.025	13.627	1	.000	1.095
Tackles	-.002	.014	.029	1	.865	.998
Blocks	-.241	.093	6.713	1	.010	.786
Clearances completed	.100	.032	9.631	1	.002	1.105
Goal	2.703	.302	80.251	1	.000	14.919
Constant	-15.256	4.138	13.592	1	.000	.000
***Level of significance was set at 0.05 level**						

In this logistic regression (Table no. 4), some factors has been considered as independent variable like Possession, Passing accuracy, Passes attempted, Passes completed, Total attempts, Attempts on target, Corners taken, Offsides, ball recovered, tackles, blocks, clearances completed. **β** is the estimated coefficient for the predictor variable in the logistic regression model. It indicates the direction and magnitude of the relationship between the predictor and the dependent variable. A positive β suggests that as the predictor increases, the likelihood of the dependent event occurring (e.g., winning a match) also increases and vice versa for a negative β. S.E. (Standard Error) measures the variability or precision of the β coefficient estimate. Smaller standard errors indicate more precise estimates of the β coefficient. Wald χ^2 (Wald Chi-Square) statistic tests the null hypothesis that the β coefficient for a predictor is equal to zero (no effect). A larger Wald Chi-Square value indicates a stronger evidence against the null hypothesis. df Degrees of Freedom is 1 for each individual predictor in the model, reflecting the number of parameters estimated for that predictor. Sig (p-value) is the probability that the observed association (or a more extreme one) could occur by random chance if the null hypothesis is true. A p-value less than 0.05 (the significance level) indicates that the predictor variable has a statistically significant effect on the dependent variable. Exp(B) (Exponentiated β coefficient) known as the odds ratio, Exp(B) indicates how the odds of the dependent event occurring change with a one-unit increase in the predictor variable. For example, an Exp(B) of 1.089 for «Possession» means that a 1% increase in possession is associated with an 8.9% increase in the odds of the dependent event (e.g., winning).

Table 5. Describes the model summery of this logistic regression model

Model Summary		
-2 Log likelihood	Cox & Snell R Square	**Nagelkerke R Square**
221.543*	.566	**.755**

The model›s log likelihood gauges how well it fits the data. Here Log likelihood value is 221.543. How much of the variation in the outcome variable is explained by the model is determined by the Cox & Snell R Square (0.566), It is between 0 and 1. The Nagelkerke R Square illustrates the percentage of the outcome variable›s variation that the model accounts for. Despite being modified to take into account the number of predictor variables in the model, it is similar to the Cox & Snell R Square (Table no. 5).

Table 6. Shows statistical goodness of fit test

Hosmer and Lemeshow Test		
Chi-square	df	**Sig***
5.939	8	**.654**
***Level of significance was set at 0.05 level**		

The Hosmer and Lemeshow test table for logistic regression shows the statistical results by which one can understand the test for goodness of fit (Table no. 6). If the significance level is below 0.05, then the data is fit poorly, but here the value of significance is 0.654, which means the data is well fitted.

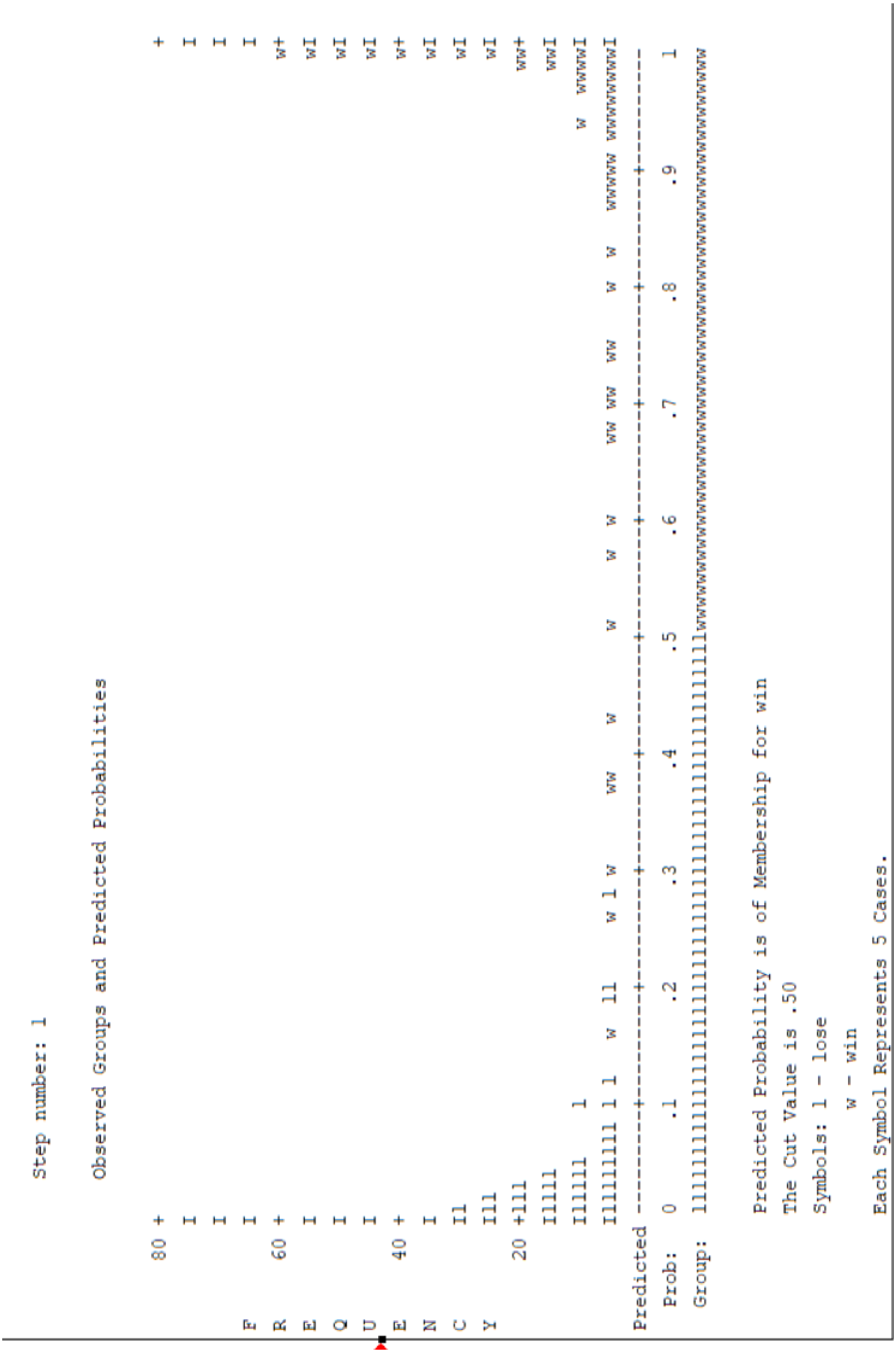

Figure 1. The probability graph is showing the separation between the two groups of winners and loosers.

DISCUSSION

This study's goal was to use a logistic regression method to pinpoint crucial elements of a football game that were significantly related to get success in the UEFA Champions League. Six factors out of the competition's thirteen were linked to winning, including possession, passes attempted, passes completed, ball recoveries, cleared areas, and goals. These factors are intrinsically connected to how well the opposition perceives and attacks (Peña et al., 2013) by the use of Binary Logistic Regression (Forward: LR Method). Seven additional factors were against winning as well. The tournament featured well-balanced teams, but various task-related functional constraints may affect player behaviour during reception.

Elite football teams can benefit from understanding game styles and training goals, as performance indicators do not significantly explain match outcomes in both modelling approaches. The logistic regression analyses as shown in table no 3 achieved 87.3% classification accuracy, which is good in terms of a statistical analysis model. This confirms the necessity of such models in the analysis of sport performance. With regard to the UEFA Champions League, it appears that the kinds and combinations of performance indicator disparities between successful and failing teams can matter more than the absolute values of such differences. The observation of this phenomena in this setting highlights similarities with previous research on human motor control and variation of movement (Glazier & Davids, 2009; Latash et al., 2002). Future studies could compare margin to win/loss (the metric employed in this study), as margin might provide a different viewpoint on performance than the binary result of win/loss (Sargent & Bedford, 2013; Stewart et al., 2007). It has also been utilised in basketball to discover key time events that impact team success on a quarter-by-quarter basis, which can provide coaches with a critical tactical and technical focus (Ruano et al., 2013). By utilising an integrative approach and creating multidisciplinary metrics that particularly take into account multiple performance indicators, this prediction model's sophistication could be further increased.

These results are consistent with past studies on the Norwegian football league (Tenga, Holme, et al., 2010a, 2010b; Tenga, Ronglan, et al., 2010) and Spanish Professional Football League (Lago-Ballesteros et al., 2012), which implied that counterattacks were superior as there were many offensive elaborations in terms of creating goals, where factors such as attempts on target, total attempts, passing accuracy, ball possession has been involved. In the matches that were examined, approaching the scoring area, searching for adequate shooting space, and dodging shots when the opposition is putting defensive pressure on you might have been important factors. It may have implied, albeit hypothetically, that teams employed defensive strategies to close the gap between defensive players and increase player density (particularly in the score area) (Castellano & Alvarez, 2013). This tactic would increase defensive pressure and reduce open space for cutting passes, which would reduce the effectiveness of team possession (Lago-Ballesteros et al., 2012), While it could lead to better counterattack scenarios when balls are recovered (Ruano et al., 2012).

In the UEFA Champions League, factors such as ball possession, pass success, successful passes, and crosses had been found to differentiate between teams that would win and lose (Lago-Peñas & Lago-Ballesteros, 2011) and Spanish Professional Football League (Lago-Peñas et al., 2010).

Studies showed that the most effective attacking strategy is to keep the ball on the ground, try to pass it continuously, and patiently look for the best scoring opportunities rather than cross the ball carelessly into the area. Short passes increase the likelihood of sending the ball to expected destinations, whereas crosses are more likely to cause commotion during ball possession because they are more unpredictable (Oberstone, 2009), Successful one-on-one interactions can be unpredictable, which can create unexpected scoring opportunities (Luhtanen et al., 2001). Failure or improper dribbling greatly increases the chance that the opposition will launch counterattacks and score. In close games, Aerial Advantage had no effect, but overall, it significantly increased winning probabilities (+26%). In aerial duels, competing for long passes and crosses (Liu et al., 2013). There were more aerial duels in the game, which led to more long passes and crosses. This "winning formula" in aerial duels does not hold true in close games, most likely because the frequency of long passes and crosses declined as the match got closer. Nevertheless, the current finding may imply that winning aerial long passes and crosses can raise the likelihood of winning in general.

It's thought that not much research has been done on defence in football competitions (Almeida et al., 2014). It was found that immediately regaining possession of the ball following interceptions and tackles was correlated with the outcome of football games (Vogelbein et al., 2014). In a similar vein, a study found that a two standard deviation increase in the variable Tackle would lead to a 27 percent increase in the probability of winning in all games, including close games. Tackle needs to be able to foresee and select the precise place and moment to execute the action (Williams et al., 2012) and It most likely has to do with having the best possible environmental perception of the ball's speed, location, and opponents (Williams et al., 2012). Consequently, increasing the chances of winning could be achieved by making sensible and successful tackles. Previously, it was found that red and yellow cards also differ between winning, drawing and losing teams (Lago-Peñas et al., 2010; Peñas et al., 2011). Study's findings showed that a red card would decrease the chances of winning every game and close games by 14%, as the punished player's team suffers from numerical inferiority. Furthermore, one Yellow Card had also a very negative effect on the probability of winning for close games, but a negligible (9%) impact for the match. After one yellow card, cautioned player use to avoid challenging tackles or physically hardcore defending skills to avoid the chances of being sent off by getting another yellow card. As yellow card make the player less aggressive, this make the player a little bit less effective especially in close games, which showes very negligible impact in winning or loosing a football match (Bar-Eli et al., 2006). Though it's thought of as an effective modelling technique for monitoring relationships between key performance factors and match results (Almeida et al., 2014), In some chaotic matches, it is less evident of having strong correlations between individual match statistics and the probability of winning has been mediated by other influencing factors or may even be "random" effects. Some study's tiny sample size from a single competition might shows some lacking in the indicator values come from competing teams, which lay affect to one another. Like current study, including more participants should be included in future research (Almeida et al., 2014; Mackenzie & Cushion, 2013). Situational elements such as importance of the match and venue sometimes play a thing to consider when assessing the performance of a football match. Variables pertaining to team and opponent strength (e.g., qualified teams from the group stage, successful and unsuccessful teams) can be added to further model building. This research only looked at the within team effect, which represented the effect of team values changing from match to match.

CONCLUSION

According to the study, there is a strong link between some important factors and winning a professional football championship game. It implies that while creating training schedules and team dynamics, coaches and athletes should take these factors into account. The results of matches are greatly impacted by team differences in kickoff and goal conversion rates, according to the logistic regression model. The results show which game mechanics should be the main focus of training to maximise player proficiency and which performance indicators elite analysts should prioritise. Athletes' time for skill development is limited in elite settings as they must prioritise fitness, strength, injury prevention, match review and preparation, and recovery. Clubs should concentrate on helping coaches manage their time well.

ACKNOWLEDGEMENTS

First and foremost, we would like to express our sincere appreciation to Prof. M. Elayaraja & Dr. Anindita Das, whose guidance and expertise were instrumental throughout the entire research process. Their insightful feedback and encouragement significantly enhanced the quality and depth of this study.

REFERENCES

Almeida, C. H., Ferreira, A. P., & Volossovitch, A. (2014). Effects of Match Location, Match Status and Quality of Opposition on Regaining Possession in UEFA Champions League. *Journal of Human Kinetics*, 41, 203–214. https://doi.org/10.2478/hukin-2014-0048

Bar-Eli, M., Tenenbaum, G., & Geister, S. (2006). Consequences of players' dismissal in professional soccer: A crisis-related analysis of group-size effects. *Journal of Sports Sciences*, 24(10), 1083–1094. https://doi.org/10.1080/02640410500432599

Carling, C., Wright, C., Nelson, L., & Bradley, P. (2013). Comment on "Performance analysis in football: A critical review and implications for future research." *Journal of Sports Sciences*, 32. https://doi.org/10.1080/02640414.2013.807352

Castellano, J., & Alvarez, D. (2013). Uso defensivo del espacio de interacción en fútbol. (Defensive use of the interaction space in soccer). RICYDE. *Revista Internacional de Ciencias Del Deporte*, 9, 126–136. https://doi.org/10.5232/ricyde2013.03203

Castellano, J., Casamichana, D., & Lago, C. (2012). The Use of Match Statistics that Discriminate Between Successful and Unsuccessful Soccer Teams. *Journal of Human Kinetics*, 31(2012), 137–147. https://doi.org/10.2478/v10078-012-0015-7

Clemente, F. M., Sarmento, H., & Aquino, R. (2020). Player position relationships with centrality in the passing network of world cup soccer teams: Win/loss match comparisons. Chaos, *Solitons & Fractals*, 133, 109625. https://doi.org/10.1016/j.chaos.2020.109625

Glazier, P., & Davids, K. (2009). On analysing and interpreting variability in motor output. *Journal of Science and Medicine in Sport / Sports Medicine Australia*, 12, e2-3; author reply e4. https://doi.org/10.1016/j.jsams.2009.03.010

Higham, D., Hopkins, W., Pyne, D., & Anson, J. (2014). Performance Indicators Related to Points Scoring and Winning in International Rugby Sevens. *Journal of Sports Science & Medicine*, 13, 358–364.

Hughes, M. D., & Bartlett, R. M. (2002). The use of performance indicators in performance analysis. *Journal of Sports Sciences*, 20(10), 739–754. https://doi.org/10.1080/026404102320675602

Ievoli, R., Palazzo, L., & Ragozini, G. (2021). On the use of passing network indicators to predict football outcomes. *Knowledge-Based Systems*, 222, 106997. https://doi.org/10.1016/j.knosys.2021.106997

Igiri, Chinwe Peace1 & ; Nwachukwu, Enoch Okechukwu. (2014). An Improved Prediction System for Football a Match Result. http://ir.mtu.edu.ng/xmlui/bitstream/handle/123456789/113/an-improved-football-prediction-systempdf.pdf?sequence=1&isAllowed=y

Karanfil, F. (2017). An empirical analysis of European football rivalries based on on-field performances. *Sport Management Review*, 20(5), 468–482. https://doi.org/10.1016/j.smr.2016.12.003

Lago-Ballesteros, J., Lago-Peñas, C., & Rey, E. (2012). The effect of playing tactics and situational variables on achieving score-box possessions in a professional soccer team. *Journal of Sports Sciences*, 30(14), 1455–1461. https://doi.org/10.1080/02640414.2012.712715

Lago-Peñas, C., & Lago-Ballesteros, J. (2011). Game Location and Team Quality Effects on Performance Profiles in Professional Soccer. *Journal of Sports Science & Medicine*, 10(3), 465–471.

Lago-Peñas, C., Lago-Ballesteros, J., Dellal, A., & Gómez, M. (2010). Game-Related Statistics that Discriminated Winning, Drawing and Losing Teams from the Spanish Soccer League. *Journal of Sports Science & Medicine*, 9(2), 288–293.

Lago-Peñas, C., Lago-Ballesteros, J., & Rey, E. (2011). Differences in performance indicators between winning and losing teams in the UEFA Champions League. *Journal of Human Kinetics*, 27(2011), 135–146. https://doi.org/10.2478/v10078-011-0011-3

Latash, M. L., Scholz, J. P., & Schöner, G. (2002). Motor control strategies revealed in the structure of motor variability. *Exercise and Sport Sciences Reviews*, 30(1), 26–31. https://doi.org/10.1097/00003677-200201000-00006

Liu, H., Hopkins, W., Ruano, M., & Molinuevo, J. (2013). Inter-operator reliability of live football match statistics from OPTA Sportsdata. *International Journal of Performance Analysis in Sport*, 13, 803–821. https://doi.org/10.1080/24748668.2013.11868690

Luhtanen, P., Belinskij, A., Häyrinen, M., & Vänttinen, T. (2001). A comparative tournament analysis between the EURO 1996 and 2000 in soccer. *International Journal of Performance Analysis in Sport*, 1. https://doi.org/10.1080/24748668.2001.11868250

Mackenzie, R., & Cushion, C. (2013). Performance analysis in football: A critical review and implications for future research. *Journal of Sports Sciences*, 31(6), 639–676. https://doi.org/10.1080/02640414.2012.746720

Moura, F. A., Martins, L. E. B., & Cunha, S. A. (2014). Analysis of football game-related statistics using multivariate techniques. *Journal of Sports Sciences*, 32(20), 1881–1887. https://doi.org/10.1080/02640414.2013.853130

Oberstone, J. (2009). Differentiating the Top English Premier League Football Clubs from the Rest of the Pack: Identifying the Keys to Success. *Journal of Quantitative Analysis in Sports*, 5(3). https://doi.org/10.2202/1559-0410.1183

Opsahl, T., & Panzarasa, P. (2009). Clustering in weighted networks. *Social Networks*, 31(2), 155–163. https://doi.org/10.1016/j.socnet.2009.02.002

Peña, J., Rodríguez-Guerra, J., Buscà, B., & Serra, N. (2013). Which skills and factors better predict winning and losing in high-level men's volleyball? *Journal of Strength and Conditioning Research*, 27(9), 2487–2493. https://doi.org/10.1519/JSC.0b013e31827f4dbe

Peñas, C., Lago Ballesteros, J., & Rey, E. (2011). Section III – Sport, Physical Education & Recreation Differences in performance indicators between winning and losing teams in the UEFA Champions League. *Journal of Human Kinetics*, 27, 135–146. https://doi.org/10.2478/v10078-011-0011-3

Reilly, T., Cabri, J., & Araújo, D. (2005). Science and Football V: The Proceedings of the Fifth World Congress on Sports Science and Football. Routledge.

Ruano, M., Gómez López, M., Peñas, C., & Sampaio, J. (2012). Effects of game location and final outcome on game-related statistics in each zone of the pitch in professional football. *European Journal of Sport Science*, 12, 393–398. https://doi.org/10.1080/17461391.2011.566373

Ruano, M., Lorenzo Calvo, A., Ibáñez, S., & Sampaio, J. (2013). Ball possession effectiveness in men's and women's elite basketball according to situational variables in different game periods. *Journal of Sports Sciences*, 31, 1578–1587. https://doi.org/10.1080/02640414.2013.792942

Sargent, J., & Bedford, A. (2013). Evaluating Australian Football League Player Contributions Using Interactive Network Simulation. *Journal of Sports Science & Medicine*, 12(1), 116–121.

Stewart, M., Mitchell, H., & Stavros, C. (2007). Moneyball Applied: Econometrics and the Identification and Recruitment of Elite Australian Footballers. *International Journal of Sport Finance*, 2, 231–248.

Tenga, A., Holme, I., Ronglan, L., & Bahr, R. (2010a). Effect of playing tactics on achieving score-box possessions in a random series of team possessions from Norwegian professional soccer matches. *Journal of Sports Sciences*, 28, 245–255. https://doi.org/10.1080/02640410903502766

Tenga, A., Holme, I., Ronglan, L. T., & Bahr, R. (2010b). Effect of playing tactics on goal scoring in Norwegian professional soccer. *Journal of Sports Sciences*, 28(3), 237–244. https://doi.org/10.1080/02640410903502774

Tenga, A., Ronglan, L., & Bahr, R. (2010). Measuring the effectiveness of offensive match-play in professional soccer. *European Journal of Sport Science*, 10, 269–277. https://doi.org/10.1080/17461390903515170

Tim McGarry , David I. Anderson , Stephen A. Wallace , Mike D. Hughes & Ian & M. Franks. (2002). Sport competition as a dynamical self organizing system. https://moldham74.github.io/AussieCAS/papers/McGarry.pdf

UEFA.com. (n.d.). UEFA Champions League. UEFA.Com. Retrieved July 9, 2023, from https://www.uefa.com/uefachampionsleague/

Vogelbein, M., Nopp, S., & Hökelmann, A. (2014). Defensive transition in soccer – are prompt possession regains a measure of success? A quantitative analysis of German Fußball-Bundesliga 2010/2011. *Journal of Sports Sciences*, 32(11), 1076–1083. https://doi.org/10.1080/02640414.2013.879671

Wheatcroft, E. (2021). Forecasting football matches by predicting match statistics. *Journal of Sports Analytics*, 7(2), 77–97.

Williams, A. M., Ward, P., Bell-Walker, J., & Ford, P. R. (2012). Perceptual-cognitive expertise, practice history profiles and recall performance in soccer: Perceptual-cognitive expertise. *British Journal of Psychology*, 103(3), 393–411. https://doi.org/10.1111/j.2044-8295.2011.02081.x

Willoughby, K. A. (2002). Winning Games in Canadian Football: A Logistic Regression Analysis. *The College Mathematics Journal*, 33(3), 215–220. https://doi.org/10.1080/07468342.2002.11921944

Zheng, S., & Man, X. (2022). An Improved Logistic Regression Method for Assessing the Performance of Track and Field Sports. *Computational Intelligence and Neuroscience*, 2022, e6341495. https://doi.org/10.1155/2022/6341495

Contact Information:

Karuppasamy Govindasamy
Department of Physical Education and Sports Sciences, College of Science and Humanities, SRM Institute of Science and Technology, Kattankulathur - 603 203, Tamil Nadu, India.
Email:gowthamadnivog@gmail.com
Mobile: +91-9597726499