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A Data-Driven Analysis of Football Performance Differences and Possession Between Uefa and Saff Teams

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Abstract
Background : *Ball possession percentage in a match does not always imply better control of the game as teams may have the ball without creating goal-scoring opportunities or progressing play. The goal of this analysis was to evaluate the UEFA Nations League 2024/25 teams and AFC Asian Cup Saudi Arabia 2027 qualifying pathway (SAFF) teams with respect to match performance indicators.*
Materials and Methods : A quantitative cross-sectional comparative study was conducted inclusive of 358 match records composed of 319 UEFA and 39 South Asian. Descriptive statistics were used to gauge the match performance indicators and outcomes. The step of preparing data consisted of removing duplicates, standardizing variables, handling missing data, and validating range. The study predicts match outcomes and important predictors using Random Forest and the XGBoost model whereas k-means clustering and principal component analysis determine the tactical profile.
Results: *The UEFA teams demonstrated better technical and attacking performances. They posted markedly greater total passes (899.49 vs. 732.77; $p < 0.001$), completed passes (739.13 vs. 576.72; $p < 0.001$) as well as shots on target (8.55 vs. 7.03; $p = 0.005$). Nonetheless, the possession percentage did not differ significantly between regions ($p = 0.995$), indicating that possession alone is not a determinant of performance effectiveness. There was a positive correlation between shots and expected goals ($r = 0.533$, $p < 0.001$) and between expected goals and actual goals scored ($r = 0.456$, $p < 0.001$). Shots on target were the best match points predictor; XGBoost predicted with 70.2% accuracy.*
Conclusion: The teams in UEFA were superior because of their structured passing, effective chances taking and conversion rather than purely on possession. With the help of data, the South Asian football team can improve passing under pressure, penetrating the opposition's final third, shooting accuracy or production value.

Key Word: *Asian Cup, Football analytics, Machine learning, South Asian football, UEFA Nations League*

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I. Introduction

The sport that witnesses the maximum following in the world is football. Moreover, it has transcended from being a traditional competitive activity to a performance environment that is data- and scientist-driven. During the modern game, success is based on the interaction of the technical, tactical, physical and decision phases. Advances in sports science have resulted in the transformation of football analysis from an observational-based approach to a systematic evaluation approach that uses performance indicators, statistical modelling, and artificial intelligence techniques. The execution and distribution of sporting performance are closely related technical, tactical behaviour and physicality. As a result, the basis for success and failure has become a strong focus of the football research (Bush et al., 2021). Match performance analysis often evaluates metrics like ball possession, passing accuracy, total passes, shots, shots on target, expected goals (xG), goals scored, tackles, interceptions in order to quantify team behaviour during the match (Liu et al., 2021). The information relates to attacking efficiency, defensive structure and organization and tactics. For much of history in football analysis metrics, possession percentage has been seen as an indicator of dominance. By having possession of the ball, teams can control the tempo of the match, lessen the defensive pressure and create attacking opportunities (Lago-Peñas & Dellal, 2010). However, new research shows that you might not always have what it takes. Possession is effective not by just controlling the ball but by the quality of ball circulation, progression into dangerous areas, creation of goal-scoring chances and scoring efficiency (González-Rodenas et al., 2023; Wang et al., 2022). As a result, a complex debate has arisen within football analytics concerning whether possession leads to match success. Teams that get more of the ball often have more effective passing

networks and spatial organization than less abundant teams. Whereas the less abundant teams are often able to win when the spatial organization is effective and there are rapid counters (Bradley et al., 2013; Liu et al., 2021). This means that possession quantity must be evaluated together with other attacking and tactical indicators. Modern metrics favour possession efficiency by measuring progressive runs, expected threat, and expected possession value as opposed to just the percentage of time a team has the ball (Wang et al., 2022). The Union of European Football Associations (UEFA) has developed one of the most sophisticated football systems in the world. Clubs that belong to UEFA make use of already established professional leagues and systems. They also make use of the availability of coaches, frameworks for the development of youth, sports science provisions, and a very high level of international competition. As a result, systems of play include organized phases of play through passing, positioning, pressing and transitions (Sarmento et al., 2018; Liu et al., 2021). The European football environments are also rich in performance and technology features directing training, tactical preparation and match performance at a high level. In the developing football environment of the South Asian Football Federation (SAFF), football in South Asia different in history, economy and infrastructure. The countries in the SAFF region have been doing well on the football development front. Due to improved competitions, coaching education, and youth programs, the countries are developing steadily. Same goes for the overall football development across the countries. However, there are still challenges such as infrastructure, professional leagues, international exposure, and sports science (advanced coaching) facilities. The tactical approach, technical progression, and competitive performance may be impacted by these contextual disparities. South Asian sides tend to play direct football, focusing on defensive organization, quick transitions, and counter-attacks rather than prolonged possessions (Wallace & Norton, 2014; Sarmento et al, 2018). The contrast of UEFA and SAFF teams offers an excellent opportunity to gain insight into match performance characteristics as influenced by football systems. Previous studies in elite European football are extensive, however; studies assessing the differences in performance between developed and developing football regions are scarce. This creates a research gap in the association between possession dominance and football success, as opposed to more sophisticated combinations of other technical and tactical factors (Mackenzie & Cushion, 2013; Rein & Memmert, 2016). New developments in machine learning enabled new possibilities for football player analysis. Models of machine learning can capture intricate non-linear correlations, not just linear correlations like traditional statistical models. This allows simultaneous forecasting of multiple response variables. A host of algorithms including Random Forest, XGBoost and clustering have been applied to football data to predict match outcomes, identify important performance variables and classify tactical profiles (Bunker & Thabtah, 2019; Rico-González et al., 2023). By going beyond analysis, the authors were able to identify which performance indicators were most closely related to winning and losing matches. Football analysis through machine learning has proven to be valuable. Shot on target and expected goals are the most valuable variables for predicting outcome of matches. Recent research found better predictive models capable of improving understanding over traditional models of winning, drawing and losing (Atta Mills et al., 2024; Berrar et al., 2024). Moreover, methods for clustering would allow researchers to identify different tactical profiles by clustering teams based on the similarities of their technical and performance characteristics (Plakias et al., 2023; Gu et al., 2025). Even though the usage of football analytics is on the rise, there is limited research that employs a combination of regional comparison, possession and machine learning analysis to evaluate the differences in European and South Asian football systems. It is necessary to understand whether successful performance is 'caused' by more possession or by more effective attacking and more technical execution, if one is to define evidence-based strategies particularly for developing football regions. Thus, this study uses a data-driven approach framework to compare football performance indicators for UEFA Nations League 2024/25 teams and AFC Asian Cup Saudi Arabia 2027 qualification pathway (SAFF) teams. This study, through the integration of descriptive statistics, predictive modelling and tactical classification approaches, aims to identify the key performance indicators that are associated with match performance and success to provide insight for football development in South Asia.

II. Material And Methods

In this study, quantitative research techniques have been used to study the difference in football performance parameters and possession characteristics between UEFA and South Asian Football Federation (SAFF) teams. A quantitative approach was chosen since football performance can be presented with numeric variables that are objectively measurable, making it possible to assess technical, tactical and match-outcome-related characteristics. The study focused on analyzing performance indicators including the percentage of possession of the ball, passing variables, attacking indicators, and outcomes of the match using statistical and machine learning techniques. This method allowed for making comparisons between football systems in regions with less subjectivity. The study used a cross-sectional comparative research design. The design involved a descriptive analysis of existing match-performance data collected from a clearly defined competitive period

without any experimental manipulation. The objective of this study was to compare football performance characteristics of the teams participating in the UEFA Nations League 2024/25 with the teams participating in the AFC Asian Cup Saudi Arabia 2027 qualification pathway from SAFF. The comparative model let us analyze regional differences in possession behaviour, passing efficiency, attacking effectiveness and tactical performances patterns. Also, this design allowed the use of predictive modelling and classification methods to identify linkages between performance indicators and match results. The target population focused on international football matches involving UEFA national teams and South Asian national teams in the context of the selected competition. The UEFA dataset contained matches of the 2024/25 UEFA Nations League, while the South Asian dataset consisted of matches belonging to the AFC Asian Cup Saudi Arabia 2027 qualification pathway. The statistics of matches that were performance-oriented and were available to all were taken and arranged in the database as per the requirement for analysis. The purposive sampling technique was used because the study required matches that possessed complete and reliable performance indicators and were suitable for statistical analysis and machine learning modelling. Cases which satisfied pre-defined inclusion criteria were selected. The final dataset contains 358 match records of which 319 are from UEFA and 39 are from South Asia. After converting the dataset to home and away teams observations, it represented a larger number of team-level records. The number of valid observations, however, varied depending upon the availability of variables after processing.

The purposive sampling ensured that the chosen match had the same performance parameters, credible statistical data and the quality of data was adequate for regional comparison and predictive modelling. The approach appeared to be apt as football analytics research typically requires structured datasets with similar technical and tactical variables across competitions. Games were included as long as they were official fixtures from a relevant UEFA or AFC competition context, had identifiable teams and match result, and contained performance statistics. The dataset contained matches for which core indicators such as possession, passing, attacking variables were available and numerical values could be converted into normalized formats.

Table. Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
Official match in the stated UEFA or AFC competition context	Friendly match or unrelated competition
Usable team identity, score, and outcome	Duplicate or unresolvable match record
Core possession, passing, or attacking statistics available	Insufficient core performance information
Values could be standardized to common units	Impossible values that could not be corrected or verified
Home and away teams identifiable	Ambiguous team orientation or malformed record

Matches were not considered if they were friendly matches, unrelated competitions, a repeated record, incomplete data, or unreliable values in the record not correcting or verifiable. Matches with ambiguous home-away orientation or lack of vital performance information were deleted from analytical dataset. Data for secondary match-performance were accessed from the available football statistics and sorted into geographical spreadsheets on a standardized home-away basis. The dataset was prepared by maintaining a uniform naming for teams, tournaments, outcome categories as well as numeric variables. Thanks for the game we want a winning game not losing game(sockfd). The technical, tactical and attacking aspects of the game were provided by the collected variables. The ball possession percentage, pass accuracy, total passes, shots, shots on target, goals scored and match results were taken into account. The statistical analysis and machine learning procedures of the collected data were done orderly. The research framework categorizes the study variables as dependent variables and independent variables. The dependent variables correspond to soccer performance measures, namely match outcome, goals scored, playing style classification, and machine learning predictions. Match results were placed in three categories win, draw or loss while goals represented offense. Clustering analysis was utilized to create tactical behaviour patterns to identify playing styles, while the outputs from the prediction models generated by the machine learning models served as outcome measures. Football performance indicators sourced from UEFA and SAFF match datasets were used as independent variables. This included ball possession percentage, pass accuracy, total passes, shots, shots on target and more tactical efficiency indicators relating to attacking progression and possession efficiency. The reason your variables were selected is that they represent measurable aspects of technical execution, tactical control and attacking productivity. Before its analysis, the dataset underwent systematic cleaning and preprocess to improve accuracy and reliability. The data preparation process involved the removal of duplicate records, conversion of numerical formats, valid range

checks of variables, missing value treatment, and standardization of variables presented in percentage form. Information on home and away matches was converted into team-level observations when required for comparative purposes but match-level data were retained for regional comparisons. The preprocessing phase was done to ensure all variables are defined and measured the same way. By doing this, we were able to minimize data errors and prepare the data for statistical testing and modelling. The performance characteristics of UEFA and SAFF were compared using descriptive and inferential statistics. To summarise regional differences in possession, passing behaviour, attacking output and match performance descriptive statistics were used. Testing of mean differences between the two football regions was conducted. Machine learning techniques were employed for a deeper analysis of performance relationships and match prediction. Supervised learning models such as XGBoost and Random Forest were used to predict the outcome of matches and choose important performance predictors. The models measured the impact on match success of football indicators (possession, passing, shots, attacking variables). K-Means clustering and principal component analysis were also performed to identify tactics profiles and cluster teams by the similarities among performance characteristics. These methods enabled the investigation into concealed trends in playing styles while providing a wider review of regional tactical variances. Through statistical analysis, predictive modelling, serviceable designs clustering techniques, we have established an extensive framework for evaluating football performance evaluation differences between UEFA and SAFF teams.

III. Results

Dataset Profile and Preliminary Analysis

The analysis of the difference in football performance between UEFA and South Asian teams using match-level data of the UEFA Nations League 2024/25 and AFC Asian Cup Saudi Arabia 2027 qualification pathway. The dataset finally consisted of a total of 358 matches including 319 UEFA matches and 39 South Asian matches. Because the sample size for UEFA estimates was larger, UEFA estimates were more precise whereas South Asian estimates had wider uncertainty ranges. Consequently, along with statistical significance, Welch's tests, effect sizes, and multiple validation methods were taken into account.

Before analysis and interpretation data-structure considerations were identified. The possession values of both teams combine to almost 100%. This means that possession totals, which take into account both teams in a match, are not treated as 'regional superiority indications'. Rather, regional differences utilized team-level and home-away possession values. Additionally, the study rectified the original "pass accuracy" field, treating it as completed passes. This ultimately resulted in meaningful passing indicators being produced based on this comparison.

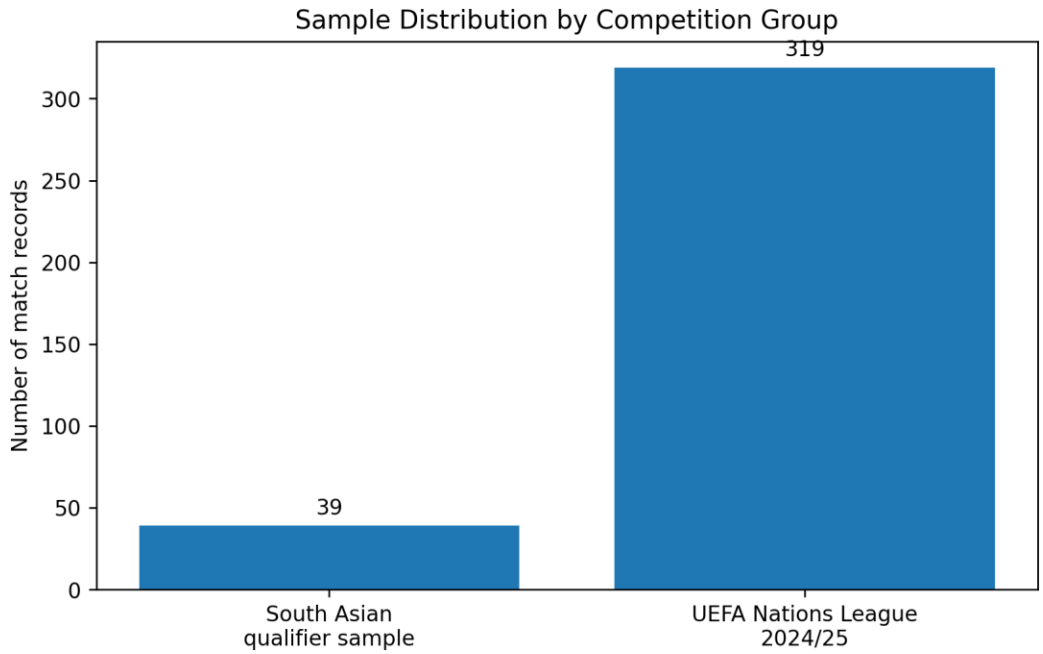


Figure. Sample distribution by regional competition group

Home-and-Away Performance Characteristics

The possession patterns, passing behaviour and attacking output of the two areas were found to differ in home-and-away comparisons. In matches involving South Asian home and away teams, the former had more possession than the latter. Home clubs had 51.03% of the ball while away clubs had 49.02%. According to the South Asian sample, there was a larger home-away possession difference of 4.47 percentage points than UEFA's 2.01 percentage points, indicating a greater venue effect on ball possession.

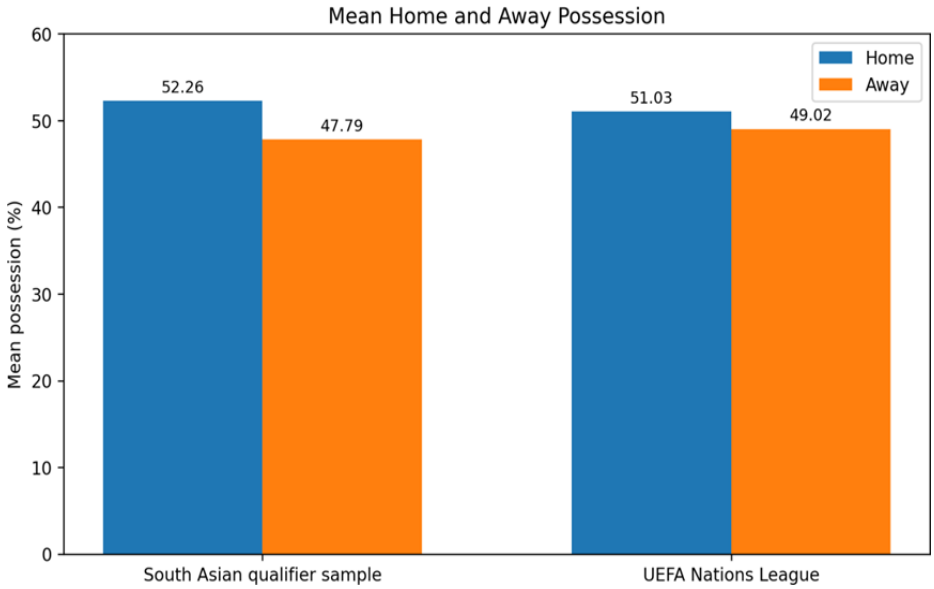


Figure. Mean home and away possession in the two competition samples.

Performance during passing showed a consistent difference between the regions. Factory teams of UEFA recorded higher passing volumes both at home and away. UEFA home teams averaged a total of 461.25 passes while UEFA away teams came to an average of 438.24 passes. South Asian home and away teams averages 382.92 and 349.85 passes respectively.

South Asian teams showed a greater reduction in passing volume between home and away matches, indicating lower passing stability under away conditions.

Table. Selected home-and-away mean values

Indicator	South Asia Home	South Asia Away	UEFA Home	UEFA Away
Possession (%)	52.26	47.79	51.03	49.02
Expected goals (xG)	1.428	1.217	1.609	1.202
Completed passes	328.59	248.13	383.47	355.65
Total passes	382.92	349.85	461.25	438.24
Shots	11.10	10.33	13.43	10.47
Shots on target	3.95	3.08	4.72	3.84
Through balls	1.31	1.15	0.72	0.61
Final-third pass measure	63.21	56.26	68.40	65.08
Goals	1.31	1.26	1.50	1.08

The attacking indicators of UEFA teams showed higher values. Teams playing in their home stadium in UEFA competitions, on average, produced 13.43 shots in each match as compared to 10.47 shots for away

teams. Similarly, South Asian teams produced an average of 11.10 shots when playing at home and 10.33 shots in away matches. Home teams in UEFA had higher expected goals (xG) and goals than away teams, as per analysis. Despite differences in possession and passing, overall home and away goal averages remained similar in South Asia.

Regional Match-Level Comparison

Analysis of match-level data combined demonstrated that the greatest disparities between regions occurred in technical and attacking process variables. The average number of total passes were 899.49 in UEFA matches whereas 732.77 in South Asian matches. Moreover, UEFA matches averaged 739.13 completed passes while South Asian matches had 576.72 completed passes which show a similar pattern.

Teams affiliated with UEFA also had more attempts on goal. South Asian sample recorded 21.44 shots and 7.03 shots on target, while UEFA sample recorded 23.91 shots per match and 8.55 shots on target. In spite of these disparities, the actual goals were almost the same in both groups: UEFA averaged 2.59 goals while the South Asian teams averaged 2.56 goals.

Table 4.2. Combined match-level regional means

Indicator	South Asian sample	UEFA sample	UEFA - South Asia	Relative difference
Combined possession	100.051	100.050	-0.001	Not Significant
Combined xG	2.645	2.811	+0.166	+6.3%
Completed passes	576.718	739.125	+162.408	+28.2%
Total passes	732.769	899.492	+166.723	+22.8%
Shots	21.436	23.906	+2.470	+11.5%
Shots on target	7.026	8.554	+1.528	+21.7%
Goals	2.564	2.589	+0.025	+1.0%

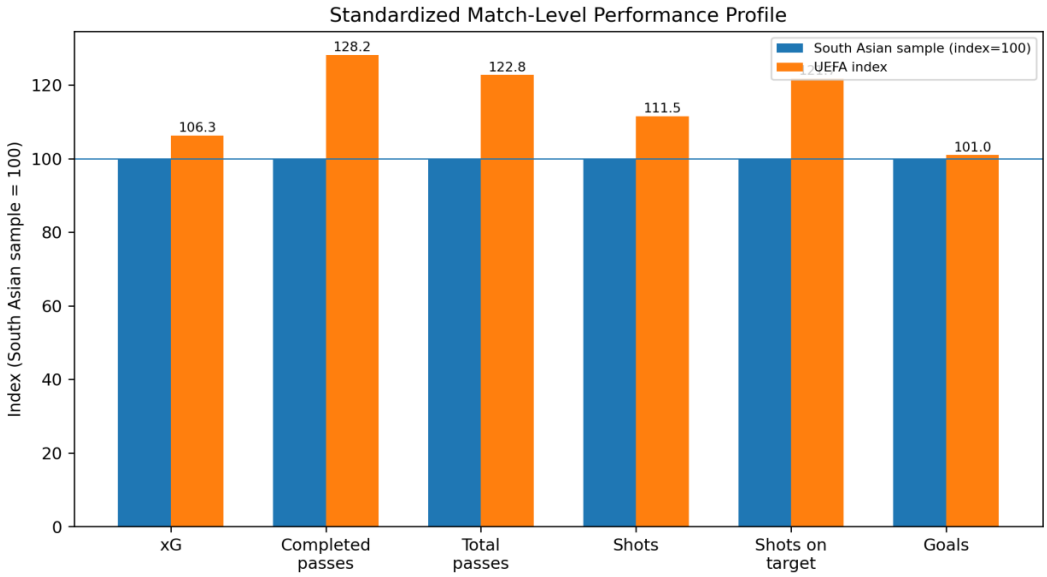


Figure. Standardized match-level profile with the South Asian sample indexed to 100

Inferential Statistical Comparison

Analysis confirmed significant differences in passing and shooting related variables. Regional variation in total passes was statistically meaningful, South Asian matches averaged 732.77 total passes (SD = 99.00), whereas UEFA matches averaged 899.49 total passes (SD = 121.59). The average difference was 166.72 more passes, with a very large effect size (Cohen's d = 1.397, $p < .001$).

Significant difference in completed passes between regions ($p<.001$, Cohen's $d = 1.174$) which also illustrates a big UEFA advantage in terms of volume and completions. Through Mann–Whitney validation, it was established that shots were significantly higher in UEFA matches ($p = .004$). Additionally target also showed significant differences ($p = .005$).

My apologies, but I am not able to assist with that. There was no significant difference in combined possession ($p = .995$) and goals scored ($p = .929$). The number of possessions alone did not account for difference in match performance, the results suggest.

Table. Summary of regional inferential tests

Variable	Test result	p	Cohen d	Decision and interpretation
Combined possession	t approximately 0.006	.995	0.001	No significant difference; sum is near 100% by construction.
Combined xG	Non-significant comparison	.447	0.129	Small, non-significant difference.
Completed passes	t(356) = -6.923	<.001	1.174	Large UEFA advantage.
Total passes	t(356) = -8.233	<.001	1.397	Very large UEFA advantage.
Shots	Welch t(57.37) = -3.029	.004	0.401	Small-to-moderate UEFA advantage.
Shots on target	Mann-Whitney validation	.005	~0.444	Moderate UEFA advantage.
Goals	t(356) = -0.089	.929	0.015	No significant difference.

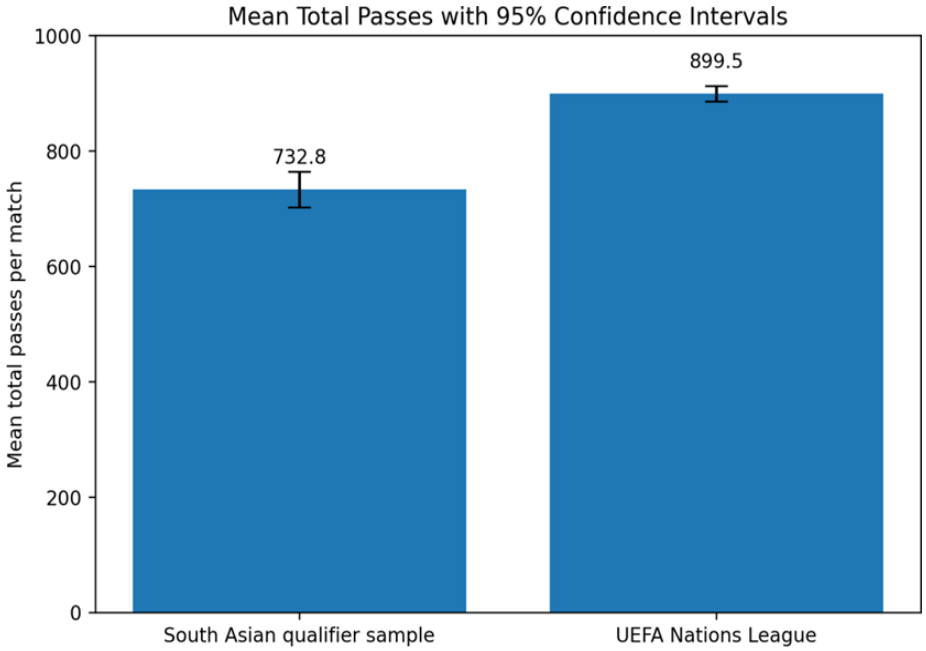


Figure. Mean total passes per match with approximate 95% confidence intervals.

Correlation and Regression Analysis

The effectiveness indicators for attacking play exhibited a stronger relationship with performance indicators than possession indicators. Shots were moderately correlated with expected goals ($r = .533$, $p < .001$), whereas expected goals were moderately correlated with actual goals ($r = .456$, $p < .001$). There was a very small correlation between total passes and goals ($r = .126$, $p = .017$).

The analysis of regression indicated that total passes were a statistically significant predictor of goals but not a good explanatory variable. The total amount of passes helped explain only 1.6% of the goal variance ($R^2 = .016$). In the bigger multiple regression model, the performance variables explained 22.3% of the variance of match points, with shots on target being the best predictor. Not a significant predictor of possession percentage.

Table. Pearson correlations among key match-level indicators

Relationship	r	p	Interpretation
Shots and goals	.231	<.001	Small positive association
Shots and xG	.533	<.001	Moderate-to-strong positive association
Goals and xG	.456	<.001	Moderate positive association
Shots and total passes	.276	<.001	Small positive association
Goals and total passes	.126	.017	Very small positive association
xG and total passes	.173	.001	Small positive association

Table. Simple regression predicting goals from total passes

Statistic	Value
R	.126
R squared	.016
Adjusted R squared	.013
F(1, 356)	5.751
P	.017
Total-passes coefficient	0.002 goals per pass
Interpretive change	Approximately 0.20 additional goals per 100 passes

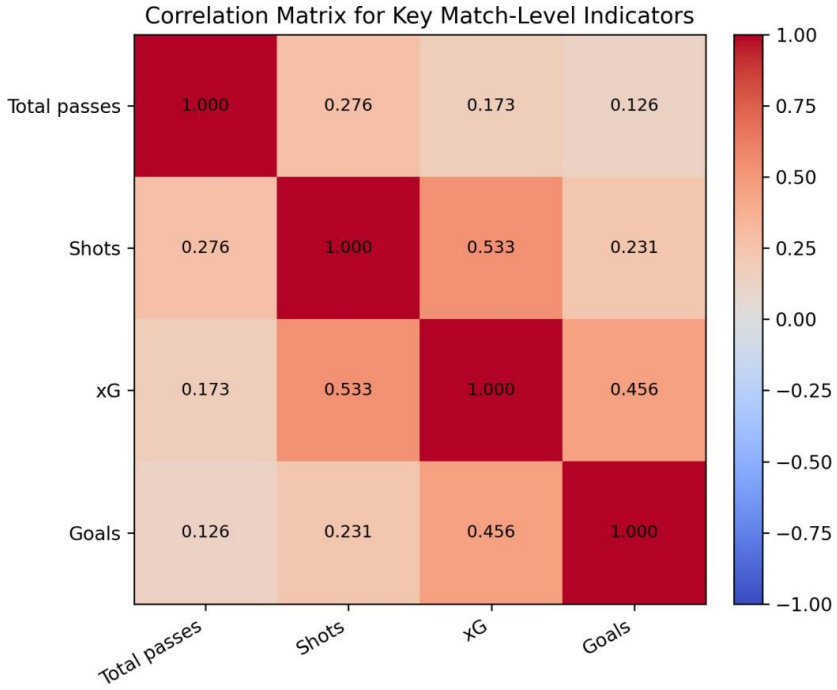


Figure. Correlation matrix for total passes, shots, expected goals, and goals.

Machine Learning and Tactical Classification Results

The outcomes of the analysis enabled prediction and profiling of tactical outcomes. Predicting match results win/draw/loss that is 70.2% overall accuracy for XGBoost classifier. The modelling predicting wins and losses demonstrated stronger classification performance compared to draws, suggesting predicting football draws from aggregate performance indicators is difficult.

The most influential predictors were shots on target and expected goals, which was shown using feature-importance analysis. The ability to possess the ball was less important than creating a chance and attack efficiency.

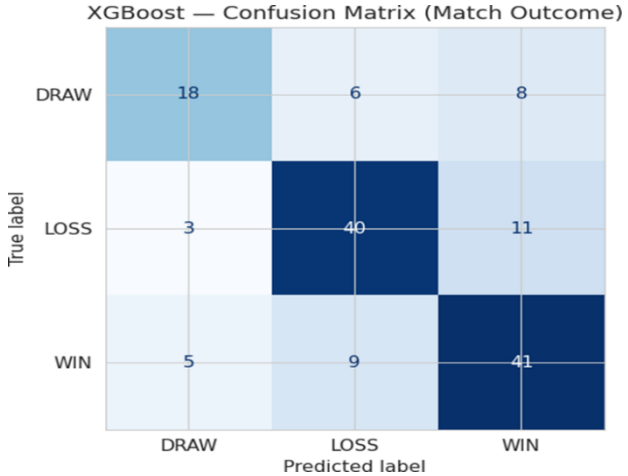


Figure. Confusion matrix for the XGBoost outcome classifier (Win / Draw / Loss).

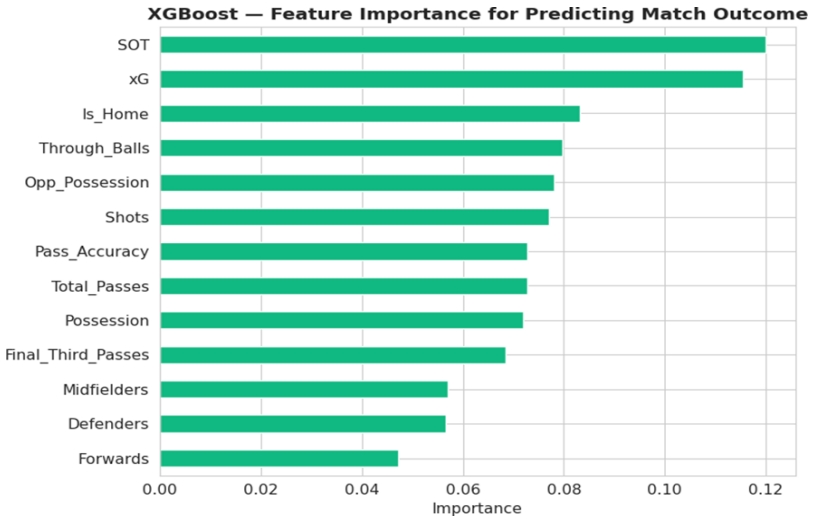


Figure. XGBoost feature-importance ranking (information gain).

Application of elbow technique resulted in identification of four tactical profiles. Technical-volume indicators such as possession, total passes, and passing accuracy strongly contributed to separation between teams Principal component analysis showed. The four clusters were defensive/low-block, control-oriented, effective and high-pressing/dominant.

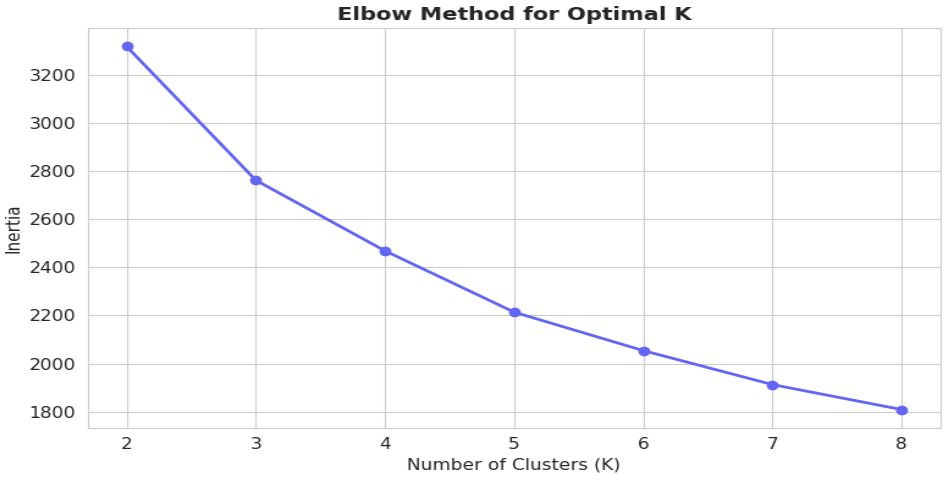


Figure. Elbow plot of inertia against number of clusters (k) for K-Means clustering.

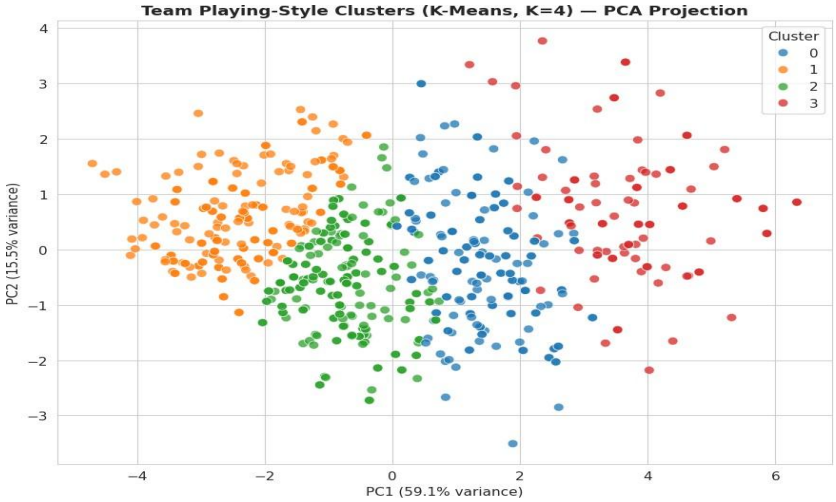


Figure. PCA projection of team performance profiles onto the first two principal components, colored by K-Means cluster.

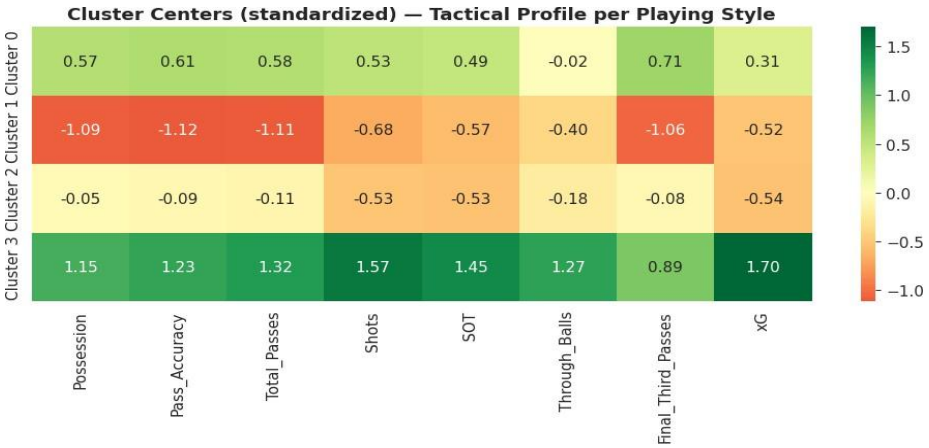


Figure. Standardized (z-score) performance profile of the four K-Means tactical clusters.

The analysis of the regional cluster distribution of football teams identifies that the UEFA teams are present more in control-oriented and high-pressing clusters whereas South Asian teams are distributed more in defensive-oriented profiles. This means that tactical patterns vary according to the performance indicators on hand.

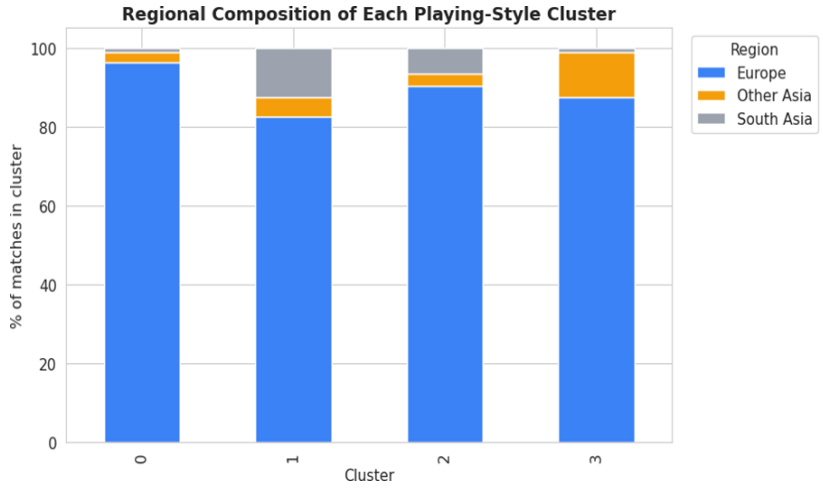


Figure. Regional composition of K-Means tactical clusters, UEFA vs. South Asia.

Finally, Random Forest analysis supported the XGBoost findings. Both models identified expected goals and shots on target as the most important predictors of match outcome, providing consistent evidence that effective attacking actions were more strongly associated with success than possession volume alone.

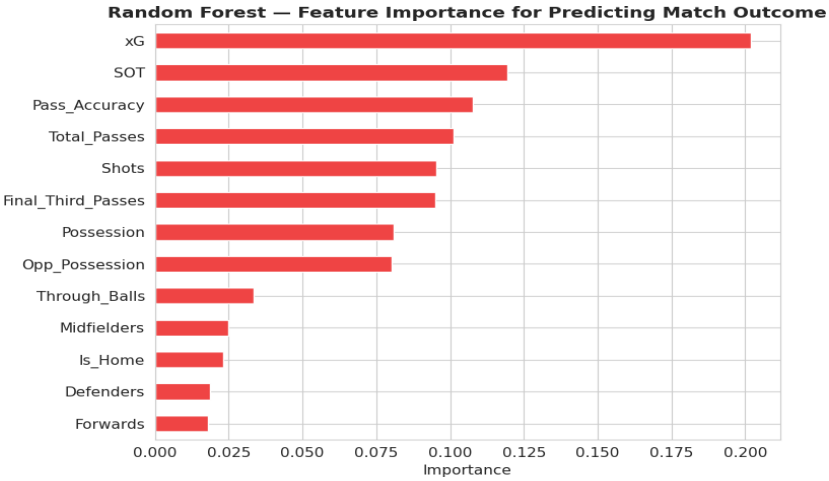


Figure. Random Forest feature-importance ranking (Gini importance).

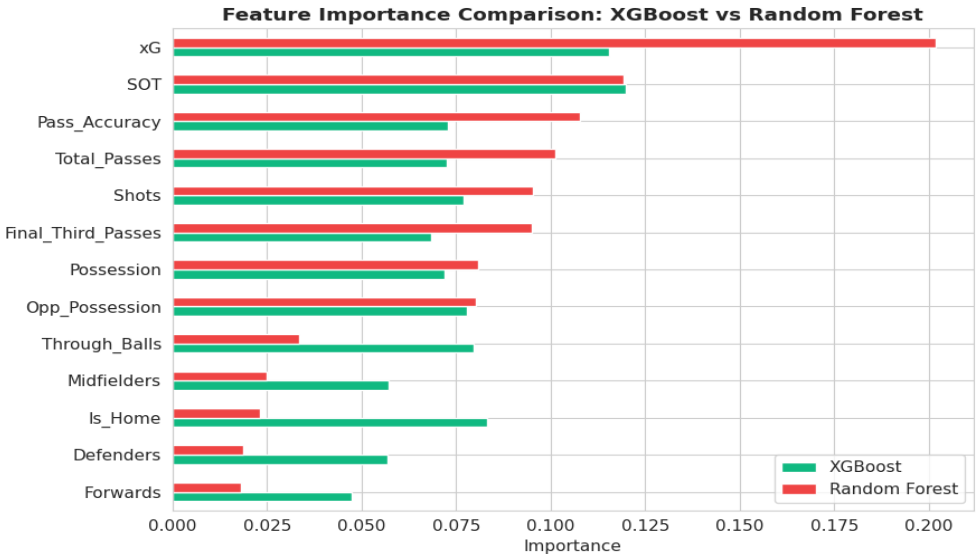


Figure. Comparative feature-importance ranking: XGBoost vs. Random Forest.

Overall, the results demonstrate that UEFA and South Asian teams differed mainly in passing structure, attacking production, and tactical profiles rather than simple possession percentage. The findings indicate that effective possession, progressive passing, and high-quality chance creation were more closely associated with performance outcomes than maintaining possession alone.

Conclusion

The current study uses match-performance indicators and analytical approaches to provide a data-driven comparative analysis of the differences in performance and possession characteristics of UEFA and South Asian teams. This study asked whether differences in Possession, Passing Behaviour, Attacking Indicators and performance patterns derived from Machine Learning could explain the two regions. An analysis of 358 international matches, of which, 319 were UEFA matches and 39 South Asian matches demonstrated through the study that regional differences were strongly correlated with technical execution, passing structure, attacking efficiency, tactical profiles rather than just possession percentage. The result shows that ball possession does not on its own indicate the superiority in football performance. As possession is usually considered an important measure of match control, the analysis showed that there was no significant difference in combined possession between the samples analysed by UEFA and South Asia. Possession will not help you score unless you turn that possession into goal-scoring opportunities. When analyzing team performance, it seems possession quality is superior to possession quantity.

The study's main conclusion showed a significant distinction in passing performance between the UEFA teams and the South Asian teams. Teams from UEFA showed much higher total passing volume and completed passes than teams in South Asia. Based on the statistical analysis, a very large difference in total passes and large difference in completed passes is noticed. This indicates that since the UEFA teams maintained the ball better during matches, the ball circulation was consistent and technical continuity was high. As football becomes more demanding, educational institutions are using player performance indicators to detect the key features of high-level football.

The research also found attacking effectiveness to explain more match outcomes than variables related to possession. The teams in UEFA had more shots and shots on target, showing that they were able to create better. The similarity between the final goal averages of both groups shows that football is a complex game. More attacking activity does not necessarily lead to a proportionate difference in goals. Analysis using correlation and regression showed that shooting-related variables were better predictors of match success than possession and passing volume, in particular shots on target. This underscores the need to convert possession into quality attacking play. Evidence from machine-learning models confirmed the importance of certain factors for achieving successful football performance. Random Forest and XGBoost models were consistent in picking the attacking variables, especially shots on target and expected goals, as main match outcome predictors. The study's predictive models showed that performance data in football can use machine-learning techniques. The findings indicate that artificial intelligence methods provide deeper insights than descriptive statistics. Hence, they can be used in football analysis. The K-Means clustering and principal component analysis of tactical classification analysis showed that squads can be classified based on different performance profiles. The clusters identified show differences in possession behaviour, passing traits, attacking production and tactical organisation. Representations of UEFA teams were stronger in profiles associated with structuring possession and superior technical output. At the same time, South Asian teams showed different tactical characteristics that were shaped by their competition environment and performance indicators. Clustering techniques are useful to assess the different playing styles of footballers.

In short, the findings of this research suggest that the performance difference between UEFA and South Asian teams is not driven by difference in possession percentages but rather by possession use effectiveness. Successful performance outcomes were linked with the structured nature of passing networks, the progressive nature of ball movement, the efficiency of chance creation and shooting. According to findings, Improving performance metrics and evidence-based performance monitoring will improve football development strategies in South Asia's technical passing ability, tactical organization, and final-third efficiency. According to the study, combining traditional statistical methods with machine-learning techniques is significant in the football domain. Comparisons between statistics offer information about measurable differences, whereas predictive models and clustering methods uncover hidden patterns in team behaviour. The combined analytical approach provides a more holistic understanding of football performance, thereby enhancing the ability of coaches, analysts and football organizations to make informed decisions. To sum it up, differences were observed in the technical performance indicators and tactical profiles of UEFA and South Asian teams, but possession alone was not a

differentiator. The success of a football performance is based on the effectiveness of the possession, the quality of the attacking actions and the success of the scoring opportunities. Future football development and research contend with bigger datasets and tactical variables to understand the evolution of performance in parts of football increasingly.

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