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Original Article

Comparative analysis of key performance indicators in Euroleague and national basketball leagues

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Abstract
Background: Understanding the performance metrics that underpin team success in the dynamic professional basketball world is crucial. This study originated in the context of increasing academic and professional interest in performance analytics, focusing on how teams in elite leagues, such as the Euroleague and their respective national leagues, adapt and perform based on specific key performance indicators (KPIs). **Purpose:** The primary objective of this research is to bridge the existing bibliographic gap by comparing the effectiveness of various KPIs in predicting match outcomes in both the Euroleague and National Basketball Leagues. This comparison aims to identify how strategic adaptations and performance measures differ according to the unique demands and styles of the respective competitions. **Methodology:** The study utilized two main datasets: one encompassing all Euroleague 2022–23 matches and the other compiling cumulative statistics from Euroleague teams over three seasons. Machine learning techniques, including Random Forest, Logistic Regression, and Support Vector Machines, were employed along with the Boruta algorithm for feature selection to enhance predictive accuracy and SHapley Additive exPlanations (SHAP) for the interpretability of the model output. **Results:** The analysis identified that certain KPIs, such as the effective field goal percentage, defensive ratings, and assists-to-turnover ratio, vary significantly in their impact on game outcomes between Euroleague and National League games. These variations imply that teams may need to tailor their strategies depending on the league in which they play. **Conclusions:** This study significantly advances the field of sports analytics by providing a detailed comparative analysis of basketball performance metrics across two competitive settings. It offers practical insights that can help coaches and analysts optimize team performance and strategic planning. Moreover, sophisticated data analysis techniques have allowed for a deeper understanding of the complex dynamics that influence basketball game outcomes, thereby making a significant contribution to the literature and practice of sports performance analysis.
Keywords: sports analytics, performance analysis, basketball metrics, machine learning, SHAP

Introduction

In recent years, there has been a significant surge in interest regarding the examination of athletic performance. This interest spans both academic research and its real-world implementation in sports (Plakias et al., 2023a; Plakias et al., 2023b). In the realm of professional basketball, success is often measured by a multifaceted evaluation of a team's performance. Coaches, analysts, and enthusiasts scrutinize various metrics and statistics to understand the dynamics of the game and gauge a team's proficiency (Izzo et al., 2023). The Euroleague showcases the pinnacle of European basketball, featuring teams that have honed their skills to compete on the grandest stage (Bourdas et al., 2022). The high intensity and caliber of the games in this elite competition render it an invaluable source of insight into the performance of top-tier basketball teams. However, to comprehend a team's overall capabilities and strategies fully, we must also examine its performance within the context of its domestic league.

A focal point within performance analysis is the study of performance indicators (PIs), which play a pivotal role in offering valuable insights (Hughes & Bartlett, 2002; Kapsalis et al., 2023). However, to derive more useful and reliable conclusions, researchers and team coaching staff focus on the use of KPIs, which are the metrics that contribute most significantly to success (Butterworth et al., 2013; Plakias et al., 2024). Various methods have been used to identify KPIs in basketball. Mikołajec et al. (2021) used econometrics and modeling prediction techniques, utilizing descriptive statistics, variable correlation comparisons, and multiple regression analyses in EuroLeague matches from 2003 to 2016. Lampis et al. (2023) employed three algorithms (logistic regression (LR), random forests (RF), and extreme gradient boosting trees) and predictive ensemble methods analyzing data from 5214 matches across four different European basketball tournaments (EuroLeague, EuroCup, Greek Basket League, and Spanish Liga ACB) for the period 2013-2018. Li et al. (2023) applied K-Means clustering and C5.0 decision trees for games in the Chinese Basketball Association (CBA). Zhou et al. (2024) used multiple linear regression (MLR) and quantile regression (QR) analysis for NBA games. While these

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methods provide significant insights, they cannot offer holistic interpretability and precise estimation of each variable's influence on match outcomes.

In the scholarly literature on basketball, several studies have addressed variances in performance metrics across different competitions, revealing distinct patterns and factors influencing team performance. For instance, Mandić et al. (2019) compared the NBA and Euroleague, emphasizing differences in game pace and possessions per game due to divergent athletic and tactical focuses. Similarly, Paulauskas et al. (2018) highlighted significant disparities in performance statistics related to body size and basketball skills between Euroleague and NBA players during the EuroBasket 2015. Further emphasizing the contextual influence on basketball performance, Muro et al. (2020) discussed how competition levels affect various aspects of basketball events, including intensity and risk factors. This perspective is complemented by studies like Ermiş et al. (2019), who pointed out performance variations between Euroleague players' contributions to their national teams, suggesting differing demands and expectations in international versus domestic settings. The impact of league-specific characteristics on PIs was also explored by Tormo et al. (2015), who examined free throw incidence across national and European leagues, and Oliveira-Da-Silva et al. (2013) who identified higher intensity demands in the Euroleague compared to domestic leagues for elite female basketball players. Despite these valuable insights, there appears to be a bibliographic gap specifically concerning the differences in KPIs for men's basketball teams when comparing their performances in the Euroleague with their respective games in national competitions.

Understanding the performance metrics that underpin success in professional basketball is crucial, particularly in a competitive landscape where the Euroleague and national leagues demand distinct strategic adaptations. The necessity for this research stems from the observed bibliographic gap in comparative studies focusing on KPIs across different competitive contexts. The context of this work is grounded in the growing interest in performance analytics within elite basketball competitions, where understanding the differential impact of KPIs can significantly influence coaching strategies and game outcomes. Given the current research landscape, which largely focuses on performance metrics within specific basketball leagues without extensive comparative analyses across different competitive environments, our study hypothesized that KPIs influencing victories in the Euroleague might significantly differ when these teams compete in their respective domestic leagues. This hypothesis is based on the premise that strategic adaptations and player performances are distinctly tailored to the unique demands and styles of each competition. Therefore, the primary aim of this article is to bridge the bibliographic gap by identifying which KPIs are most influential in winning games in the Euroleague and then comparing these KPIs to performances in national leagues to discern any significant differences. By doing so, this study provides a comprehensive insight into the tactical and strategic adaptations required for success in different competitive settings, thereby contributing to both the academic field of sports analytics and practical coaching methodologies.

This manuscript distinguishes itself with several unique contributions to the field of sports analytics. Firstly, it conducts a comprehensive KPI analysis across two distinct competitive contexts, systematically identifying and comparing the KPIs for Euroleague teams within both the Euroleague and their domestic competitions. This approach provides novel insights into how different playing environments influence team performance strategies, marking a significant advancement in understanding strategic adaptations in professional basketball. To explore the differential impact of KPIs across the Euroleague and national basketball leagues, we employed a multifaceted research approach incorporating both traditional statistical analyses and advanced machine learning techniques. Initially, we collected comprehensive datasets encompassing all matches from the Euroleague 2022-23 season and cumulative statistics from Euroleague teams over three seasons, including their performances in domestic leagues. Secondly, the study utilizes advanced machine learning (ML) techniques to enhance predictive accuracy and interpretability. By integrating RF, LR, and Support Vector Machines (SVMs), alongside the Boruta feature selection method and SHAP model, the research not only pinpoints the most crucial KPIs but also elucidates their impacts on match outcomes in a detailed and comprehensible manner. In particular, for interpretability, we utilized SHAP values, which allowed us to quantify the impact of each feature on the model's predictions. This step was crucial for understanding the underlying relationships within the data and provided actionable insights into the most influential KPIs. Finally, the empirical validation of theoretical predictions through rigorous machine learning processes and robust evaluation metrics such as accuracy, recall, precision, F1-score, and ROC curves, ensures that the study's findings are both theoretically sound and practically viable. These attributes underscore the manuscript's substantial contribution to existing literature, offering innovative perspectives and methods that could profoundly impact the application and understanding of performance analytics in professional basketball.

Material & methods

Sample

Two distinct datasets were utilized for this study. The first dataset encompassed all Euroleague 2022-23 matches, spanning the regular season and playoffs. It consisted of two observations per match, one for each team, resulting in a total of 656 observations extracted from 328 matches. Each observation included the match outcome (win or loss) along with the 80 variables derived from the Instat Basketball analysis platform, offering team statistics. The table in Appendix A shows the 80 variables together with their respective definitions. This initial dataset aimed to identify the most influential among the 80 variables concerning the match's result.

The second dataset focused on the cumulative statistics, averaged per match, of the teams engaged in the Euroleague over the last three seasons (2020-21, 2021-22, 2022-23), in both their Euroleague and domestic league fixtures. The table in Appendix B shows the 51 teams that participated in the Euroleague in the 3 aforementioned seasons (18 + 15 + 18). However, Olympiacos 2020-21 season was excluded from this group, as it did not participate in the 1st division of the Greek league.

Consequently, the second dataset comprised 50 observations, each corresponding to a different team. Each observation in the second dataset featured 160 variables, with 80 related to Euroleague matches and another 80 tied to National league matches. From this second dataset, only the variables determined to significantly influence a team's success were considered. The second dataset was employed to conduct a comparative analysis between KPIs in the Euroleague and their corresponding metrics in the national leagues.

Procedure

Data was acquired from Instat Basketball in distinct Excel sheets, one for each team (access on 15/10/2023 upon request). Instat Basketball facilitates data export in XLS format. Previous research has tested the reliability and validity of the data contained in Instat Basketball, showing very high values (Bustamante-Sánchez et al., 2022). The authors subsequently merged these individual Excel sheets into a single comprehensive sheet, making essential adjustments to prepare the data for subsequent analysis.

Machine learning Analyses

Problem definition: In this study, our main goal was to develop an explainable machine learning approach that could identify essential informative factors influencing match outcome predictions. We also explored the impact of these factors on the model's output, with a specific focus on post hoc explainability. To accomplish this, we treated the task of predicting match outcomes as a binary classification problem. To be specific, we divided the observations into two categories: (i) the "win" group, comprising 328 observations where teams emerged victorious and (ii) the "lose" group, consisting of 328 observations where teams lost.

Feature Engineering: StandardScaler library was applied for data normalization, which is a crucial step in ensuring fair comparisons between different features by scaling them to a standard range. Normalization enhances the performance and reliability of machine learning models. Subsequently, we utilized the Boruta algorithm for feature selection (FS), a powerful technique that helps identify the most relevant features for prediction. Boruta efficiently evaluates feature importance by comparing the importance of observed features against a shadow feature set. This rigorous selection process ensures that only the most informative features are considered, enhancing the accuracy and interpretability of our predictive model.

Learning process: In our learning process, we employed a diverse set of ML classifiers, including RF, LR, and SVM, each optimized with hyperparameters to enhance their predictive power. To rigorously evaluate the performance of these models, we adopted a stochastic validation strategy: 70% training/30% testing. To evaluate the models' effectiveness, we utilized a comprehensive set of performance metrics on the testing set. These metrics included accuracy, which measures the overall correctness of predictions, recall and precision, which assess the model's ability to capture relevant instances and minimize false positives respectively, and F1-score, which balances the trade-off between precision and recall.

Additionally, we analyzed the confusion matrix, providing a detailed breakdown of true positive, true negative, false positive, and false negative predictions, offering insights into model performance across different classes. Furthermore, we utilized ROC curves, which graphically represent the model's ability to discriminate between positive and negative instances at various thresholds. This comprehensive evaluation approach ensured a thorough assessment of the models' predictive capabilities and robustness. Furthermore, we utilized accuracy, a widely adopted measure for assessing the overall performance of our models.

Interpretation: The SHAP model plays a crucial role in enhancing the interpretability of machine learning models. It quantifies the impact of each feature on a model's prediction, revealing intricate relationships within complex datasets based on game theory. By employing SHAP, we gain a deeper understanding of the importance of specific informative factors in predicting match outcomes (Moustakidis et al., 2023).

Statistical analyses

For the 18 resultant variables, Kolmogorov-Smirnov tests were conducted on the sample of 50 teams (second dataset) for the values of the PIs in both the Euroleague and their respective domestic leagues. Paired samples t-tests were applied to variables that exhibited a normal distribution in both the Euroleague and the domestic leagues. In cases where the data did not follow a normal distribution, the corresponding non-parametric Wilcoxon's signed-ranks test was employed.

All analyses were carried out using IBM SPSS statistical software (version 29.0). The significance level was set at $p<0.05$. Cohen's d was computed to indicate the effect size, which was categorized as follows: trivial ($d=0.0$ to 0.19), small ($d=0.2$ to 0.49), medium ($d=0.5$ to 0.79), large ($d=0.8$ to 1.29), and very large ($d\geq1.3$).

Results

In this section are presented the selected factors from the Boruta FS algorithm, the testing performance metrics of the employed ML classifiers and the interpretation of the model output of the best performed ML classifier as well as the results of the statistics following the identification of the main contributing factors for the Euroleague and the domestic leagues.

Machine Learning

Table 1 demonstrates the 18 most informative factors after the implementation of the Boruta algorithm for FS. The factors were prioritized in order of importance, from highest to lowest.

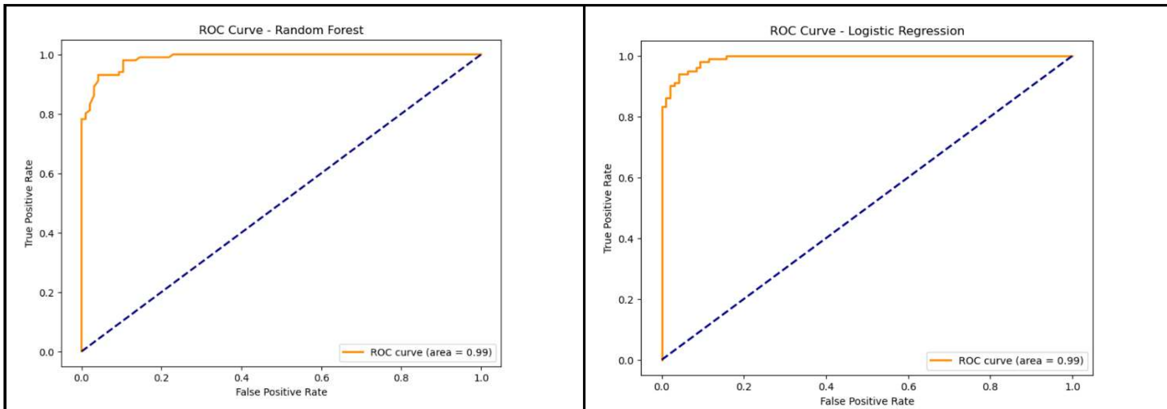
Table 1. Most informative identified factors.

Ranking	Feature	Type of Variable
1	Contested_field_goals_made	Numeric
2	Rebounds	Numeric
3	Contested_field_goals_percent	Numeric
4	True_shooting_percentage	Numeric
5	Effective_field_goal _percentage	Numeric
6	threept_field_goals_percent	Numeric
7	Steals_to _turnovers	Numeric
8	Assists_to_turnovers	Numeric
9	Net_rating	Numeric
10	Defensive_Efficiency	Numeric
11	Defensive_rating	Numeric
12	Field goals_percent	Numeric
13	Offensive_rating	Numeric
14	Field_goals_made	Numeric
15	Points_per_possession	Numeric
16	Points	Numeric
17	Points_off_turnovers	Numeric
18	Defensive_rebounds	Numeric

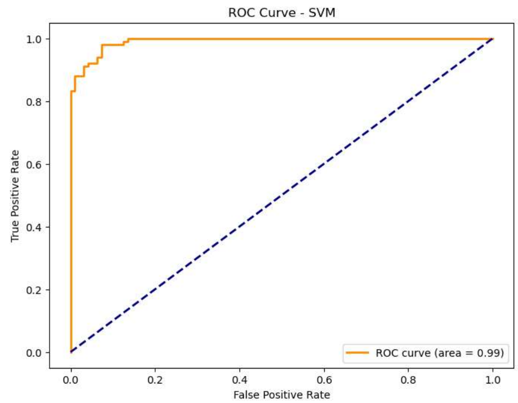
Table 2 summarizes the testing performance results for the employed ML classifiers in the 18 most informative factors in our binary task. The best testing performance was achieved from the LR classifier. Specifically, LR achieved 94.92% accuracy, 95.83% recall, 93.88% precision and 94.85% f1-score. On the other hand, the lowest testing performance in this binary task was achieved by RF. In particular, RF achieved 91.88% accuracy, 90.62% recall, 92.55% precision and 91.58% f1-score. Figure 1 presents the ROC curve performance of the employed ML classifiers.

Table 2. Performance metrics for the employed ML classifiers.

Classifier	Accuracy (%)	Recall (%)	Precision (%)	f1-score (%)	Hyperparameters	Confusion matrix	
RF	91.88	90.62	92.55	91.58	maximum depth= 20, number of estimators= 200	87 7	9 94
LR	94.92	95.83	93.88	94.85	C=1	92 6	4 95
SVM	93.91	95.83	92.00	93.88	C= 1, kernel= linear	92 8	4 93



(a) (b)



(c)

Figure 1. ROC curves for (a) RF, (b) LR and (c) SVM classsfier.

Figure 2 illustrates the influence of the most informative factors on the output of the best-performing model, which is the LR ML model. Figure 2a displays the most influential predictive factors in descending order, providing a top-down perspective. The colors represent the risk level associated with match observations, with red indicating high values and blue indicating low values. Specifically, high defensive rating values correspond to a higher likelihood of losing the match, establishing a clear association between defensive rating and match outcome. Additionally, high values in factors such as 'field goals made' exert a positive influence on the match's outcome, while low values in offensive rating, points, and effective field goal percentage are negatively associated with winning the match. Figure 2b depicts the average influence of the selected informative factors on the model's output magnitude. Notably, defensive rating, offensive rating, points, and effective field goal percentage significantly contribute to the model's output. Conversely, factors such as field goals made, rebounds, and contested field goals made have a moderate impact.

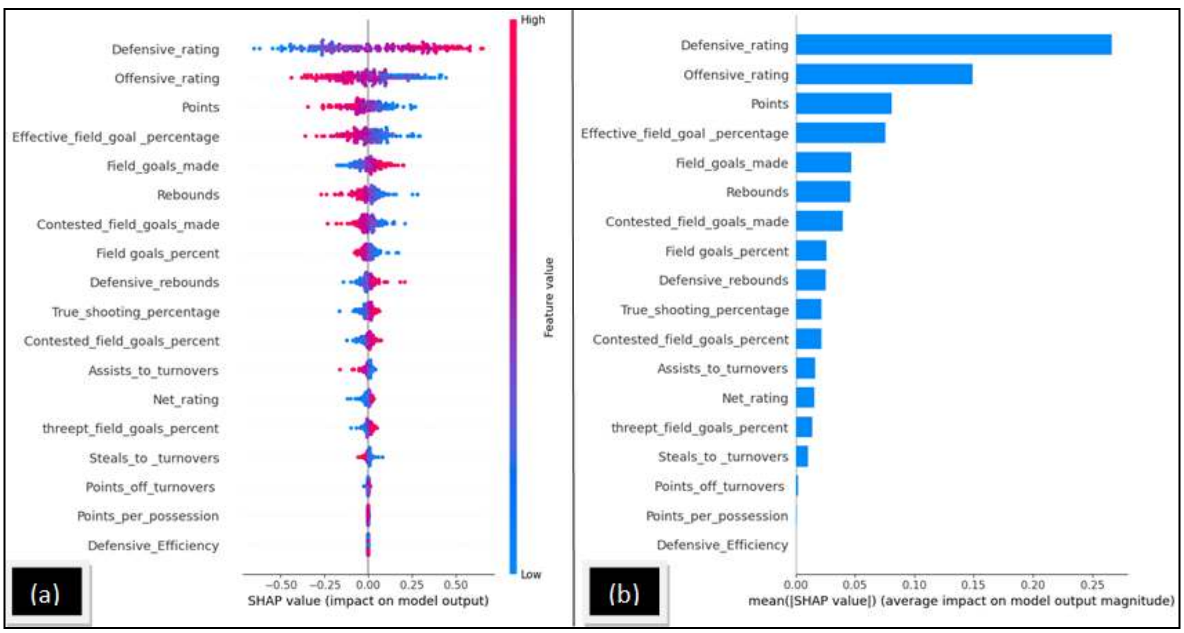


Figure 2. This figure showcases two key aspects: (a) the distribution of SHAP values for the LR classifier, trained on features selected by the Boruta algorithm and (b) the SHAP feature importance corresponding to each feature across the testing instances.

Statistics

Table 3 displays the means and standard deviations for the 18 variables, both for the Euroleague and the domestic leagues.

Table 3. Descriptive Statistics (Means and Standard Deviations) for the 18 KPIs in both the Euroleague (EURO) and Domestic National Leagues (NAT)

Descriptive Statistics							
Variable	**Mean± SD**	**Variable**	**Mean± SD**	**Variable**	**Mean± SD**	**Variable**	**Mean± SD**
Points_NAT	86.00 ± 3.13	Rebounds_EURO	29.65 ± 1.80	Steals_to_turnovers_NAT	0.58 ± 0.07	Contested_field_goals_percent_EURO	45.61 ± 1.91
Points_EURO	79.01± 3.66	Defensive_rating_NAT	92.15 ± 4.04	Steals_to_turnovers_EURO	0.52 ± 0.06	Points_off_turnovers_NAT	12.31 ± 1.32
Field_goals_made_NAT	30.40 ± 1.39	Defensive_rating_EURO	97.88 ± 3.22	Effective_field_goal_percentage_NAT	56.80 ± 2.45	Points_off_turnovers_EURO	10.93 ± 1.26
Field_goals_made_EURO	28.37 ± 1.25	Defensive_Efficiency_NAT	1.04 ± 0.04	Effective_field_goal_percentage_EURO	54.20 ± 2.08	Points_per_possession_NAT	1.03 ± 0.04
Field_goals_percent_NAT	48.82 ± 2.05	Defensive_Efficiency_EURO	1.11 ± 0.04	True_shooting_percentage_NAT	64.60 ± 2.41	Points_per_possession_EURO	0.98 ± 0.04
Field_goals_percent_EURO	46.87 ± 1.78	Net_rating_NAT	11.34 ± 5.32	True_shooting_percentage_EURO	61.46 ± 2.42	Defensive_rebounds_NAT	23.53 ± 1.41
threept_field_goals_percent_NAT	37.87 ± 2.28	Net_rating_EURO	-0.36 ± 5.22	Contested_field_goals_made_NAT	24.36 ± 1.28	Defensive_rebounds_EURO	21.32 ± 1.29
threept_field_goals_percent_EURO	36.55 ± 2.41	Assists_to_turnovers_NAT	1.63 ± 0.21	Contested_field_goals_made_EURO	23.25 ± 1.30	Offensive_rating_NAT	103.4 ± 3.39
Rebounds_NAT	32.45 ± 1.95	Assists_to_turnovers_EURO	1.39 ± 0.15	Contested_field_goals_percent_NAT	47.81 ± 2.33	Offensive_rating_EURO	97.52 ± 3.86

The Kolmogorov-Smirnov test revealed that out of the 36 variables used from the second dataset, only 4 (Points_per_possession_NAT, Points_per_possession_EURO, Defensive_rebounds_EURO, Offensive_rating_NAT) did not conform to a normal distribution ($p < 0.05$) (Table 4). Therefore, in 3 pairs (Points_per_possession, Defensive_rebounds, Offensive_rating), the non-parametric Wilcoxon Signed Ranks Test was applied, while in the remaining 15 Paired Samples t-Test was employed.

Table 4. Kolmogorov–Smirnov Tests for the 18 KPIs in both the Euroleague (EURO) and Domestic National Leagues (NAT)

Tests of Normality (Kolmogorov–Smirnov)							
Variables	**Sig.**	**Variables**	**Sig.**	**Variables**	**Sig.**	**Variables**	**Sig.**
Points_NAT	.200*	threept_field_goals_percent_EURO	.200*	Defensive_Efficiency_NAT	.200*	Effective_field_goal_percentage_EURO	0.079
Points_EURO	.200*	Rebounds_NAT	0.183	Defensive_Efficiency_EURO	.200*	True_shooting_percentage_NAT	.200*
Points_per_possession_NAT	0.008	Rebounds_EURO	.200*	Net_rating_NAT	.200*	True_shooting_percentage_EURO	.200*
Points_per_possession_EURO	0.038	Defensive_rebounds_NAT	.200*	Net_rating_EURO	0.088	Contested_field_goals_made_NAT	0.068
Field_goals_made_NAT	.200*	Defensive_rebounds_EURO	0.045	Assists_to_turnovers_NAT	0.096	Contested_field_goals_made_EURO	.200*
Field_goals_made_EURO	.200*	Offensive_rating_NAT	0.016	Assists_to_turnovers_EURO	0.169	Contested_field_goals_percent_NAT	.200*
Field_goals_percent_NAT	.200*	Offensive_rating_EURO	.200*	Steals_to_turnovers_NAT	0.087	Contested_field_goals_percent_EURO	.200*
Field_goals_percent_EURO	.200*	Defensive_rating_NAT	0.162	Steals_to_turnovers_EURO	0.055	Points_off_turnovers_NAT	.200*
threept_field_goals_percent_NAT	.200*	Defensive_rating_EURO	.200*	Effective_field_goal_percentage_NAT	.200*	Points_off_turnovers_EURO	.200*

Tables 5 and 6 indicate that, for all 18 variables contributing significantly to the team's wins or losses, there is a statistically significant difference between the values in the Euroleague and the corresponding values in the domestic leagues.

Table 5. Paired Samples t-Tests on the 15 Pairs of variables that followed a Normal Distribution

Pairs	t	df	Sig. (2-tailed)	Pairs	t	df	Sig. (2-tailed)
Points_NAT - Points_EURO	15.134	49	0.000	Assists_to_turnovers_NAT - Assists_to_turnovers_EURO	9.484	49	0.000
Field_goals_made_NAT - Field_goals_made_EURO	10.974	49	0.000	Steals_to_turnovers_NAT - Steals_to_turnovers_EURO	5.313	49	0.000
Field_goals_percent_NAT - Field_goals_percent_EURO	8.136	49	0.000	Effective_field_goal_percentage_NAT - Effective_field_goal_percentage_EURO	8.641	49	0.000
threept_field_goals_percent_NAT - threept_field_goals_percent_EURO	4.085	49	0.000	True_shooting_percentage_NAT - True_shooting_percentage_EURO	10.378	49	0.000
Rebounds_NAT - Rebounds_EURO	12.671	49	0.000	Contested_field_goals_made_NAT - Contested_field_goals_made_EURO	6.122	49	0.000
Defensive_rating_NAT - Defensive_rating_EURO	-9.957	49	0.000	Contested_field_goals_percent_NAT - Contested_field_goals_percent_EURO	8.124	49	0.000
Defensive_Efficiency_NAT - Defensive_Efficiency_EURO	-10.705	49	0.000	Points_off_turnovers_NAT - Points_off_turnovers_EURO	6.420	49	0.000
Net_rating_NAT - Net_rating_EURO	13.742	49	0.000				

Paired Samples Test

Table 6. Wilcoxon Signed Ranks Tests on the 3 Pairs of variables that did not follow a Normal Distribution

Wilcoxon Signed Ranks Test	Points_per_possession_EURO - Points_per_possession_NAT	Defensive_rebounds_EURO - Defensive_rebounds_NAT	Offensive_rating_EURO - Offensive_rating_NAT
Z	-5.867	-6.128	-6.115
Asymp. Sig. (2-tailed)	0.000	0.000	0.000

From table 7 it can be seen that the differences between the teams regarding their performance in the Euroleague and the domestic leagues were: a) moderate in the variables threept_field_goals_percent (d=0.578) andSteals_to_turnovers (d=0.751), b) large in the variables Field_goals_percent (d= 1.151), Effective_field_goal_percentage (d=1.122), Contested_field_goals_made (d=0.866), Contested_field_goals_percent (d=1.149) and Points_off_turnovers (d=0.908), and c) very large in the variables Points (d=2.14), Points_per_possession (d=1.578), Rebounds (d=1.792), Defensive_rebounds (d=1.837), Offensive_rating (d=1.803), Defensive_rating (d=-1.408), Defensive_Efficiency (d=-0.154), Net_rating (d=1.943), Assists_to_turnovers (d= 1.341) and True_shooting_percentage (d=1.468).

Table 7. Effect Sizes (Cohen's d) resulting from the Comparisons of the 18 Variables between the Euroleague (EURO) and Domestic National Leagues (NAT). The minus sign (-) indicates higher values in the Euroleague, while in all other cases, the values are higher in the domestic leagues.

Pairs	**Cohen's d**	**Pairs**	**Cohen's d**
Points_NAT - Points_EURO	2.140	Defensive_Efficiency_NAT - Defensive_Efficiency_EURO	-1.514
Points_per_possession_NAT - Points_per_possession_EURO	1.578	Net_rating_NAT - Net_rating_EURO	1.943
Field_goals_made_NAT - Field_goals_made_EURO	1.552	Assists_to_turnovers_NAT - Assists_to_turnovers_EURO	1.341
Field_goals_percent_NAT - Field_goals_percent_EURO	1.151	Steals_to_turnovers_NAT - Steals_to_turnovers_EURO	.751
threept_field_goals_percent_NAT - threept_field_goals_percent_EURO	.578	Effective_field_goal_percentage_NAT - Effective_field_goal_percentage_EURO	1.222

Effect Sizes

Rebounds_NAT Rebounds_EURO	-	1.792	True_shooting_percentage_NAT True_shooting_percentage_EURO	-	1.468
Defensive_rebounds_NAT Defensive_rebounds_EURO	-	1.837	Contested_field_goals_made_NAT Contested_field_goals_made_EURO	-	.866
Offensive_rating_NAT Offensive_rating_EURO	-	1.803	Contested_field_goals_percent_NAT Contested_field_goals_percent_EURO	-	1.149
Defensive_rating_NAT Defensive_rating_EURO	-	-1.408	Points_off_turnovers_NAT Points_off_turnovers_EURO	-	.908

Discussion

Through a robust application of advanced machine learning techniques, including RF, LR, and SVMs, complemented by the Boruta FS and SHAP model for interpretability, this research provides a sophisticated understanding of which factors most strongly predict match outcomes and how these factors differ by competition context. Furthermore, the findings of this research significantly contribute to the sports analytics domain by elucidating how KPIs differ between the Euroleague and national leagues. This dual analysis not only bridges a critical bibliographic gap but also enhances our comprehension of how strategic and performance demands shift depending on the competitive environment.

The effectiveness of field goals, as reflected by effective field goal percentage (eFG%), stood out as a critical factor in both competition settings. Literature corroborates this finding, indicating that eFG% is often a determinant of game outcomes across various basketball leagues (Li et al., 2023; Malarranha et al., 2013; Mandić et al., 2019). This suggests a universal applicability of this metric across competitive levels, reinforcing its utility in strategic game planning and player performance evaluation. However, while the importance of eFG% is well-documented, our analysis further enriches this understanding by quantifying its variable impact between different leagues, potentially reflecting variations in defensive strategies or offensive efficiency that are unique to each league's style of play.

Furthermore, assists are a key metric in basketball, often serving as an indicator of team cohesion and effectiveness in offensive execution. The significant finding in our study for assists-to-turnovers, points to the critical role of efficient ball handling and distribution in securing game victories. This observation resonates with the insights from Terner and Franks (2021), who discuss the predictive power of assist rates in assessing team performance. By enhancing our understanding of the strategic deployment of assists within game play, particularly in creating scoring opportunities while minimizing turnovers, teams can better orchestrate their offensive plays and improve overall team dynamics.

Rebounds have consistently been identified as a critical factor in basketball analytics, often correlating strongly with game outcomes due to their direct impact on possession control. The significant emphasis on rebounds reflects findings similar to those in Han and Choi (2020) and Leicht et al. (2017), where rebounding prowess, particularly defensive rebounds, was associated with winning outcomes. This aligns with our study's findings where rebounds, particularly defensive rebounds, showed a notable difference between winning and losing teams. This suggests that successful teams possess a robust rebounding strategy, reinforcing the need for teams to focus on enhancing this aspect of their game to increase their chances of victory.

Defensive metrics, particularly defensive ratings, also highlight a distinct influence in the Euroleague compared to domestic leagues. This divergence points to the tactical sophistication and higher stakes associated with Euroleague games, where minimizing opponent scores is paramount. The significant role of defensive strategies in the Euroleague aligns with broader findings by Milanović et al. (2019), who point out the critical nature of defensive actions in influencing game outcomes at the Olympic level. This divergence in defensive impact between leagues may also reflect differences in player skills, coaching strategies, or even the physicality of the game, which varies widely across different competitive environments (Muro et al., 2020). Furthermore, steals, indicative of aggressive and effective defensive play, were also highlighted as a significant factor in our study, aligning with insights from Milanović et al. (2019), who emphasized the importance of steals in contributing to winning performances at the Olympic level.

These nuanced understandings of KPIs in basketball underscore the adaptability and strategic foresight required in coaching and game management. They also suggest that while certain performance metrics like eFG% and rebounds are universally important, their specific applications and impact can vary markedly between different types of competitions. Such insights are invaluable for refining training programs and game-day strategies, ensuring that teams are better equipped to compete at their peak in varied competitive environments. Collectively, the study enriches the strategic toolkit available to basketball teams, offering nuanced insights that can drive more informed decision-making in both preparation and real-time game management.

Despite the comprehensive analysis and significant contributions of this study, several limitations must be acknowledged. Firstly, the analysis is confined to the performance data from the Euroleague and National leagues over specific seasons, which may not fully encapsulate the dynamics or potential changes in playing styles and team strategies that evolve over time (Barreira & Morgado, 2023; García-Izquierdo et al., 2012). Additionally, the study relies on the accuracy and completeness of the data provided by the Instat Basketball platform. While this platform is highly regarded (Bustamante-Sánchez et al., 2022), the potential for missing or inaccurately recorded data could affect the validity of the findings. Furthermore, the machine learning models employed, although sophisticated, are dependent on the assumption that past performances are indicative of future outcomes, which in sports can be a precarious assumption due to the unpredictable nature of games and player performances. Lastly, this study employs a static analytical method that, while commonly used, provides only a snapshot of performance, disregarding the dynamic nature of matches (Pratas et al., 2018). In contrast, dynamic analysis considers the game's state at each moment, providing a more comprehensive understanding of performance patterns and outcomes (Prieto et al., 2015). These limitations suggest areas for further research, including longitudinal studies and the use of the dynamic method to enrich the understanding of performance differences in basketball.

Conclusions

This study represents a significant advancement in the field of sports analytics by systematically analyzing and comparing KPIs in professional basketball across two distinct competitive environments: the Euroleague and national leagues. Through a robust application of advanced machine learning techniques, this research has not only elucidated the most influential KPIs but also highlighted the variation in their impact between different competitions. The empirical validation of these findings, supported by sophisticated models such as RF, LR, and SVMs, ensures that our conclusions are both theoretically sound and practically viable, underpinning the study's substantial contribution to the literature.

The importance of this research to the specialized scientific community cannot be underestimated. It fills a critical bibliographic gap by providing a nuanced understanding of how PIs vary significantly between international and domestic competitions. This differentiation is crucial for developing more tailored training programs and game strategies that are sensitive to the specific demands of each competition type. Moreover, the use of SHAP values for interpretability allows for a deeper insight into the data, helping researchers and practitioners alike understand the complex dynamics that influence game outcomes.

For coaches, analysts, and scouters, the practical applications of this study are manifold. By identifying which performance metrics are most indicative of success in different league settings, coaching staff can optimize their strategies to exploit these insights effectively. For instance, the emphasis on effective field goal percentage (eFG%) and defensive ratings in the Euroleague suggests a need for focused training on shooting efficiency and defensive tactics in preparation for these high-caliber matches. Additionally, the impact of assists and rebounds provides strategic data points for adjusting team dynamics and player roles depending on the opponent's league standard.

In conclusion, this research not only advances our understanding of sports analytics by integrating complex ML tools into the analysis of basketball performance but also offers actionable insights that can significantly enhance the preparation and execution of basketball strategies across various levels of professional play. The findings from this study serve as a cornerstone for future explorations into the adaptive nature of sports performance analysis, paving the way for more sophisticated and context-sensitive approaches in sports science.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest.

Appendices

Appendix A:

Table Appendix A. The 80 variables related to team statistics with their respective definitions

Assists	A key pass that has led to the scoring of a point. Passes leading to free throws are not tagged as assists.
Assists_to_turnovers	This index literally shows the ratio between the assists and the turnovers. It is a great index for the point guards, the higher the index, the better playmaking skills they have.
Blocks	Block is when a player attempts a field goal but an opposing player deflects the shot attempt during the shooting motion. Usually, this is the most attractive defensive part in basketball.
Catch_and_drive_attempted	Play occurs when a player receives the ball, makes a dribble or dribbles and then attempts a field goal.
Catch_and_drive_made	Play occurs when a player receives the ball, makes a dribble or dribbles and then makes a field goal.
Catch_and_drive_shots_made_percent	The ratio between successful and total attempted catch and drive shots (CnD+/CnD)*100 = CnD%.
Catch_and_shoot_attempted	Play which is finished by a jumping shot at least 3 meters from the rim by a player who controlled the ball less than 2 seconds or didn’t dribble.
Catch_and_shoot_made	Play which is finished by a succesful jumping shot at least 3 meters from the rim by a player who controlled the ball less than 2 seconds or didn’t dribble.
Catch_and_shoot_shots_made_percent	Play which is finished by a succesful jumping shot at least 3 meters from the rim by a player who controlled the ball less than 2 seconds or didn’t dribble.Percentage of made shots.
Contested_field_goals	If there is an opponent between the rim and a shooter - it’s a contested shot. Total attempts

Contested_field_goals_made	If there is an opponent between the rim and a shooter - it's a contested shot. Successful attempts
Contested_field_goals_percent	The ratio between successful and total attempted contested field goals (CFG+/CFG)*100 = CFG%.
Cuts_attempted	A play when a player attempting to shoot receives the ball while running towards the rim. It also includes screens,fast breaks and situations when a player gets open at the rim.
Cuts_attempted_percent	The ratio between successful and total shots attempted after cut (UCF+/UCF)*100 = UCF%.
Cuts_made	Successfuls plays of a player attempting to shoot receives the ball while running towards the rim. It also includes screens,fast breaks and situations when a player gets open at the rim.
Defensive_Efficiency	The number of points allowed per game divided by the number of defensive possessions per game, multiplied by 100.
Defensive_rating	The number of points allowed per 100 possessions by a team. For a player, it is the number of points per 100 possessions that the team allows while that individual player is on the court.Formula is : 100*((Opp Points)/(Opp POSS)) = DRAT
Defensive_rebounds	When the ball jumps out of the basket after an unsuccessful shot attempt, the person who catches the ball first is recording a rebound. defensive rebounds DREB are rebounds acquired by a team after successful defense.
Defensive_rebounds_percent	This statistic shows how often the player or team can rebound the ball and limit the number of scoring chances for the offense. It is calculated by dividing the total number of defensive rebounds generated by the player or team by the total number of rebounds availiable. Multiply the result by 100 to get a percentage. DRB% = Defensive rebounds/(Defensive rebounds + Opponents offensive rebounds)*100
Deflections	When a player touches the ball while the opposing team has the possession, this action is recorded as a deflection.
Draw_foul_rate	The formula is a ratio between the fouls drawn and the field goals attempted
Drives_made	Drives which finish with a successful field goal attempt of the player who made the drive. A drive occurs when a player goes towards the basket with face ahead while dribbling.
Drives_percent	The ratio between successful and total attempted field goals after a drive (DRIVE+/DRIVE)*100 = DRIVE%.
Drives_with_shot	Drives which finish with a field goal attempt of the player who made the drive. A drive occurs when a player goes towards the basket with face ahead while dribbling.
Effective_field_goal _percentage	The statistic accounts for the fact that a three-point field goal is worth more than a two point field goal, as described by basketball-reference. The formula is (FGM + 0.5 * 3PM) / FGA *100.
Field goals_percent	The ratio between successful and total attempted field goals (FG+/FG)*100 = FG%.
Field_goals_attempted	Shows how many field goals have been attempted overall (successful + unsuccessful).
Field_goals_made	Field goal is every shot or lay-up attempted to the basket from a player. The only exceptions are when a shot is attempted but the person is fouled and free-throws also do not count to the field goals. However, if a player scores a shot and is fouled simultaneously, then the field goal does count.
Fouls	Every physical contact which is not made according to the applied basketball rules is penalized by a foul. Fouls can be given for unsportsmanlike behavior as well.
Fouls_drawn	The amount of fouls committed against a player or a team.
Free_throws_attempted	Free throw is a shot from the top line of the paint rewarded to a team when the is committed, each committed foul earns the opposing team free throws.
Free_throws_made	Counts the successful free throw attempts.
Free_throws_percent	The ratio between successful and total attempted free throws (FT+/FT)*100 = FT%.
Hand_off_attempted	A play when a ball handler is squeezed between his opponent and teammate and passes the ball to his teammate for a shot attempt.
Hand_off_attempted_percent	The ratio between successful and total attempted hand offs (HO+/HO)*100 = HO%.
Hand_off_made	A successful play when a ball handler is squeezed between his opponent and teammate and passes the ball to his teammate for a shot attempt.
Isolation_shots_percent	The ratio between successful and total attempted isolation shots (IS+/IS)*100 = IS%.
Isolations_attempted	Shows how many offensive plays when a team gives the ball handler room to play one-on-one against his opponent.
Isolations_made	A successful offensive play when a team gives the ball handler room to play one-on-one against his opponent.
Net_rating	Difference between the offensive and defensive rating. If the defensive is bigger than the offensive,then the net rating is negative.
Offensive_rating	The number of points scored per 100 possessions by a team. For a player, it is the number of points per 100 possessions that the team scores while that individual player is on the court.
Offensive_rebounds	When the ball jumps out of the basket after an unsuccessful shot attempt, the person who catches the ball first is recording a rebound. Offensive rebounds OREB are rebounds acquired by the team who attempted a missed shot.
Offensive_rebounds_percent	Offensive rebound percentage is an estimate of the percentage of available offensive rebounds a team grabbed out of all possible rebounds on the offensive end. ORB% = Offensive

	rebounds/(Offensive rebounds + Opponents defensive rebounds)*100
Picknpops_percent	The ratio between successful and total attempted Pick and Pops (PnP+/PnP)*100 = PnP%.
PnP_attempted	An offensive play in which a player sets a screen (pick) for a teammate handling the ball and then instead of getting inside the paint, jumps out at the 3-point line or at the mid-range, or just stays where the screen was set. PnP attempts are the shots attempted after the PnP.
PnP_made	An offensive play in which a player sets a screen (pick) for a teammate handling the ball and then instead of getting inside the paint, jumps out at the 3-point line or at the mid-range, or just stays where the screen was set. PnP made are the shots the succesful shots after the PnP.
PnR_Handlers_attempted	An offensive play in which a player sets a screen (pick) for a teammate handling the ball and then slips behind the defender (rolls). PnR Handlers is when a ball handler makes a shot attempt.
PnR_Handlers_made	An offensive play in which a player sets a screen (pick) for a teammate handling the ball and then slips behind the defender (rolls). PnR Handlers is when a ball handler makes a successful shot.
PnR_handlers_successful_percent	The ratio between successful and total attempted isolation shots (PnRH+/PnRH)*100 = PnRH%.
PnR_Rollers_attempted	An offensive play in which a player sets a screen (pick) for a teammate handling the ball and then slips behind the defender (rolls). PnR Rollers is when a screener attempts a shot.
PnR_Rollers_made	An offensive play in which a player sets a screen (pick) for a teammate handling the ball and then slips behind the defender (rolls). PnR Handlers is when a screener makes a successful shot.
PnR_Rollers_successful_percent	The ratio between successful and total attempted isolation shots (PnRR+/PnRR)*100 = PnRR%.
Points	In basketball, the result is tracked by scored points. A shot can earn 1, 2 or 3 points, depending on the location from where the shot is taken.
Points_off_turnovers	How many points a team has scored after the opposite team commits a turnover.
Points_per_possession	Total points scored per game divided by possessions per game.
Possesions	A team is in possession when a player is holding, dribbling or passing the ball. Team possession ends when the defensive team gains possession or the ball hits the rim of the offensive team.
Post_up_shots_percent	The ratio between successful and total attempted post up shots (PS+/PS)*100 = PS%.
Posts_up_attempted	When an offensive player receives the ball within 4,5 meters with his back to the basket and makes a shot attempt.
Posts_up_made	When an offensive player receives the ball within 4,5 meters with his back to the basket and makes a successful shot.
Rebounds	When the ball jumps out of the basket after an unsuccessful shot attempt, the person who catches the ball first is recording a rebound.
Screens_off_attempted	A play when a player gets free for a shot out of a set screen from around the rim towards the three point line. It includes running around, deflecting and getting free off a screen.
Screens_off_made	A play when a player gets free for a successful shot out of a set screen from around the rim towards the three point line. It includes running around, deflecting and getting free off a screen.
Screens_off_shots_percent	The ratio between successful and total attempted post up shots (SO+/SO)*100 = SO%.
Steals	When a team possesses the ball and the opposing team gets the ball back to their possession without conceding a basket or stopping the time, then the opposing team and the player who returned the possession to his team records a steal.
Steals_to _turnovers	The ratio between steals and total turnovers (STL/TO)*100 = STL/TO%.
threept_field_goals _attempted	Shows how many three point field goals have been attempted overall (successful + unsuccessful).
threept_field_goals _percent	The ratio between successful and total attempted three point field goals (3PT+/3PT)*100 = 3PT%.
threept_field_goals made	Counts the successful three point field goal attempts.
Transition_attacks _percent	The ratio between successful and total attempted transition attacks (TRA+/TRA)*100 = TRA%.
Transitions_attempted	A play when a team attacks after transition.Transition refers to the process of changing from defense to offense. Transitions can be easily mistaken with fast breaks, but transition offense occurs between the fast break and the set half-court offense.
Transitions_made	A play when a team makes a succesfull attack after transition.
True_shooting_percentage	True shooting percentage is a measure of shooting efficiency that takes into account field goals, 3-point field goals, and free throws.Formula is: Points Scored/(2*(Field goals attempted + 0.44*Free throws attempted))*100
Turnover_Ratio	The percentage of a team's or player's possessions that end in a turnover (for 100 possessions)
Turnovers	When a team loses possession of the ball without attempting a field goal, no matter if the game has or hasn't stopped, then a turnover for this team and player, who committed it, is recorded.
twopt_field_goals_ attempted	Shows how many two point field goals have been attempted overall (successful + unsuccessful).
twopt_field_goals_ made	Counts the successful two point field goal attempts.

twopt_field_goals_ percent	The ratio between successful and total attempted two point field goals (2PT+/2PT)*100 = 2PT%.
Uncontested_field_ goals_attempted	Field goals attempted when there's no opponent between the rim and the shooter.
Uncontested_field_ goals_percent	The ratio between successful and total attempted uncontested field goals (UCF+/UCF)*100 = UCF%.
Uncontested_field_ goals_made	Successful field goals made when there's no opponent between the rim and the shooter

Appendix B:

Table Appendix B. The 51 teams that competed in the Euroleague in the last 3 years

N	**TEAMS**		
	2022-2023	**2021-2022**	**2020-2021**
1	ALBA Berlin	ALBA Berlin	ALBA Berlin
2	Anadolu Efes SK	Anadolu Efes SK	Anadolu Efes SK
3	AS Monaco Basket	AS Monaco Basket	ASVEL Lyon-Villeurbanne
4	ASVEL Lyon-Villeurbanne	ASVEL Lyon-Villeurbanne	BC Barcelona
5	BC Barcelona	BC Barcelona	BC Khimki
6	BC Zalgiris Kaunas	BC Zalgiris Kaunas	BC Zalgiris Kaunas
7	Bitci Baskonia	Bitci Baskonia	BC Zenit Saint Petersburg
8	FC Bayern Munich	FC Bayern Munich	Bitci Baskonia
9	Fenerbahce Beko	Fenerbahce Beko	FC Bayern Munich
10	KK Partizan Mozzart Bet	KKZ Crvena Zvezda	Fenerbahce Beko
11	KKZ Crvena Zvezda	Maccabi Playtika Tel Aviv	KKZ Crvena Zvezda
12	Maccabi Playtika Tel Aviv	Olimpia Milano	Maccabi Playtika Tel Aviv
13	Olimpia Milano	Olympiacos BC	Olimpia Milano
14	Olympiacos BC	Panathinaikos	Olympiacos BC
15	Panathinaikos	Real Madrid	Panathinaikos
16	Real Madrid		PBC CSKA Moscow
17	Valencia BC		Real Madrid
18	Virtus Bologna		Valencia BC

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