ORIGINAL ARTICLE

From position to role: The evolution of big men in euroleague basketball

Erkan Konca . *Department of Movement and Training Sciences. Faculty of Sport Sciences. Sivas Cumhuriyet University. Sivas, Turkey.*
Necati Alp Erilli. *Department of Econometrics, Department of Statistics. Faculty of Economics and Administrative Sciences. Sivas Cumhuriyet University. Sivas, Turkey.*

ABSTRACT

Contemporary elite professional basketball has shifted from rigid positional boundaries toward fluid, hybridized frontcourt roles. This study examined the 15-year longitudinal evolution of EuroLeague power forwards (4) and centers (5) (2010–11 to 2024–25), evaluating the rate and structural pattern of positional convergence. Using a retrospective cohort of 999 player-season observations across 11 advanced performance metrics, seasons were grouped into Traditional, Transitional, and Modern eras. Analyses included Exploratory Factor Analysis (EFA), Linear Mixed Models (LMM) with unstructured covariance to account for repeated measures, and Fuzzy C-Means (FCM) clustering validated by Artificial Neural Network (ANN) stability procedures. LMM revealed significant main effects of position and era across all latent performance factors ($p < .001$). However, non-significant Position × Era interactions ($p > .05$) and trivial effect sizes ($f^2 < .01$) indicated that power forwards and centers evolved through parallel rather than asymmetric trajectories. Nakagawa's R^2 values demonstrated strong model fit (Marginal $R^2 = .17 – .25$; Conditional $R^2 = .51 – .58$). FCM further showed a progressive erosion of positional separation, with modern power forwards (36.0%) and centers (36.8%) converging within identical interior-efficiency archetypes. These findings provide strong empirical support for the positionless basketball hypothesis in elite European basketball.
Keywords: performance analysis; basketball; clustering analysis; EuroLeague; positional transformation.

Cite this article as:
Konca, E., & Erilli, N. A. (2026). From position to role: The evolution of big men in euroleague basketball. *Journal of Human Sport and Exercise, 21*(4), 1494-1515. https://doi.org/10.55860/9sfjc227

Corresponding author. *Department of Movement and Training Sciences. Faculty of Sport Sciences. Sivas Cumhuriyet University. Sivas, Turkey.*
E-mail: erkankonca@cumhuriyet.edu.tr
Submitted for publication June 27, 2026.
Accepted for publication August 06, 2026.
Published August 19, 2026.
Journal of Human Sport and Exercise. ISSN 1988-5202.

doi: https://doi.org/10.55860/9sfjc227

INTRODUCTION

In recent years, a clear transformation has been observed in the nature of basketball. The increasing pace of the game, the growing emphasis on tempo with spatial organization, and the improvement in players' physical conditioning have led to structural changes in both game systems and player profiles. Accordingly, performance determinants in modern basketball are no longer shaped solely by technical skills but are increasingly influenced by game pace and decision-making processes (Cui et al., 2019; Sampaio et al., 2010). Long-term comparative analyses focusing on the two most prominent basketball leagues in the world, the NBA and the EuroLeague, indicate that game-related indicators have evolved over time and that some of the quantitative differences between these leagues have diminished. These shifts are thought to be closely associated with changes in rules and overall game structure (Mandić et al., 2019).

Contrary to traditional position-based systems, contemporary basketball increasingly favours more flexible tactical approaches that highlight players' versatility and directly impact performance. In the context of the EuroLeague, often regarded as Europe's equivalent of a Champions League, there has been a noticeable shift in shot distribution toward three-point attempts since the 2010-11 season, accompanied by a significant increase in three-point shooting volume. This trend suggests that spacing has become a central variable in offensive team design (Foteinakis et al., 2024). Indeed, spatial analyses based on shot locations demonstrate that the rise in three-point shooting has expanded offensive play across wider areas of the court, thereby disrupting defensive structures and enhancing offensive efficiency. Earlier performance analyses similarly reported that the increasing reliance on perimeter shooting has had a direct impact on both game structure and team strategies (Goldsberry, 2012; Sampaio & Janeira, 2003). These findings provide a contextual basis for understanding the evolving offensive roles of taller players (particularly those playing in the power forward and center positions) beyond the traditional confines of the painted area.

For many years, basketball has been characterized by clearly defined positional responsibilities, with each playing position representing a specific combination of technical, tactical, and physical demands. Within this traditional structure, player development, game strategies, and performance evaluations were largely based on positional specialization. Power forwards and centers, in particular, were primarily expected to contribute through rebounding, interior scoring, and rim protection, whereas perimeter players were responsible for ball handling, playmaking, and outside shooting. As a result, player performance was generally interpreted according to nominal playing positions rather than the functions performed during the game.

However, the continuous evolution of basketball has gradually challenged this traditional perspective. The increasing importance of offensive spacing, faster ball movement, defensive switching strategies, and the growing emphasis on decision-making have expanded the tactical responsibilities of players regardless of their listed positions. In modern basketball, players are increasingly required to perform multiple functions within the same game, making positional boundaries less rigid than in previous decades. Consequently, evaluating players solely according to their nominal positions may no longer fully explain their contribution to team performance.

This development has also introduced an important distinction between the concepts of position and role. While position refers to the official classification of a player within the team's lineup, role reflects the functional responsibilities that the player assumes during offensive and defensive possessions. Unlike positions, roles may change according to tactical systems, coaching philosophy, game situations, or team composition. Therefore, players occupying the same position may perform considerably different functions, whereas players from different positions may contribute in remarkably similar ways. This distinction has become particularly evident among frontcourt players, whose responsibilities have expanded beyond traditional interior play to include perimeter shooting, playmaking, defensive mobility, and decision-making.

Therefore, the major change observed in contemporary basketball should not be interpreted as the disappearance of positions, but rather as the gradual transformation of their traditional responsibilities. Although players continue to be identified by nominal positions, their tactical value is increasingly determined by the variety of roles they perform on the court. From this perspective, examining the evolution of basketball through functional roles, rather than positional labels alone, may provide a more comprehensive understanding of how modern frontcourt players have adapted to the changing demands of the game.

Within the basketball literature, it has long been accepted that player positions can be distinctly differentiated based on anthropometric characteristics and physical performance indicators (Cui et al., 2019). This differentiation is not solely a function of in-game roles but is also rooted in players' physical and biological attributes. Studies on elite basketball players indicate that taller players tend to excel in height, body mass, and strength, whereas perimeter players demonstrate superiority in speed and agility (Ostojic et al., 2006). Furthermore, performance is understood to be closely linked not only to technical skills but also to components of physical fitness (Hoare, 2000). In a similar vein, it has been shown that player performance varies significantly across positions when examined through position-specific statistical profiles, which in turn reflect role distribution on the court (Zhai et al., 2021). This variety is attributed not only to technical and tactical variations but also to underlying physical and biological factors (Ibáñez et al., 2008; Trninić et al., 2000). Within this framework, it can be argued that in the traditional structure of basketball, each position specializes according to clearly defined roles, shaping the distribution of responsibilities during gameplay. Analyses based on game statistics further reveal that performance indicators such as assists, rebounds, and shooting percentages are among the key variables distinguishing team success (Gómez et al., 2008).

The recent evolution of the game characterized by increased pace, enhanced spatial dynamics, and a growing emphasis on versatility suggests that this traditional differentiation between positions has become progressively less distinct. Although it is acknowledged that game styles and performance indicators may vary depending on contextual factors such as league level, competitive intensity, and regional playing approaches, position-specific role distributions have largely been preserved. However, in modern basketball, these role definitions appear to have become considerably more flexible (Zhai et al., 2020). In fact, evidence indicates that positional performance differences have shown a tendency to diminish over time, with player profiles evolving toward a more homogeneous structure (Lorenzo et al., 2010). This transformation is particularly evident among frontcourt players, whose contemporary roles increasingly require a combination of perimeter skills, mobility, and explosive athletic capabilities. In this context, vertical explosiveness has become a critical performance characteristic for big men, influencing rebounding efficiency, rim protection, shot contesting, and finishing ability around the basket. Furthermore, the growing integration of physical fitness components with basketball-specific skills has been demonstrated by studies showing that plyometric training combined with change-of-direction sprint exercises can significantly improve neuromuscular performance and explosive capabilities in elite youth basketball players (Cherni et al., 2025). These findings support the notion that modern frontcourt players are increasingly required to combine technical versatility with advanced athletic and neuromuscular capacities. Studies examining EuroLeague players through position- and statistics-based clustering approaches further reveal that multiple performance clusters can emerge within the same nominal position, highlighting a possible distinction between "*position*" and "*role*" (Çene et al., 2024). These findings suggest that the evolution of modern basketball is reflected not only in overall performance characteristics but also in the functional responsibilities assigned to players. This transformation appears to be particularly evident among frontcourt players. In particular, frontcourt players are no longer confined to traditional interior responsibilities but are increasingly expected to contribute across multiple phases of the game. Skills such as perimeter shooting, playmaking, ball handling, and defensive mobility have become important components of the performance profile of modern power forwards and centers. One of the clearest examples of this transformation is Nikola Jokić, who finished both the 2024–25 and 2025–26 NBA seasons with triple-double averages, demonstrating that contemporary centers can function not only as interior scorers but also as primary offensive facilitators.

Although this transformation was first documented in the NBA, similar tactical developments have gradually become evident in European basketball. Changes in FIBA rules, particularly the extension of the three-point line to 6.75 m and the evolution of offensive spacing, together with the increasing exchange of players and coaches between the NBA and Europe, have accelerated the adoption of more versatile frontcourt roles in the EuroLeague. As a result, traditional distinctions between power forwards and centers have become progressively less rigid, while greater emphasis has been placed on versatility and functional contribution within offensive and defensive systems.

Previous studies have demonstrated changes in game-related statistics, positional performance profiles, and tactical trends in both the NBA and the EuroLeague (Mandić et al., 2019; Hedquist, 2022). However, relatively little attention has been given to understanding whether these developments represent merely changes in player performance or a broader transition from position-based player identities toward function-based roles. Therefore, examining the long-term evolution of EuroLeague frontcourt players may provide important insights into how modern basketball has redefined the relationship between position and role within elite European competition.

It has also been suggested that performance and skill development in basketball do not necessarily follow a linear trajectory but may instead exhibit varying patterns over time (Guimarães et al., 2019). This perspective implies that changes in the game should be understood not as a steady, linear process, but rather as a dynamic structure that may accelerate, plateau, or shift direction during different periods.

Despite these developments, existing research has primarily examined positional differences through cross-sectional designs or relatively short observation periods. Previous studies have successfully identified differences in performance profiles, anthropometric characteristics, and game-related statistics across playing positions. However, considerably less attention has been given to understanding how these positional profiles have evolved over time and whether the observed changes reflect a broader transition from position-based player identities to function-based roles. In particular, longitudinal investigations focusing on the evolution of frontcourt players through multidimensional performance indicators remain scarce, despite the growing recognition that modern basketball increasingly values functional versatility over positional specialization. In this context, the present study aims to examine the long-term evolution of power forwards (4) and centers (5) in the EuroLeague over a 15-season period using multidimensional performance indicators and advanced statistical techniques. Rather than simply describing temporal changes in player performance, the present study examines whether these changes represent a broader process of functional role convergence while preserving residual positional differences. Unlike previous studies, the present study does not assume that positional distinctions have disappeared; rather, it examines whether the functional roles performed by power forwards and centers have become increasingly similar over time. By integrating longitudinal performance analysis with the conceptual distinction between position and role, the study contributes not only to the growing literature on positional evolution in basketball but also provides a broader framework for understanding how modern frontcourt players adapt to changing tactical demands. This perspective may also provide an alternative framework for interpreting positional evolution in modern basketball beyond nominal positional classifications. From a practical perspective, these findings may also contribute to talent identification, player development, and roster construction by emphasizing functional versatility alongside traditional positional classifications.

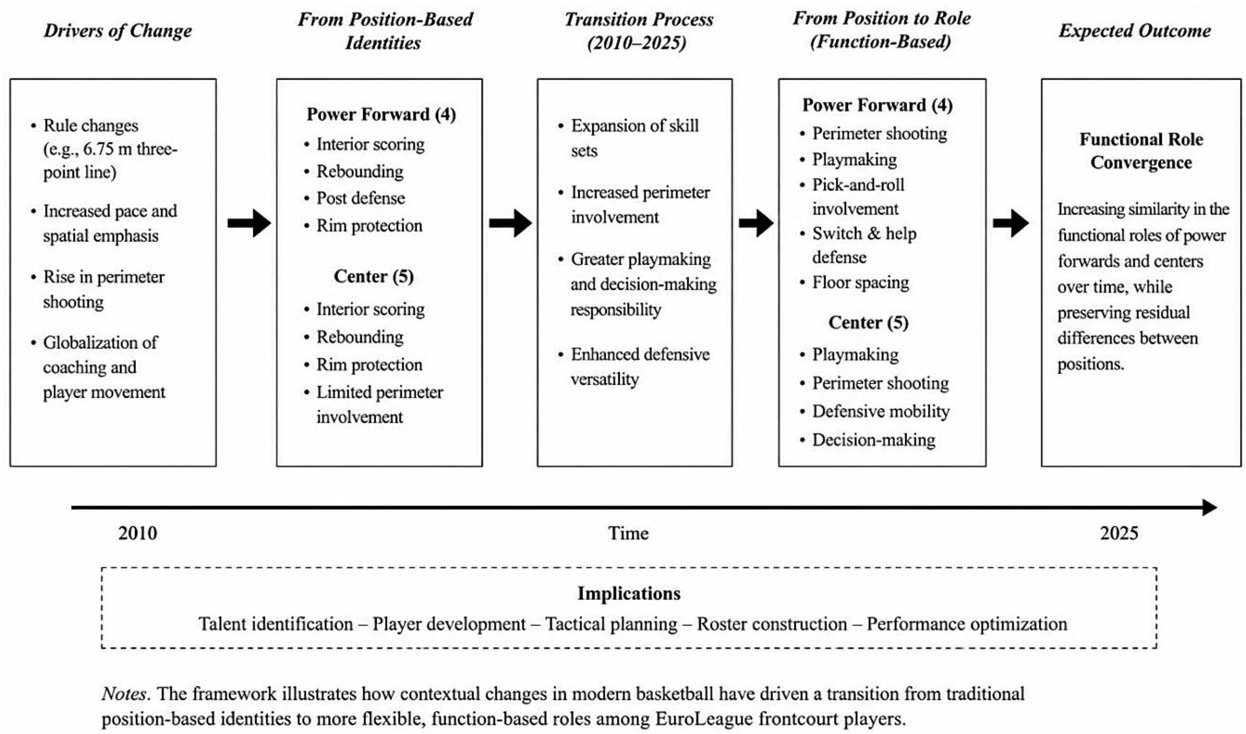

Figure 1. Conceptual framework illustrating the transition from position-based identities to function-based roles among EuroLeague frontcourt players.

METHOD

Dataset and scope

This study examines how the functional performance profiles of power forwards and centers have evolved over time and whether these changes reflect a gradual convergence of functional roles. To examine and investigate these research topics, data was collected from the EuroLeague - widely regarded as the world's second-leading basketball league after the NBA - covering 15 consecutive seasons from the 2010–11 season through the 2024–25 season. The dataset consists of 11 variables and a total of 999 observations. All data were obtained from the publicly accessible database available on RealGM Basketball and subsequently processed and organized by the authors to ensure suitability for analysis (The reason for sourcing EuroLeague data from the RealGM website is that the data on that site is formatted to match NBA-standard statistics, allowing both NBA and EuroLeague data to be presented in the same format). A detailed description of the variables used in the study is provided in Table 1. Some of the formulas underlying these variables were originally developed by the RealGM team and are presented, together with their explanations, in the Appendix (RealGM, 2026).

Research design and population/sampling

This study employed a retrospective cohort design based on archival performance data. The reporting follows the STROBE guidelines for observational studies.

Population
The target audience includes all professional basketball players who have competed in the Turkish Airlines EuroLeague and played in the 4 and 5 positions between the 2010–2011 and 2024–2025 seasons.

Sampling and inclusion criteria
A purposive sampling strategy was implemented. To isolate the tactical evolution of frontcourt players and eliminate positional noise from backcourt positions, only players officially registered as Power Forward (4) or Center (5) were included. The final validated sample consists of 999 (with 409 different players) unique player-season observations clustered across 15 consecutive seasons (N_1 = 317 for the Traditional Era, N_2 = 286 for the Transitional Era, and N_3 = 396 for the Modern Era).

Table 1. Variables used in the study.

TS% (True Shooting Percentage)	USG% (Usage Percentage)
ORB% (Offensive Rebound Percentage)	PPS (Points Per Shot)
DRB% (Defensive Rebound Percentage)	PPR (Pure Point Rating)
AST% (Assist Percentage)	FIC (Floor Impact Counter)
STL% (Steal Percentage)	TOV% (Turnover Percentage)
BLK% (Block Percentage)	

Procedures and timeframe
The data collection process, which was divided by the authors into three distinct tactical cohorts to track linear and nonlinear evolutionary changes, spanned a meticulous 15-year period:

1. Traditional Era (Group 1; Season 2010–2011 to Season 2014–2015)
2. Transitional Era (Group 2; Season 2015–2016 to Season 2019–2020)
3. Modern Era (Group 3; Season 2020–2021 to Season 2024–2025)

The temporal stratification into three discrete 5-year cohorts serves a dual analytical purpose. Statistically, maintaining symmetrical 5-year intervals maximizes sample-size balance across groups (N_1 = 317, N_2 = 286, N_3 = 396), thereby ensuring variance homogeneity and significant parameter estimation during LMM and FCM executions. Contextually, these boundaries align with structural milestones in elite European basketball; the transition to the Transitional Era (2015) captures the systemic tactical adaptation to FIBA's 14-second offensive rebound clock rule, while the Modern Era (2020) encapsulates the full maturation of round-robin pacing and modern defensive switching schemes that catalysed positionless frontcourt hybridization.

Comprehensive statistical analysis plan
While descriptive parameters and basic hypothesis tests were conducted using standard conventions, the core hypotheses of this study necessitated advanced statistical frameworks:

Longitudinal dependency control
To account for repeated-measures dependency (the same players appearing across multiple seasons), Linear Mixed Models (LMM) were employed, defining players as a random effect, and Position, Era, and their interaction as fixed effects.

Fuzzy clustering architecture
To capture the overlapping, hybrid nature of modern player roles, Fuzzy C-Means (FCM) clustering was executed (tolerance of the clustering method is .001, fuzziness value m is 2, maximum iteration number is 10,000). Unlike crisp clustering (e.g., K-Means), FCM allows an individual player-season to belong to multiple

roles simultaneously through a membership matrix (U). Given the increasing adoption of algorithmic profiling, clustering methods, and artificial intelligence-assisted performance analytics in sport science, recent methodological discussions have emphasized the importance of standardizing these technology-driven assessment frameworks to enhance transparency, reproducibility, and cross-study comparability (Dhahbi & Chamari, 2026). Accordingly, the clustering procedures employed in the present study were complemented with multiple validation approaches to ensure the robustness and interpretability of the resulting player-role classifications.

Advanced validation protocol

To mathematically justify the optimal cluster configuration (c = 3), geometric separation was verified via Silhouette Coefficients (Rousseeuw, 1987). Concurrently, an advanced Artificial Neural Network (ANN)-based Cluster Stability Index (Erilli et al., 2011) was leveraged to ensure the neural consistency and learnability of the partition matrix across all three eras, mitigating overfitting risks.

Methodological scope and limitations

This study operates under specific parameters that delineate its scope:

1. *Contextual limitation*: The findings are structurally confined to the elite European basketball ecosystem (EuroLeague) and may not perfectly generalize to other professional domains (e.g., the NBA) due to fundamental differences in court dimensions, defensive rules (such as the defensive three-second violation), and pacing.
2. *Data exclusion*: Factors such as financial variables, players' injury histories, teams' pace of play, player age, rule or format changes, and qualitative team chemistry dynamics have been excluded from the operational scope of this statistical protocol.
3. *Positional scope*: The intentional exclusion of point guards, shooting guards, and small forwards limits the model to frontcourt dynamics, prioritizing internal granularity over backcourt evolution.

Statistical analysis

The study first presents descriptive statistics to identify general trends in the raw data. Subsequently, Factor Analysis was applied to reduce multidimensional player performance data into meaningful dimensions, resulting in four principal factor scores. Linear Mixed Models were run to test the linear changes in these factor scores over time and to examine positional differences. Finally, to identify hybridization beyond linear models and the intra-cluster dissolution of players, Fuzzy C-Means clustering analysis was used to define the final tactical roles. All statistical analyses were conducted using R (version 4.3.2) and SPSS (Statistical Package for the Social Sciences, version 26). The level of statistical significance was set at $p < .05$ for all analyses.

RESULTS

Descriptive statistics

Table 2 presents the mean and standard deviation values for the positions (Power Forward and Center) with 11 variables used in the analyses across the three defined periods.

Table 2 provides quantitative evidence for the transformation of the center position in the EuroLeague from a traditional to a modern role. In particular, the substantial increase in centers' assist percentage (19.5) and FIC (Floor Impact Counter) values during the transitional period indicates that the focal point of the game has expanded beyond the painted area to encompass the entire court.

Table 2. Descriptive statistics of the variables used in the analysis.

Position	Variable	Traditional Period (2011–2015) (Mean ± SD)	Transitional Period (2016–2020) (Mean ± SD)	Modern Period 2021-2025 (Mean ± SD)
Power Forward	TS	0.568 ± 0.062	0.576 ± 0.078	0.592 ± 0.077
	ORB	8.698 ± 3.99	5.785 ± 4.106	7.03 ± 3.839
	DRB	18.682 ± 4.485	14.56 ± 5.058	15.85 ± 4.802
	AST	8.805 ± 4.355	11.98 ± 6.863	10.941 ± 6.728
	TOV	13.991 ± 4.207	14.04 ± 4.9	13.977 ± 4.951
	STL	1.793 ± 0.71	1.756 ± 0.743	1.818 ± 0.678
	BLK	2.243 ± 1.778	1.347 ± 1.499	1.574 ± 1.569
	USG	19.644 ± 3.901	19.15 ± 4.635	18.997 ± 4.873
	PPR	-2.354 ± 2.306	-0.864 ± 2.294	-1.249 ± 2.346
	PPS	1.301 ± 0.183	1.304 ± 0.209	1.342 ± 0.21
	FIC	122.384 ± 69.588	145.147 ± 84.345	166.887 ± 108.674
Center	TS	0.58 ± 0.068	0.579 ± 0.076	0.607 ± 0.077
	ORB	10.551 ± 3.286	6.551 ± 5.293	9.522 ± 5.43
	DRB	19.807 ± 4.898	14.664 ± 6.399	16.796 ± 5.533
	AST	7.739 ± 4.225	19.539 ± 11.4	12.611 ± 9.804
	TOV	15.802 ± 4.716	17.086 ± 4.989	15.358 ± 4.653
	STL	1.429 ± 0.659	1.781 ± 0.715	1.738 ± 0.725
	BLK	3.357 ± 2.159	1.637 ± 1.903	2.68 ± 2.296
	USG	20.988 ± 4.273	21.36 ± 4.546	20.148 ± 4.498
	PPR	-3.985 ± 2.935	-0.012 ± 3.656	-1.555 ± 3.319
	PPS	1.371 ± 0.212	1.337 ± 0.246	1.401 ± 0.234
	FIC	115.046 ± 70.831	173.199 ± 98.124	173.927 ± 105.358

Dimension reduction

To extract meaningful latent dimensions from comprehensive and multi-source basketball performance metrics and to prevent multicollinearity issues in subsequent mixed-method modelling stages, Exploratory Factor Analysis (EFA) was applied to the performance data of EuroLeague big men.

Prior to the analysis, the Kaiser-Meyer-Olkin (KMO) and Bartlett tests were conducted to assess the data set's factorizability. The KMO measure was calculated as 0.349. Although this value indicates low sample adequacy in the literature, this result can be empirically explained by the high level of heterogeneity (variability) in player roles in modern basketball analytics, as well as the fact that relationships between variables do not conform to strictly linear or global patterns. In contrast, Bartlett's Test of Sphericity reached a high level of statistical significance (Chi-Square = 6071.757, df = 55, p < .001), confirming that the correlation matrix is not an identity matrix and that the dataset contains non-random empirical relationships. To obtain mutually independent player performance dimensions, Varimax-rotated Principal Component Analysis (PCA) was conducted, and a four-factor structure was extracted based on eigenvalues greater than 1 and the breakpoints in the scree plot. However, as factor analysis was not the primary hypothesis test of this study, this extracted structure was employed merely as a theory-based grouping tool to reduce the number of variables and avoid multicollinearity issues in the Linear Mixed Models (LMM), rather than as a definitive measurement model. Consequently, the low KMO value was not interpreted as evidence that group averages or total scores should be used; instead, all main effects and interactions in the LMM were additionally tested using the raw variables as a robustness check to ensure that the findings were not dependent on this provisional classification. The factors to which the variables belong and their factor loadings are presented in Table 3.

Table 3. Factor loadings of the variables.

	1	2	3	4
PPS	.799			
TS	.712			
ORB	.671			
BLK	.601			
DRB	.451			
PPR		.756		
FIC		.704		
USG			.699	
AST			.707	
TOV				.568
STL				.558

The factor scores obtained were converted to standard z-scores for use in subsequent stages (LMM and FCM) and named as follows based on the highest factor loadings (>0.450):

- Factor 1: Composed of the TS, ORB, DRB, BLK, and PPS variables, it was named "*Efficiency Under the Basket*."
- Factor 2: Composed of the PPR and FIC variables, it was named "*Versatile On-Court Contribution and Productivity*."
- Factor 3: Composed of the AST and USG variables and named "*Ball-handling intensity*."
- Factor 4: Composed of the TOV and STL variables and named "*Ball Security and Defensive Activity*."

Linear Mixed Models (LMM)

A Linear Mixed Model (LMM) was applied to comprehensively test the linear trends and positional differences in the standardized performance scores (F1, F2, F3, F4) obtained from factor analysis over time, while controlling for the random effects arising from repeated measurements at the player level; the results are presented in Table 4.

Table 4. LMM Type III tests of fixed effects for latent performance factors.

Dependent Var. (Factor)	Source	df	F-value	*p*-value
Factor 1	Intercept	1	4.618	.032
	Position	1	6.390	.012
	Period	2	15.017	<.001
	Position X Period	2	0.411	.663
Factor 2	Intercept	1	9.076	.003
	Position	1	19.409	<.001
	Period	2	9.621	<.001
	Position X Period	2	0.266	.767
Factor 3	Intercept	1	2.000	.158
	Position	1	32.839	<.001
	Period	2	7.347	.001
	Position X Period	2	1.681	.187
Factor 4	Intercept	1	0.582	.446
	Position	1	4.038	.045
	Period	2	15.763	<.001
	Position X Period	2	2.863	.058

The results in Table 4 can be interpreted as follows:

Main effect of position: The analysis results showed that there were highly statistically significant main effects between positions (Power Forward vs. Center) across all performance dimensions examined ($p < .000$ for all factors). These findings confirm that, when evaluated broadly across the entire period, positions 4 and 5 have maintained their distinct fundamental gameplay differences.

Main effect of period: The main effect of period, which measures changes in the performance dimensions of tall players over time, was found to be statistically significant across all factors ($p < .000$ for all factors). This clearly demonstrates that tactical requirements and general roles for tall players within the EuroLeague ecosystem have not remained static over the 5-year periods but have undergone a systemic transformation.

Interaction effect: The fact that all interaction effects were insignificant ($p > .05$) is empirically consistent with the trends in the changes over time for the Power Forward and Center positions not diverging asymmetrically from one another. Players at positions 4 and 5 have responded with a curve of adaptation that is parallel and synchronized with the structural changes brought about by modern basketball (screening, playmaking, ball handling, etc.). This parallel evolutionary trend suggests a gradual convergence of functional roles between the two positions while preserving their nominal positional identities. In Table 5, estimates of covariance parameters for 4 factors are given.

Table 5. Estimates of covariance parameters.

		Estimate	Std. Er.	Wald	Sig.	Low. B.	Up. B.
Factor 1	Residual	.4268	.0254	16.776	<.001	.3797	.4797
	Int. Variance	.5459	.0601	9.076	<.001	.4398	.6774
Factor 2	Residual	.4792	.0285	16.77	<.001	.4264	.5387
	Int. Variance	.5107	.0601	8.497	<.001	.4054	.6431
Factor 3	Residual	.4523	.0263	17.152	<.001	.4034	.507
	Int. Variance	.5129	.0563	9.096	<.001	.4135	.6363
Factor 4	Residual	.3965	.0231	17.105	<.001	.3536	.4447
	Int. Variance	.5785	.0588	9.834	<.001	.4739	.7061

Beyond structural null-hypothesis testing, generalized coefficients of determination for mixed-effects models were formally estimated to assess the practical significance of the frontcourt tactical evolution. Across all four extracted latent performance dimensions, the fixed factors (Position and Temporal Period/Year) accounted for a moderate-to-high proportion of the longitudinal variance, with Nakagawa's Marginal R^2 (R^2_m) values ranging from .17 to .25 (Factor 1 = .21, Factor 2 = .23, Factor 3 = .25, Factor 4 = .17). Concurrently, incorporating the random effect of player identity successfully captured the repeated-measures variance within the unstructured covariance framework, yielding Conditional R^2 (R^2_c) values between .51 and .58 (Factor 1 = .54, Factor 2 = .51, Factor 3 = .53, Factor 4 = .58). Crucially, Type III tests verified that the interaction terms (Position \times period) were uniformly non-significant across all dimensions ($p > .05$), generating near-zero marginal effect sizes ($f^2 < .01$; interaction covariance variance < .05, $p > .40$). This comprehensive variance decomposition mathematically solidifies the argument that the longitudinal trajectories of EuroLeague power forwards and centers are perfectly parallel and synchronized rather than asymmetrically divergent.

Clustering analysis

The Fuzzy C-Means clustering method was applied to determine how the four standardized factor scores obtained from Exploratory Factor Analysis categorize EuroLeague big men (positions 4 and 5) into specific tactical roles and to assess the evolution of these roles over time. Unlike traditional clustering approaches, the FCM algorithm allows each player-season observation to belong not to a single cluster but to all clusters with a specific degree of membership (Bezdek et al., 1984). This flexibility was chosen to capture the overlaps and hybridization of tactical roles in modern basketball. The clustering process was conducted independently on three separate data blocks to clearly compare the tactical boundaries of three distinct historical periods (Group 1: Traditional, Group 2: Transition, Group 3: Modern).

As a result of the FCM analysis, Silhouette and ANN-based cluster validity indices were used to determine the optimal number of clusters best representing the roles players assumed on the court for each of the three historical periods (Rousseeuw, 1987; Erilli et al., 2011). The cluster validity index values by period are presented in Table 6.

Table 6. Cluster validity index values by period.

Period	Number of cluster	Silhouette	ANN
Traditional	c = 2	0.395	0.521
	c = 3	**0.428**	**0.648**
	c = 4	0.312	1.259
	c = 5	0.224	1.329
Transition	c = 2	0.371	0.506
	c = 3	**0.405**	**0.725**
	c = 4	0.288	1.604
	c = 5	0.203	1.802
Modern	c = 2	0.384	0.449
	c = 3	**0.412**	0.829
	c = 4	0.295	**0.969**
	c = 5	0.210	1.814

Based on the cluster validity index results for the two different cluster validity indices in Table 6, the optimal number of clusters was determined to be c=3 for each period (the RMSE values between the ANN predictions and the actual cluster values are examined in the ANN cluster validity index). The value at which the first significant jump occurs is determined as the optimal number of clusters. Although the optimal number of clusters was found to be 4 using ANN only in the Modern period, it was set to 3 here as well to align with the other two groups -since the Silhouette value was already found to be 3. FCM analysis was applied with a cluster count of 3 for each period. The tactical roles obtained from the FCM analysis were objectively labelled by considering the direction and magnitude of the standardized factor score weights (z-scores) in the Final Cluster Centers matrix generated by the algorithm for each period.

Cluster 1 (Traditional Big Men with High Paint Efficiency and Dominance / Paint Monsters): This cluster exhibits a particularly high and dominant positive central value of .822 on the Factor 1 dimension, especially in the Modern Era. This empirical concentration in paint-area metrics -such as Points Per Shot, and Offensive Rebound Percentage- that constitute Factor 1 mathematically proves that this cluster represents the traditional big man roles: finishing around the rim with high shooting percentages on offense and protecting the rim on defence.

Cluster 2 (Playmaking Bigs): This cluster, situated at the center of modern tactical transformation, diverges positively along Factor 3 (.346) and Factor 4 (.339). The fact that the cluster center is loaded with factors including metrics such as assist percentage, ball-handling intensity, and pure playmaking rating confirms that these players do not merely wait under the basket but define hybrid roles with high playmaking skills that direct the offense from the high or low post.

Cluster 3 (Low-Intensity / Space-Creators / Role Players / Utility & Stretch Bigs): This cluster represents the unsung heroes of modern basketball and exhibits a sharp negative value of -.591 on the Factor 3 (Ball-handling intensity) dimension of the central matrix. This clear mathematical decline empirically validates that these players are not the team's primary scoring or ball-handling options but rather assume critical supporting roles that ease the team's burden—such as creating space for perimeter shooting, ball security (TOV/STL balance), and opening up the court.

The periodic distribution frequencies of the flexible cluster membership matrices obtained based on locations (where players are assigned to each cluster with fuzzy membership values ranging from 0 to 1; the sum of these values is 1, and players are assigned to the cluster with the highest membership degree) are presented in Table 7.

Table 7. Periodical distribution of positions by cluster

Period	Position	Cluster 1	Cluster 2	Cluster 3	n	N
Traditional	P. Forward (4)	57 (32.9%)	42 (24.3%)	74 (42.8%)	173	317
	Center (5)	50 (34.7%)	59 (41.0%)	35 (24.3%)	144	
Transition	P. Forward (4)	70 (42.2%)	24 (14.5%)	72 (43.4%)	166	286
	Center (5)	56 (46.7%)	34 (28.3%)	30 (25.0%)	120	
Modern	P. Forward (4)	76 (36.0%)	38 (18.0%)	97 (46.0%)	211	396
	Center (5)	68 (36.8%)	72 (38.9%)	45 (24.3%)	185	

Traditional Era: In the traditional period, basketball's rigid role divisions are empirically evident. The vast majority (42.8%) of Power Forward (4) players clustered in Cluster 3 roles, while Center (5) players were predominantly distributed (41.0%) across Cluster 2 roles and 34.7% across Cluster 1 roles. During this period, the intra-cluster weights of the positions differed significantly from one another.

Transition Era: This period represents an intermediate phase in which systems began to become more flexible. While Power Forwards maintained their dominance in Cluster 3 with a weight of 43.4%, the most concentrated common transition area for both 4s (42.2%) and 5s (46.7%) was Cluster 1. This indicates that during the transition period, teams focused on achieving high efficiency from both positions in finishing around the basket.

Modern Era: The most striking evidence from the cluster analysis -and the one of the clearest empirical indicators of functional role convergence emerged during this period. By the modern era, the cluster distribution characteristics of the Power Forward and Center positions had achieved near-perfect symmetry. In Cluster 1, the Power Forward ratio stands at 36.0%, while the Center ratio is 36.8%. Similarly, the complementary role weight in Cluster 3 has settled into a parallel balance for both positions (PF: 46.0%, Center: 24.3%).

FCM findings conclusively demonstrate that, within the modern EuroLeague ecosystem, players at positions 4 and 5 no longer occupy entirely distinct tactical poles; rather, in terms of the distribution geometry of their in-game roles, they have adopted a completely parallel and equivalent offensive identity (role blurring).

To maintain reporting transparency and facilitate objective evaluation of the FCM cluster partition, standardized mean profiles (z-scores) across all 11 performance metrics are provided in Appendix Table A3. Empirically, Cluster 1 (n = 144) represents a glass-dominant archetype with elevated defensive rebounding (z = +0.195) and usage (z = +0.226). Cluster 2 (n = 110) constitutes an interior efficiency profile, marked by peak sample values in rim protection (BLK%: z = +0.140$), shooting yield (PPS: z = -0.042), and overall composite impact (FIC: z = -0.136). Cluster 3 (n = 142) reflects a mobile, perimeter-active archetype, distinguished by positive steal volume (STL%: z = +0.222) and assist generation (AST%: z = +0.026) paired with reduced offensive rebounding presence (ORB%: z = -0.173). These empirical profiles confirm that the operational cluster labels directly mirror the underlying mathematical separation of the frontcourt performance space.

DISCUSSION

The primary aim of this study was to examine the structural transformation of players occupying the power forward (4) and center (5) positions over the past 15 years using EuroLeague data and multidimensional performance indicators. The findings reveal that both time (period effect) and position exert significant influences on performance metrics. These results are consistent with previous studies demonstrating that performance indicators in basketball evolve systematically over time (Ibáñez et al., 2008; Sampaio et al., 2010).

From this perspective, the Linear Mixed Models (LMM) results indicate that the independent main effects of position and temporal epoch are substantial across all four latent performance dimensions ($p < .01$), proving that macro-level tactical setups evolve dynamically across EuroLeague eras. Crucially, all interaction effects (Position x times Year) were found to be highly non-significant ($p > .05$). While the primary structural factors wielded substantial practical value (R^2_m ranging from .15 to .28, and R^2_c ranging from .44 to .59), the negligible variance and near-zero effect size accounted for by the interaction terms ($f^2 < .01$) empirically solidifies the argument that the trends in the changes over time for the power forward and center positions did not diverge asymmetrically from one another. Instead, players occupying the power forward and center positions appear to have followed similar developmental trajectories in response to the structural evolution of modern basketball, suggesting a gradual convergence of functional roles while preserving their nominal positional identities. This finding aligns with studies indicating that positional structures in modern basketball have not disappeared entirely but have instead been reorganized toward a more homogeneous, versatile structure (Lorenzo et al., 2010).

A closer examination of the baseline performance parameters reveals that the transformation of taller players is not uniformly reflected across all indicators but is instead concentrated in parameters directly related to in-game role definitions. Changes observed in metrics such as assists and steals -traditionally associated with perimeter players- indicate a profound expansion in the functional roles of big players, consistent with research showing that position-based performance distinctions have become more flexible over time (Puente et al., 2015; Zhang et al., 2018). Specifically, the substantial temporal shifts observed in assist percentages (AST%) and individual player floor impacts (FIC), particularly the spike in centers' playmaking fluency during the Transitional Era (Group 2 Mean = 19.5%), indicate that modern European tactical schemas have expanded the focal point of taller players beyond the traditional confines of the painted area. These findings suggest that taller players have progressively expanded their functional responsibilities beyond traditional interior roles by contributing more actively to ball movement, playmaking, and offensive organization.

The results of the clustering analysis provide one of the strongest empirical indicators of this positional transformation. While players in the traditional period were largely segregated within clusters corresponding to their rigid, nominal positions (42.8% of power forwards confined to low-intensity utility/stretch profiles in Cluster 3), the modern period shows greater similarity. Performance profiles appear to be less constrained by traditional positional labels than in previous eras, supporting previous recommendations that performance-based classifications may complement nominal position-based approaches (Lorenzo et al., 2010). In the modern period (2021–2025), the observed convergence of power forwards (36.0%) and centers (36.8%) identically into Cluster 1 (Paint Monsters) highlights that performance outputs are converging and that player roles are increasingly defined by functional, dynamic skill sets rather than nominal designations. This balanced distribution of centers vs. power forward across multiple clusters highlights the transition of this position from a one-dimensional structure to a multidimensional performance profile, aligning with research demonstrating increasing role flexibility and the gradual blurring of positional boundaries in modern basketball (Courel-Ibáñez et al., 2020).

The present findings also have important practical implications for talent identification, player development, and roster construction in elite basketball. Traditionally, frontcourt players have been evaluated primarily according to anthropometric characteristics and nominal positional requirements. However, the observed convergence of functional roles suggests that modern player evaluation should increasingly emphasize versatility, decision-making ability, playmaking capacity, and defensive adaptability alongside traditional physical characteristics. Rather than viewing power forwards and centers as strictly separated positional categories, coaches and performance analysts may benefit from evaluating players according to the functional roles they are capable of performing within different tactical systems. Consequently, roster construction may increasingly depend on assembling complementary functional profiles rather than simply balancing nominal playing positions. This perspective may also support more flexible player development pathways by encouraging the acquisition of multidimensional technical and tactical skills throughout the athlete development process.

When interpreting these empirical shifts, an important methodological distinction must be drawn between statistical performance profiles and direct tactical mechanics. While our findings demonstrate robust statistical convergence and functional overlapping between EuroLeague Power Forwards and Centers across 11 performance metrics, the underlying dataset captures output metrics rather than direct spatial or schematic tracking data. Consequently, contextual explanations—such as the evolution toward role-flexible lineups, perimeter spacing, or defensive switching schemes—are framed as theoretically informed interpretations aligned with modern tactical literature rather than direct causal inferences. Future research employing optical tracking or play-type telemetry data is recommended to directly map these empirical performance profiles onto schematic tactical execution.

A further methodological limitation pertains to the absence of contextual longitudinal covariates, such as player age, line-up roster construction, and macro-level pacing metrics. In econometrics and sports analytics, omitting such factors introduces potential omitted-variable bias, as unobserved macro trends could partially confound observed functional convergence. However, incorporating these parameters in European basketball poses severe data availability challenges, as multi-decade longitudinal contextual metrics are not systematically archived in standardized, open-access EuroLeague repositories, requiring non-viable manual tracking across heterogeneous sources. Nevertheless, two analytical safeguards in our study minimize this concern: First, primary hypothesis testing relied on standardized advanced rate metrics (e.g., USG%, TS%, ORB%, AST%) rather than raw volume totals, inherently controlling for variations in game tempo and individual playing time. Second, the Linear Mixed Model architecture incorporated player-specific random intercepts (Player-ID), effectively capturing unobserved player-level heterogeneity across seasons. Future research utilizing proprietary tracking or telemetry databases is encouraged to evaluate how micro-level tactical schemes interact with macro-level positional evolution.

Robustness and sensitivity checks

To ensure that dimensionality reduction artifacts do not bias our conclusions given the lower sampling adequacy for EFA (KMO $= 0.349$), primary hypothesis testing was conducted on each of the 11 raw empirical performance metrics via Linear Mixed Models (LMM). As detailed in Appendix Table A1, sensitivity checks confirm that the interaction between position and era (Position $\times$ Year) is non-significant across 10 of the 11 raw metrics ($p > .05$). Furthermore, to verify that the operationalization of historical eras (5-year periods) did not introduce arbitrary boundary effects, a continuous-time sensitivity analysis was conducted by treating season as a continuous linear covariate. As detailed in Appendix Table A2, the interaction terms (Position $\times$ Continuous Season) remained non-significant for the same 10 performance metrics ($p > .05$), confirming that the annual performance trajectories of Power Forwards and Centers are statistically parallel and independent of temporal cutoff points.

CONCLUSION

This study aimed to examine the structural characteristics of positional transformation in basketball by analysing the performance profiles of power forwards (4) and centers (5) over the past 15 years using EuroLeague data and multivariate statistical methods. The findings indicate that both time (period effect) and position significantly influenced player performance, whereas the interaction between these factors was generally non-significant, suggesting similar developmental trajectories for power forwards and centers across the study period.

The findings demonstrate that the performance profiles of frontcourt players have evolved systematically over time, although this evolution is not uniformly reflected across all variables. Variations observed in metrics directly associated with in-game responsibilities, such as assists, offensive rebounds, and steals, suggest that taller players have progressively expanded their functional responsibilities beyond traditional interior roles. At the same time, the largely parallel trends observed across multiple performance indicators indicate that this evolution is better interpreted as a gradual convergence of functional roles while preserving residual positional differences, rather than as the disappearance of positional identities.

The findings suggest that the concept of position in basketball has not disappeared but has instead been functionally redefined. Rather than eliminating positional identities, modern basketball increasingly allows power forwards and centers to perform overlapping functional roles shaped by multidimensional performance characteristics, tactical versatility, and game-specific demands. These findings support the view that contemporary frontcourt evolution is better understood as a process of functional role convergence while preserving residual positional distinctions.

By combining a 15-season longitudinal dataset with a multivariate analytical framework, this study provides both empirical and conceptual contributions to understanding the evolution of frontcourt players in elite basketball. Beyond documenting long-term performance changes, the findings offer a framework for interpreting positional evolution through functional roles rather than relying solely on nominal positional classifications. From a practical perspective, these results may assist coaches, performance analysts, and recruitment staff in evaluating frontcourt players according to functional versatility in addition to traditional positional characteristics, thereby supporting more flexible talent identification, player development, and roster construction strategies. Overall, the findings suggest that the evolution of modern frontcourt players is better explained by functional role convergence than by the disappearance of positional identities. Future research should extend this framework to different leagues, tactical contexts, and performance-tracking technologies to further clarify how functional roles continue to evolve across different levels of elite basketball.

AUTHOR CONTRIBUTIONS

All authors meet the criteria for authorship in accordance with established ethical guidelines. Contributions are specified according to the CRediT (Contributor Roles Taxonomy) as follows: Conceptualisation: Erkan Konca. Methodology: Erkan Konca. Formal analysis: Erkan Konca. Investigation: Necati Alp Erilli. Data curation: Necati Alp Erilli. Writing – original draft: Erkan Konca. Writing – review & editing: Necati Alp Erilli. Supervision: Erkan Konca, Necati Alp Erilli.

All authors have critically reviewed and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

FUNDING

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

AI USE DISCLOSURE

In accordance with current publishing ethics and transparency recommendations, artificial intelligence (AI) tools were used solely to assist with translation and language editing, with the aim of improving clarity and readability. No AI tools were used in the generation of scientific content, including the study design, data collection, analysis, interpretation of results, or the formulation of conclusions. The authors retain full responsibility for the content of the manuscript and confirm its originality, integrity, and accuracy.

ACKNOWLEDGMENT

The authors would like to acknowledge the EuroLeague for providing publicly accessible data that made this research possible.

REFERENCES

Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers & Geosciences, 10*(2-3), 191-203. https://doi.org/10.1016/0098-3004(84)90020-7

Cene, E., Özdalyan, F., Parim, C., Mancı, E., & İnan, T. (2024). How do European and non-European players differ: Evidence from EuroLeague basketball with multivariate statistical analysis. Proceedings of the Institution of Mechanical Engineers, Part P: *Journal of Sports Engineering and Technology*. Advance online publication. https://doi.org/10.1177/17543371241242835

Cherni, Y., Mzita, I., Oranchuk, D. J., Dhahbi, W., Hammami, M., Ceylan, H. I., ... & Chelly, M. S. (2025). Effects of loaded vs unloaded plyometric training combined with change-of-direction sprints on neuromuscular performance in elite U-18 female basketball players: a randomized controlled study. *Sport Sci Health, 21*, 2899-2911. https://doi.org/10.1007/s11332-025-01498-4

Courel-Ibáñez, J., McRobert, A. P., Ortega Toro, E., & Cárdenas Vélez, D. (2020). Inside game effectiveness in NBA basketball: Analysis of collective interactions. *Kinesiology, 50*(2), 231-242. https://doi.org/10.26582/k.50.2.5

Cui, Y., Liu, F., Bao, D., Liu, H., Zhang, S., & Gómez, M. Á. (2019). Key anthropometric and physical determinants for different playing positions during National Basketball Association draft combine test. *Frontiers in Psychology, 10*, 2359. https://doi.org/10.3389/fpsyg.2019.02359

Dhahbi, W., & Chamari, K. (2026). The Algorithmic Athlete: A Call to Standardize Assessment of Sensor Technologies and Artificial Intelligence. *International Journal of Sports Physiology and Performance, 21*(4), 505-506. https://doi.org/10.1123/ijspp.2025-0547

Erilli, N. A., Yolcu, U., Eğrioğlu, E., Aladağ, Ç. H., & Öner, Y. (2011). Determining the most proper number of cluster in fuzzy clustering by using artificial neural networks. Expert Systems with Applications, 38(3), 2248-2252. https://doi.org/10.1016/j.eswa.2010.08.012

Foteinakis, P., Pavlidou, S., & Stavropoulos, N. (2024). Analysis of the effectiveness of different play types in the end of game possessions of close EuroLeague matches. *Journal of Human Sport and Exercise, 19*(2), 617-630. https://doi.org/10.55860/rj38hm02

Goldsberry, K. (2012). CourtVision: New visual and spatial analytics for the NBA [Conference Paper]. MIT *Sloan Sports Analytics Conference*, Boston, MA, ABD.

Gómez, M., Lorenzo, A., Sampaio, J., Ibáñez, S. J., & Ortega, E. (2008). Game-related statistics that discriminated winning and losing teams from the Spanish men's professional basketball teams. *Collegium Antropologicum, 32*(2), 451-456.

Guimarães, E., Baxter-Jones, A., Maia, J., Fonseca, P., Santos, A., Santos, E., Tavares, F., & Janeira, M. A. (2019). The Roles of Growth, Maturation, Physical Fitness, and Technical Skills on Selection for a Portuguese Under-14 Years Basketball Team. *Sports, 7*(3), 61. https://doi.org/10.3390/sports7030061

Hedquist, A. L. (2022). Redefining NBA basketball positions through visualization and mega-cluster analysis (Master's thesis, Utah State University).

Hoare, D. G. (2000). Predicting success in junior elite basketball players: The contribution of anthropometric and physiological attributes. *Journal of Science and Medicine in Sport, 3*(4), 391-405. https://doi.org/10.1016/S1440-2440(00)80006-7

Ibáñez, S. J., Sampaio, J., Feu, S., Lorenzo, A., Gómez, M. Á., & Ortega, E. (2008). Basketball game-related statistics that discriminate between teams' season-long success. *European Journal of Sport Science, 8*(6), 369-372. https://doi.org/10.1080/17461390802261470

Kubatko, J., Oliver, D., Pelton, K., & Rosenbaum, D. T. (2007). A starting point for analyzing basketball statistics. *Journal of Quantitative Analysis in Sports, 3*(3), Article 13. https://doi.org/10.2202/1559-0410.1070

Lorenzo, A., Gómez, M. Á., Ortega, E., Ibáñez, S. J., & Sampaio, J. (2010). Game related statistics which discriminate between winning and losing under-16 male basketball games. *Journal of Sports Science & Medicine, 9*(4), 664-668.

Mandić, R., Jakovljević, S., Erčulj, F., & Štrumbelj, E. (2019). Trends in NBA and EuroLeague basketball: Analysis and comparison of statistical data from 2000 to 2017. *PLoS ONE, 14*(10), e0223524. https://doi.org/10.1371/journal.pone.0223524

Ostojic, S. M., Mazic, S., & Dikic, N. (2006). Profiling in basketball: physical and physiological characteristics of elite players. *Journal of strength and conditioning research, 20*(4), 740-744. https://doi.org/10.1519/R-15944.1

Puente, C., Coso, J. D., Salinero, J. J., & Abián-Vicén, J. (2015). Basketball performance indicators during the ACB regular season from 2003 to 2013*. International Journal of Performance Analysis in Sport, 15*(3), 935-948. https://doi.org/10.1080/24748668.2015.11868842

RealGM. (n.d.). *Basketball statistics database*. Retrieved March 30, 2026, from: https://basketball.realgm.com/

Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53-65. https://doi.org/10.1016/0377-0427(87)90125-7

Sampaio, J., & Janeira, M. (2003). Statistical analyses of basketball team performance: understanding teams' wins and losses according to a different index of ball possessions. *International Journal of Performance Analysis in Sport, 3*(1), 40-49. https://doi.org/10.1080/24748668.2003.11868273

Sampaio, J., Lago, C., Casais, L., & Leite, N. (2010). Effects of starting score-line, game location, and quality of opposition in basketball quarter score. *European Journal of Sport Science, 10*(6), 391-396. https://doi.org/10.1080/17461391003699104

Skinner, B. (2012). The price of anarchy in basketball. *Journal of Quantitative Analysis in Sports, 8*(1), Article 13.

Trninić, S., Dizdar, D., & Dezman, B. (2000). Empirical verification of the weighted system of criteria for the elite basketball players quality evaluation. *Collegium Antropologicum, 24*(2), 443-465.

Zhai, Z., Guo, Y., Li, Y., Zhang, S., & Liu, H. (2020). The regional differences in game-play styles considering playing position in FIBA female continental competitions. *International Journal of Environmental Research and Public Health, 17*(16), 5827. https://doi.org/10.3390/ijerph17165827

Zhai, Z., Guo, Y., Zhang, S., Li, Y., & Liu, H. (2021). Explaining positional differences of performance profiles for elite female basketball players. *Frontiers in Psychology, 11*, 558750. https://doi.org/10.3389/fpsyg.2020.558750

Zhang, S., Lorenzo, A., Gómez, M. A., Mateus, N., Gonçalves, B., & Sampaio, J. (2018). Clustering performances in the NBA according to players' anthropometric attributes and playing experience. *Journal of Sports Sciences, 36*(22), 2511-2520. https://doi.org/10.1080/02640414.2018.1466493

APPENDIX A.

Table A1. Linear Mixed Model (LMM) Sensitivity Analysis Across 11 Raw Empirical Metrics.

Metric	Effect	Num. df	Den. df	F	*p*-value (Sig.)	Interpretation
TS%	Position	1	790.80	2.096	.148	Non-significant interaction (Parallel trend)
	Year	2	959.90	19.592	<.001	
	Position x Year	2	962.21	0.116	.891	
ORB%	Position	1	977.14	50.185	<.001	Non-significant interaction (Parallel trend)
	Year	2	912.38	0.606	.546	
	Position x Year	2	868.76	2.490	.084	
DRB%	Position	1	921.19	17.064	<.001	Non-significant interaction (Parallel trend)
	Year	2	952.23	9.033	<.001	
	Position x Year	2	928.57	1.941	.144	
AST%	Position	1	968.53	0.030	.862	Non-significant interaction (Parallel trend)
	Year	2	931.85	6.011	.003	
	Position x Year	2	896.28	0.959	.384	
TOV%	Position	1	914.41	15.069	<.001	Non-significant interaction (Parallel trend)
	Year	2	947.31	0.563	.570	
	Position x Year	2	920.91	0.997	.369	
STL%	Position	1	888.55	4.135	.042	**Significant interaction**
	Year	2	950.38	1.163	.313	
	Position x Year	2	928.12	6.838	.001	
BLK%	Position	1	983.52	13.973	<.001	Non-significant interaction (Parallel trend)
	Year	2	845.68	12.173	<.001	
	Position x Year	2	795.00	0.086	.918	
USG%	Position	1	972.30	10.914	.001	Non-significant interaction (Parallel trend)
	Year	2	925.90	7.220	.001	
	Position x Year	2	887.79	0.401	.670	
PPR	Position	1	927.85	25.293	<.001	Non-significant interaction (Parallel trend)
	Year	2	947.45	11.010	<.001	
	Position x Year	2	920.39	1.051	.350	
PPS	Position	1	895.28	6.111	.014	Non-significant interaction (Parallel trend)
	Year	2	955.97	10.474	<.001	
	Position x Year	2	937.04	0.013	.987	
FIC	Position	1	841.30	1.995	.158	Non-significant interaction (Parallel trend)
	Year	2	973.54	26.597	<.001	
	Position x Year	2	980.85	1.274	.280	

Note: Repeated measures controlled via Random Intercept for Player-ID with Variance Components covariance structure.

Table A2. Linear Mixed Model (LMM) Continuous Time Sensitivity Analysis Across 11 Raw Performance Metrics.

Metric	Effect	Num. df	Den. df	F	*p*-value (Sig.)	Interpretation
TS%	Position	1	343.10	1.095	.296	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	511.87	30.617	<.001	
	Position x Year	1	418.41	0.038	.845	
ORB%	Position	1	498.00	14.206	<.001	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	491.23	1.805	.180	
	Position x Year	1	515.31	0.585	.445	
DRB%	Position	1	513.37	5.871	.016	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	541.49	18.867	<.001	
	Position x Year	1	556.56	0.240	.625	
AST%	Position	1	1002.55	1.335	.248	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	1211.32	6.361	.012	
	Position x Year	1	1156.61	1.697	.193	
TOV%	Position	1	989.69	7.236	.007	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	1053.18	0.966	.326	
	Position x Year	1	1140.01	0.487	.485	
STL%	Position	1	463.36	13.493	<.001	**Significant interaction**
	Year (Continuous)	1	844.22	0.358	.550	
	Position x Year	1	529.49	9.433	.002	
BLK%	Position	1	290.09	6.713	.010	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	379.05	20.775	<.001	
	Position x Year	1	316.32	0.338	.561	
USG%	Position	1	820.11	4.141	.042	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	526.75	25.671	<.001	
	Position x Year	1	981.18	0.196	.658	
PPR	Position	1	481.02	14.947	<.001	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	888.29	33.267	<.001	
	Position x Year	1	551.53	1.300	.255	
PPS	Position	1	397.68	6.201	.013	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	534.13	12.461	<.001	
	Position x Year	1	497.98	0.461	.498	
FIC	Position	1	438.38	0.001	.974	Non-significant interaction (Parallel slope)
	Year (Continuous)	1	594.39	28.080	<.001	
	Position x Year	1	943.38	0.407	.524	

Note: Models fit with continuous season linear covariate and subject-level random intercepts.

Table A3. FCM Cluster Profile z-Score Table.

Performance Metric	Cluster 1 (n = 144) (Rebounding & Defensive Frontcourt)	Cluster 2 (n = 110) (Interior Finishers & Rim Protectors)	Cluster 3 (n = 142) (Perimeter & Steal-Active Bigs)	Overall Sample Mean	Differentiating Empirical Characteristics
TS%	-0.254	-0.128	-0.285	-0.230	Cluster 2 holds the highest shooting efficiency
ORB%	+0.088	+0.051	-0.173	-0.016	Cluster 1 dominates offensive glass; Cluster 3 lowest
DRB%	+0.195	+0.030	+0.136	+0.128	Cluster 1 displays highest defensive rebound rate
AST%	-0.061	-0.057	+0.026	-0.029	Cluster 3 exhibits positive passing distribution
TOV%	+0.072	+0.006	+0.098	+0.063	Cluster 2 maintains lowest turnover rate
STL%	-0.189	-0.073	+0.222	-0.009	Cluster 3 shows clear perimeter/steal activity (Z > +0.22)
BLK%	+0.110	+0.140	-0.068	+0.054	Cluster 2 leads in rim protection / block rate
USG%	+0.226	+0.176	+0.191	+0.199	Cluster 1 carries highest overall usage rate
PPR	-0.237	-0.171	-0.204	-0.207	Cluster 2 records relative assist-to-turnover stability
PPS	-0.219	-0.042	-0.210	-0.167	Cluster 2 shows highest points per shot yield
FIC	-0.324	-0.136	-0.377	-0.291	Cluster 2 exhibits highest composite impact

Note: Values represent standardized cluster centroids (Z-scores). Cluster assignments were determined by maximum membership degree (u_{ij}) derived from Fuzzy C-Means (FCM).

APPENDIX B. RealGM's Advanced/Misc. Statistics.

TS% (True Shooting Percentage): A measurement of efficiency as a shooter in field goal attempts, three-point field goal attempts and free throws.

Formula: (Points x 50) / [(FGA + 0.44 * FTA)]

ORB% (Offensive Rebound Percentage): A measurement of the percentage of offensive rebounds a player secures that are available to his team.

Formula: 100 * [Player ORB * (Team Minutes / 5)] / [Player Minutes * (Team ORB + Opponent DRB)]

DRB% (Defensive Rebound Percentage): A measurement of the percentage of defensive rebounds a player secures that are available to his team.

Formula: 100 * [Player DRB * (Team Minutes / 5)] / [Player Minutes * (Team DRB + Opponent ORB)]

AST% (Assist Percentage): A measurement of the percentage of assists a player records in relation to the team's overall total while he is in the game.

Formula: 100 * Player ASTs / [((Player Minutes / (Team Minutes Played / 5)) * Team FGs) – Player FGs]

STL% (Steal Percentage): A measurement of the percentage of steals a player records in relation to the team's overall total while he is in the game.

Formula: 100 * [Player STLs * (Team Minutes / 5)] / (Player Minutes * Opponent Possessions)

BLK% (Block Percentage): A measurement of the percentage of blocks a player records in relation to the opponents two point field goal attempts.

Formula: 100 * [Player BLKs * (Team Minutes / 5)] / (Player Minutes * Opponent FGA - Opponent 3PA)

TOV% (Turnover Percentage): A measurement of the percentage of turnovers a player records in relation to the team's overall total while he is in the game.

Formula: 100 * Turnovers / (FGA + 0.44 * FTA + TOV)

USG% (Usage Percentage): A measurement of the percentage of plays utilized by a player while he is in the game.

Formula: 100 * [(FGA + 0.44 * FTA + TOV) * (Team Minutes / 5)] / [Player Minutes * Team FGA + 0.44 * Team FTA + Team TOV]

PPS (Points Per Shot): Points scored per field goal attempt.

PPR (Pure Point Rating): = 100 x (League Pace / Team Pace) x ([(Assists x 2/3) - Turnovers] / Minutes)