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Analysis of volleyball matches based on normalized indicators of competitive activity

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Abstract

Background and Study Aim The analysis of volleyball matches plays a key role in understanding game dynamics, evaluating tactical effectiveness, and optimizing player training. The aim of this study is to identify key patterns and trends that influence the performance of volleyball players and teams.

Material and Methods Data from the European Volleyball Federation's *European Golden League – Men*, 2024, were used for the analysis. The sample included competitive performance indicators of 210 players from 12 teams, categorized by playing position: Setter, Middle Blocker, Opposite, Outside Spiker, and Libero. The data were normalized to calculate key metrics, including total points scored, serve efficiency, reception efficiency, attack efficiency, and blocking efficiency. Statistical analysis involved calculating means, medians, and standard deviations, as well as conducting correlation and cluster analyses. Correlations were assessed using Spearman's method, and visualization was performed using a correlation network graph. Cluster analysis was conducted using the K-means method to group players by position. Regression analysis was applied to determine relationships between performance indicators and player effectiveness.

Results The analysis showed that the use of normalized data allowed for the identification of the best players in each team, except for the Libero and Setter positions. The average total points scored by team leaders was 76.4 ± 12.3, while attack efficiency reached 0.82 ± 0.15. Correlation analysis revealed a positive correlation between Ace and Ace per Set ($r = 0.983$) for players in the Setter and Outside Spiker positions, as well as between Total Points and Total Points ($r = 0.976$) for Middle Blockers. Cluster analysis identified three groups of players: consistent performers (Total Points in the range of 35–45), high-performing leaders (Total Points > 60 and Total Points > 80), and players in supporting roles (key performance indicators below 30). Regression analysis established equations demonstrating the influence of the number of sets played and attack efficiency on player performance.

Conclusions The obtained results demonstrate the significance of normalized indicators for assessing the effectiveness of gameplay actions in volleyball. Correlation and cluster analyses identified key patterns, such as strong relationships between scoring actions (e.g., aces and attack points) and their impact on overall team performance. The regression equations provide an analytical basis for predicting player performance based on their game metrics. These findings can be utilized to optimize tactical preparation and develop individualized training programs aimed at enhancing team effectiveness.

Keywords: competitive performance, player effectiveness, correlation analysis, cluster analysis, regression modeling

Introduction

The analysis of volleyball matches is one of the key areas of research, allowing for the identification of game patterns, the evaluation of tactical decision-making effectiveness, and the optimization of athlete training. The use of match statistics provides extensive opportunities for a detailed study of the factors influencing team success. However, data fragmentation and the diversity of representation methods create challenges in the systematization and practical application of such research.

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The analysis of matches in team sports is widely used to identify game patterns, evaluate tactical strategies, and determine factors influencing team performance. In football, such studies focus on the systematization of match data [1, 2], the impact of game tempo and player fatigue [3], and the development of approaches for talent identification and development [4]. In rugby, match analysis helps identify key player characteristics [3, 5], while in futsal, research emphasizes the specifics of in-game actions and their systematization [6].

The analysis of volleyball matches plays a key role in understanding game patterns, evaluating tactical decisions, and optimizing the training process. Research covers a wide range of topics, including data systematization and the assessment of gameplay effectiveness [7, 8], the use of analysis to enhance coaching efficiency [9, 10, 11], and the study of player interaction networks on the court [12, 13]. Particular attention is given to the specifics of gameplay actions, such as attacking and team rotation [14, 15], as well as match analysis considering physiological indicators [16].

Among studies on sports statistics, several focus on the use of normalized indicators of competitive performance [17, 18, 19, 20]. The authors argue that this approach allows for the evaluation of individual athletes' or teams' success in competition while considering multiple performance metrics.

Existing publications demonstrate a variety of approaches to volleyball match analysis. Some studies focus on examining players' attacking actions, including setter plays and attack receptions [21, 22]. Other works explore tactical aspects, such as the development of game phases and scoring strategies [23, 24]. Certain publications emphasize age categories and anthropometric characteristics of players, highlighting their impact on match outcomes [25, 26].

The analysis of existing publications highlights studies dedicated to the impact of physical and temporal characteristics on player performance. For example, some works examine parameters such as the duration of game phases, physical workload, and action efficiency at different stages of competitions [27, 28]. These studies emphasize the importance of a detailed analysis of playing roles and match phases to optimize the training process.

Particular attention is given to establishing benchmark performance indicators. For instance, research aims to determine optimal zones for setting plays and analyzes their influence on overall team performance [29, 30]. This approach allows for the development of coaching recommendations aimed at improving game quality.

Additionally, the effectiveness of players in different positions, such as middle blockers and defensive players, is studied. These works emphasize the combination of technical and tactical aspects that influence match outcomes [24, 31].

Furthermore, several studies focus on match analysis considering gender-specific differences. For example, research explores variations in game strategies between men's and women's teams, allowing for the identification of unique aspects of athlete preparation [32, 33, 34].

Despite the large body of research, the systematization of approaches to match analysis remains insufficiently explored, particularly in the context of utilizing statistics from open sources such as volleyball federation websites, clubs, and specialized platforms.

The aim of this study is to identify key patterns and trends that influence the performance of volleyball players and teams.

Materials and Methods

Sources

The data source for this study was the European Volleyball Federation website, specifically the *European Golden League – Men*, 2024, under the *STATISTICS – Player Stats* section [35]. Extracted data included competitive performance metrics of volleyball players (n = 210) categorized by position: Setter, Middle Blocker, Opposite, Outside Spiker (Hitter), and Libero. The participants represented 12 teams: Azerbaijan, Belgium, Croatia, Czechia, Estonia, Luxembourg, North Macedonia, Portugal, Romania, Spain, Ukraine. Data were collected from matches played in the semifinals and finals.

Tournament Results (Semifinals and Finals)

Semifinal Matches:

1. Croatia vs. Estonia: 3:2 (25-20, 24-26, 25-21, 19-25, 15-13)
2. Czechia vs. Ukraine: 0:3 (24-26, 16-25, 20-25)

Final Matches:

1. Estonia vs. Czechia: 2:3 (25-20, 22-25, 33-31, 25-27, 12-15)
2. Croatia vs. Ukraine: 1:3 (25-23, 19-25, 26-28, 19-25)

Procedure

The data were cleaned and transformed: unnecessary columns were removed, percentage signs were eliminated, tables were merged, and new columns were added for analysis. A total of 26 competitive performance indicators were included (Table 1). For ease of analysis, abbreviations were introduced: (S-) for serving, (R-) for reception, (A-) for attack, and (B-) for blocking.

The player positioning scheme is presented in Figure 1.

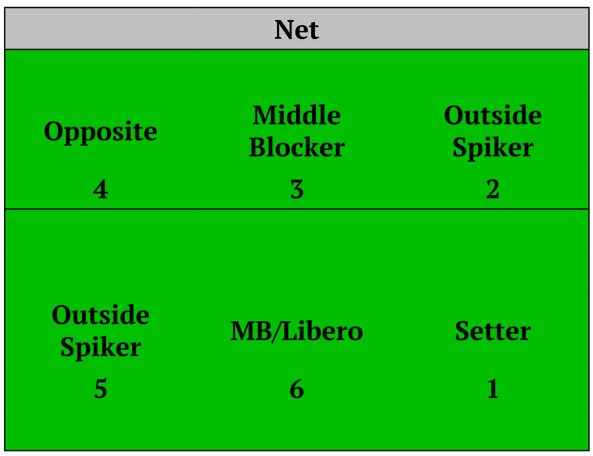

Figure 1. Player Positioning Scheme. Note: MB - Middle Blocker; 1, 2, 3, 4, 5, 6 – game zones

Table 1. Competitive Performance Indicators

No.	Indicator Name	Description
1	Name	Player's name (e.g., Märt TAMMEARU)
2	Matches	Number of matches the player participated in
3	Sets	Number of sets the player participated in
4	Total Points	Total points scored by the player
5	Side-Out	Points achieved after receiving service
6	Break Point	Points achieved after serving
7	P-Total Points	Repeated value of total points scored (possible duplicate)
8	S-Ace	Number of aces performed by the player
9	S-Error	Number of service errors
10	S-Ace per Set	Average number of aces per set
11	S-Efficiency	Serve efficiency, expressed as a percentage
12	R-Total	Total number of receptions
13	R-Error	Number of reception errors
14	R-Negative	Number of negative receptions
15	R-Excellent	Number of excellent receptions
16	R-Excellent %	Percentage of excellent receptions
17	R-Efficiency	Reception efficiency, expressed as a percentage
18	A-Total Points	Total attack points
19	A-Error	Number of attack errors
20	A-Blocked	Number of blocked attacks
21	A-Excellent	Number of excellent attacks
22	A-Excellent %	Percentage of excellent attacks
23	A-Efficiency	Attack efficiency, expressed as a percentage
24	B-Net	Number of blocks
25	B-Points	Points scored from blocks
26	B-Points per Set	Average number of block points per set

Note. P- Total Points, S- Serve, R- Reception, A- Attack, B- Block.

The raw data were supplemented with efficiency calculations based on the following formulas:

- S-Efficiency = (S-Total Points / Sets) + (S-Ace / Sets) - (S-Error / Sets)
- R-Efficiency = (R-Total / Sets) + (R-Excellent / Sets) - (R-Error / Sets)
- A-Efficiency = (A-Total Points / Sets) + (A-Excellent / Sets) - (A-Error / Sets) - (A-Blocked / Sets)

Normalized indicators of total points (*P-Total Points Normalized*) were also calculated.

Statistical Analysis

To analyze the data, mean values, medians, standard deviations, as well as the minimum and maximum values of athletes' competitive performance indicators were determined. The Shapiro-Wilk test for normality indicated that the data did not follow a normal distribution. Therefore, Spearman's method was used for correlation analysis. Network graphs were utilized to visualize correlation matrices. Cluster and regression analysis methods were also applied. The data were normalized using the MinMaxScaler method. Cluster analysis was performed using the K-means method for each player position and for the combined dataset of all positions. Cluster visualization was conducted using scatter plots.

Regression analysis was conducted to develop regression equations that determine the dependence of gameplay efficiency (serving, reception, attack, blocking) on various competitive performance indicators. The general regression equation is as follows:

$$y=\beta_0+\beta_1 \cdot x_1+\beta_2 \cdot x_2+\beta_3 \cdot x_3+\beta_4 \cdot x_4$$

where:

y – dependent variable;

β_0 – intercept (constant term);

β_1, β_2, β_3, β_4 – coefficients of the independent variables;

x_1, x_2, x_3, x_4 – independent variables.

To determine the best players on each team, the data were sorted by *P-Total Points Normalized*, and the top-ranked players for each team were identified. The *Libero* and *Setter* positions were excluded from the top player rankings due to their specific roles in the game (e.g., *Libero* does not participate in blocking, and *Setter* rarely engages in serve reception).

Normalized data were used for cluster analysis. All calculations and visualizations were performed in the PyCharm CE development environment using the *pandas*, *scikit-learn*, *seaborn*, and *matplotlib* libraries.

Results

The most significant statistical indicators of competitive performance analysis are presented in Tables 2 and 3. Table 2 contains the competitive performance results of players, supplemented with additional data for analysis.

Player evaluation across all performance indicators was conducted using a normalization method. Ranked positions of players were calculated for each team based on normalized data. In Table 2 (column A26), only one player from each team is shown – specifically, the top-ranked player within their team (excluding *Libero* and *Setter*).

Table 3 presents the ranked positions of players from the Ukraine team based on normalized data.

As a result of the correlation analysis, graphical visualizations of the correlation matrix were obtained for each player position (Figure 2, as an example for the Opposite role). The Spearman correlation method was used due to the non-normal distribution of the data. The correlation network graph illustrates the relationships between various numerical performance indicators of the players. All variables exhibit positive correlations, ranging from 0.771 to 1.0, indicating statistically significant dependencies. The strongest correlations are observed between A-Total Points and A-Excellent (0.984), as well as between A-Excellent and P-Total Points (0.982), suggesting a strong interconnection between the number of points scored and the quality of attacking actions. The correlation between A-Excellent % and A-Efficiency (0.795) is the lowest among the presented values, yet it remains high, confirming its significance. This suggests that the percentage of excellent actions influences overall efficiency but is not the sole determining factor.

Based on the regression analysis, regression equations were obtained for various volleyball actions (*serve, reception, attack, block*) (Table 4). These equations demonstrate how different factors influence the effectiveness of each action.

In the original dataset, the results for *Serve* did not include detailed information on player performance efficiency (only percentage-based efficiency related to aces and service errors). Therefore, a recalculation of combined serve efficiency was performed using normalized indicators.

For each player, the following indicators were normalized: number of sets (Sets), total points scored on serve (S-Total Points), number of aces (S-Ace), number of service errors (S-Error), and number of aces per set (S-Ace per Set).

The combined efficiency (*Combined_Efficiency*) was then calculated, incorporating all these normalized indicators using the following formula:

$$CE = N_1 + N_2 + N_3 - N_4 + N_5$$

where:

N_1 – normalized number of sets played,
N_2 – normalized total points scored on serve,
N_3 – normalized number of aces,
N_4 – normalized number of service errors,
N_5 – normalized number of aces per set.

Similarly, for the technical action «Reception.»

The regression equations (Table 4) for various volleyball actions present the obtained regression models based on the average performance metrics for different player positions. These equations illustrate the relationship between action-specific variables (such as total points, errors, aces, etc.) and the overall performance indicator *P-Total Points*.

For the *Serve* action, the regression equations demonstrate how variables such as *S-Total Points, S-Ace, S-Error, S-Ace per Set,* and *S-Efficiency* influence the total points scored by a player.

In the *Reception* action, the regression equations include variables *R-Total, R-Error, R-Negative, R-Excellent, R-Excellent %,* and *R-Efficiency*, illustrating their impact on player performance.

Similarly, the equations for the *Attack* action contain variables *A-Total Points, A-Error, A-Blocked, A-Excellent, A-Excellent %,* and *A-Efficiency*, emphasizing their importance.

Finally, the equations for the *Block* action focus on variables *B-Net, B-Points,* and *B-Points per Set*, highlighting their role in determining player efficiency.

Regression equations are also created for each team. As an example, Table 5 presents the regression equations for the Ukraine team.

The equations in Table 5 take into account key performance indicators for *Serve, Reception, Attack,* and *Block*, allowing for an assessment of how individual factors influence overall effectiveness.

For example, the *Serve Equation* includes variables such as total points, number of aces, and number of errors, enabling an evaluation of how these metrics impact serve efficiency. Similarly, the *Reception Equation, Attack Equation,* and *Block Equation* incorporate relevant indicators for each action.

These equations will help coaches and analysts better understand which aspects of the game require attention to improve team performance.

For cluster analysis, the data were standardized

Table 2. Competitive Performance Results (Excerpt), n = 210

Name	Team	Position	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20	A21	A22	A23	A24	A25	A26
Yurii SEMENIUK	UKR	Middle Blocker	8	29	76	47	29	100	8	11	.28	-3	2	0	1	0	0	0	85	4	5	50	59	48	1	18	.62	1.0
Petar DIRLIC	CRO	Opposite	8	33	170	119	51	135	8	15	.24	-5	3	0	1	1	33	33	299	20	15	153	51	39	0	9	.27	1.0
Märt TAMMEARU	EST	Outside Spiker	8	30	125	88	37	108	4	16	.13	-11	200	11	48	60	30	20	230	12	16	113	49	37	0	8	.27	1.0
Ferre REGGERS	BEL	Opposite	6	25	136	84	52	97	13	31	.52	-19	9	1	5	0	0	-11	208	17	15	115	55	40	1	9	.36	.8
Mateja GAJIN	LUX	Outside Spiker	6	20	85	63	22	63	3	20	.15	-27	2	1	1	0	0	-50	158	14	18	72	46	25	0	10	.5	.68
Alexandre FERREIRA	POR	Outside Spiker	6	25	120	79	41	80	7	20	.28	-16	4	0	2	0	0	0	227	15	28	109	48	29	0	4	.16	.96
Lukas VASINA	CZE	Outside Spiker	8	30	117	76	41	116	12	28	.4	-14	119	10	22	31	26	15	194	15	12	96	49	36	0	9	.3	.936
Jordi RAMÓN FERRAGUT	SPA	Outside Spiker	6	22	116	66	50	98	10	29	.45	-19	151	12	36	54	36	25	148	4	7	91	61	54	0	15	.68	.928
Filip SAVOVSKI	MKD	Middle Blocker	6	24	62	35	27	88	4	14	.17	-11	7	2	2	1	14	-29	64	3	3	38	59	50	0	20	.83	.816
Luka MARTTILA	FIN	Outside Spiker	6	25	97	60	37	106	12	30	.48	-17	170	7	29	51	30	22	193	16	21	80	41	22	1	5	.2	.776
Alexandru RATA	ROU	Opposite	6	26	119	76	43	99	13	17	.5	-4	1	0	1	0	0	-100	216	17	16	102	47	32	2	4	.15	.7
Andrey MELNIKOV	AZE	Opposite	6	19	88	70	18	67	7	22	.37	-22	29	1	12	3	10	-3	173	18	24	80	46	22	0	1	.05	.518
	Mean																											
		Libero	4.31	13.586	.379	.207	.172	.759	.069	.31	.006	.059	56.759	3.931	12.414	14.759	16.621	3.323	.759	.069	.034	.31	4.897	.077	.0	.0	.0	.038
		Middle Blocker	4.019	13.019	23.87	14.889	8.981	38.759	1.444	5.074	.084	2.055	3.759	.278	.944	.889	15.556	.297	28.056	1.926	1.519	16.241	45.685	2.436	.333	6.204	.359	.314
		Opposite	4.207	13.621	46.31	31.759	14.552	41.207	3.655	9.172	.17	1.754	7.138	.828	2.414	1.552	7.448	.502	8.69	6.517	7.138	39.966	33.931	5.011	.207	2.724	.121	.272
		Outside Spiker	4.121	12.591	33.348	22.288	11.061	37.0	2.561	7.455	.119	1.641	56.545	4.258	13.545	12.833	14.015	3.42	61.333	4.318	5.273	28.106	32.136	4.002	.182	2.682	.139	.267
		Setter	4.469	14.031	6.375	2.219	4.156	39.062	2.188	4.625	.098	1.743	1.188	.25	.719	.031	1.031	.078	4.75	.312	.219	2.5	33.594	.338	.188	1.688	.072	.236
	Std Dev																											
		Libero	2.537	1.235	1.86	.94	.928	3.532	.371	1.671	.032	.219	59.89	3.918	13.733	18.711	15.431	2.888	3.522	.258	.186	1.491	19.882	.386	.0	.0	.0	.186
		Middle Blocker	2.61	1.162	22.547	13.589	9.651	34.565	2.016	5.362	.111	1.247	3.952	.529	1.22	1.269	24.148	.445	25.432	2.064	1.83	15.133	26.273	1.637	.752	6.654	.321	.297
		Opposite	2.769	1.699	56.469	38.694	18.677	44.52	4.79	11.062	.206	1.417	25.089	3.339	8.382	5.792	17.1	1.533	95.086	7.458	7.999	49.47	2.996	4.815	.559	3.788	.14	.332
		Outside Spiker	2.737	1.134	38.435	25.513	13.654	39.68	3.646	8.87	.142	1.32	62.81	5.006	15.427	16.452	12.666	3.007	68.294	4.73	5.96	32.644	21.653	3.597	.426	3.352	.16	.307
		Setter	2.984	1.563	7.452	3.348	4.887	38.428	3.053	5.74	.126	1.429	1.575	.568	1.224	.177	5.834	.221	5.512	.535	.491	3.672	33.103	.431	.592	2.306	.09	.276

Note. A1: Matches; A2: Sets; A3: P-Total Points; A4: P-Side-Out; A5: P-Break Point; A6: S-Total Points; A7: S-Ace; A8: S-Error; A9: S-Ace per Set; A10: S-Efficiency; A11: R-Total; A12: R-Error; A13: R-Negative; A14: R-Excellent; A15: R-Excellent %; A16: R-Efficiency; A17: A-Total Points; A18: A-Error; A19: A-Blocked; A20: A-Excellent; A21: A-Excellent %; A22: A-Efficiency; A23: B-Net; A24: B-Points; A25: B-Points per Set; A26: P-Total Points Normalized. Team Abbreviations: UKR - Ukraine; CRO - Croatia; EST - Estonia; BEL - Belgium; LUX - Luxembourg; POR - Portugal; CZE - Czechia; SPA - Spain; MKD - North Macedonia; FIN - Finland; ROU - Romania; AZE - Azerbaijan; Name: Player's name; Team: Team; Position: Position; Matches: Number of matches; Sets: Number of sets; P-Total Points: Total points; P-Side-Out: Side-outs; P-Break Point: Points scored on own serves (break points); S-Total Points: Total points scored on serve; S-Ace: Number of aces on serve; S-Error: Number of errors on serve; S-Ace per Set: Aces per set; S-Efficiency: Serve efficiency; R-Total: Total number of receptions; R-Error: Number of reception errors; R-Negative: Number of negative receptions; R-Excellent: Number of excellent receptions; R-Excellent %: Percentage of excellent receptions; R-Efficiency: Reception efficiency; A-Total Points: Total points in attack; A-Error: Number of attack errors; A-Blocked: Number of blocked attacks; A-Excellent: Number of excellent attacks; A-Excellent %: Percentage of excellent attacks; A-Efficiency: Attack efficiency; B-Net: Points scored in net defense; B-Points: Total points scored on block; B-Points per Set: Points per set on block; P-Total Points Normalized: Normalized total points.

Table 3. Competitive Performance Results of Ukraine Team Players (Ranked Positions by Column A26: P-Total Points Normalized)

Name	Position	A 1	A 2	A 3	A 4	A 5	A 6	A 7	A 8	A 9	A 10	A 11	A 12	A 13	A 14	A 15	A 16	A 17	A 18	A 19	A 20	A 21	A 22	A 23	A 24	A 25	A 26
Yurii SEMENIUK	Middle Blocker	8	29	76	47	29	100	8	11	.28	3.345	2	0	1	0	0	.069	85	4	5	50	59	4.345	1	18	.62	1.0
Dmytro YANCHUK	Outside Spiker	7	27	93	54	39	93	6	21	.22	2.889	125	7	19	17	14	5.0	154	14	9	82	53	7.889	0	5	.19	.744
Yevhenii KISILIUK	Outside Spiker	8	27	84	55	29	93	11	26	.41	2.889	145	10	31	33	23	6.222	137	9	13	66	48	6.704	1	7	.26	.672
Serhii YEVSTRATOV	Setter	8	29	16	2	14	84	8	6	.28	2.966	0	0	0	0	0	.0	5	1	0	2	40	.207	0	6	.21	.593
Maksym DROZD	Middle Blocker	6	20	40	22	18	65	6	13	.3	2.9	5	0	1	2	40	.35	42	1	0	26	62	3.35	1	8	.4	.526
Danylo URYVKIN	Opposite	8	27	76	53	23	82	6	17	.22	2.63	0	0	0	0	0	.0	131	8	16	67	51	6.444	0	3	.11	.447
Mikola RUDNYTSKYI	Middle Blocker	6	12	25	14	11	27	2	5	.17	2.0	1	0	0	0	0	.083	24	3	1	15	62	2.917	0	8	.67	.329
Dmytro DOLGOPOLOV	Setter	8	24	8	1	7	28	1	3	.04	1.083	0	0	0	0	0	.0	4	0	0	3	75	.292	0	4	.17	.296
Viktor SHAPOVAL	Opposite	5	14	37	17	20	47	10	9	.71	3.429	4	2	0	0	0	.143	57	8	5	24	42	4.857	1	3	.21	.218
Denys VELETSKYI	Middle Blocker	2	5	10	6	4	12	0	2	.0	2.0	0	0	0	0	0	.0	12	1	0	8	67	3.8	0	2	.4	.132
Mykyta LUBAN	Outside Spiker	4	8	16	11	5	21	1	5	.12	2.125	45	1	13	1	2	5.625	20	4	1	12	60	3.375	0	3	.38	.128
Dmytro TERYOMENKO	Middle Blocker	1	3	7	6	1	9	0	0	.0	3.0	9	1	5	0	0	2.667	14	2	0	6	43	6.0	0	1	.33	.092
Oleksandr KOVAL	Middle Blocker	3	5	7	5	2	15	1	3	.2	2.6	0	0	0	0	0	.0	10	0	1	5	50	2.8	0	1	.2	.092
Oleksandr NALOZHNYI	Outside Spiker	5	8	10	7	3	10	1	1	.12	1.25	14	3	6	1	7	1.5	20	2	1	8	40	3.125	0	1	.12	.08
Dmytro SHAPOVAL	Opposite	2	7	6	3	3	8	1	1	.14	1.143	0	0	0	0	0	.0	15	2	1	5	33	2.429	0	0	.0	.035

Note. A1: Matches; A2: Sets; A3: P-Total Points; A4: P-Side-Out; A5: P-Break Point; A6: S-Total Points; A7: S-Ace; A8: S-Error; A9: S-Ace per Set; A10: S-Efficiency; A11: R-Total; A12: R-Error; A13: R-Negative; A14: R-Excellent; A15: R-Excellent %; A16: R-Efficiency; A17: A-Total Points; A18: A-Error; A19: A-Blocked; A20: A-Excellent; A21: A-Excellent %; A22: A-Efficiency; A23: B-Net; A24: B-Points; A25: B-Points per Set; A26: P-Total Points Normalized (Ranking).

(Figure 3). This approach allows for the analysis of results across all player positions and actions. The clusters were characterized as follows:

1. Cluster 0: Players in this cluster demonstrate moderate results across all key indicators. This suggests stability and an average level of contribution to the team. These players typically perform their roles without significant deviations, maintaining balance within the team.
2. Cluster 1: This cluster includes players with high values in key categories such as *S-Total Points* and *A-Total Points*. This indicates significant attacking activity and high in-game efficiency. Players in this cluster are the primary offensive forces of the team, capable of scoring a large number of points and executing crucial gameplay tasks.
3. Cluster 2: Players in this cluster have lower values across all indicators. This may suggest a smaller contribution to team statistics or specialized roles requiring fewer statistical inputs. Players in this cluster may perform important supporting functions, contributing to the team in other aspects of the game.

Discussion

The aim of this study was to identify key patterns and trends influencing the performance of volleyball players and teams. The results demonstrated that normalized data allow for the precise identification of key players within teams, except for the *Libero* and *Setter* positions.

Strong correlations were found between major performance indicators, such as *S-Ace* and *S-Ace per Set* (r = 0.983), as well as *P-Total Points* and *A-Total Points* (r = 0.976). Cluster analysis categorized players into three groups based on their contribution to team performance, while regression equations enabled a quantitative assessment of the impact of gameplay actions on overall effectiveness.

An analysis of various studies shows that

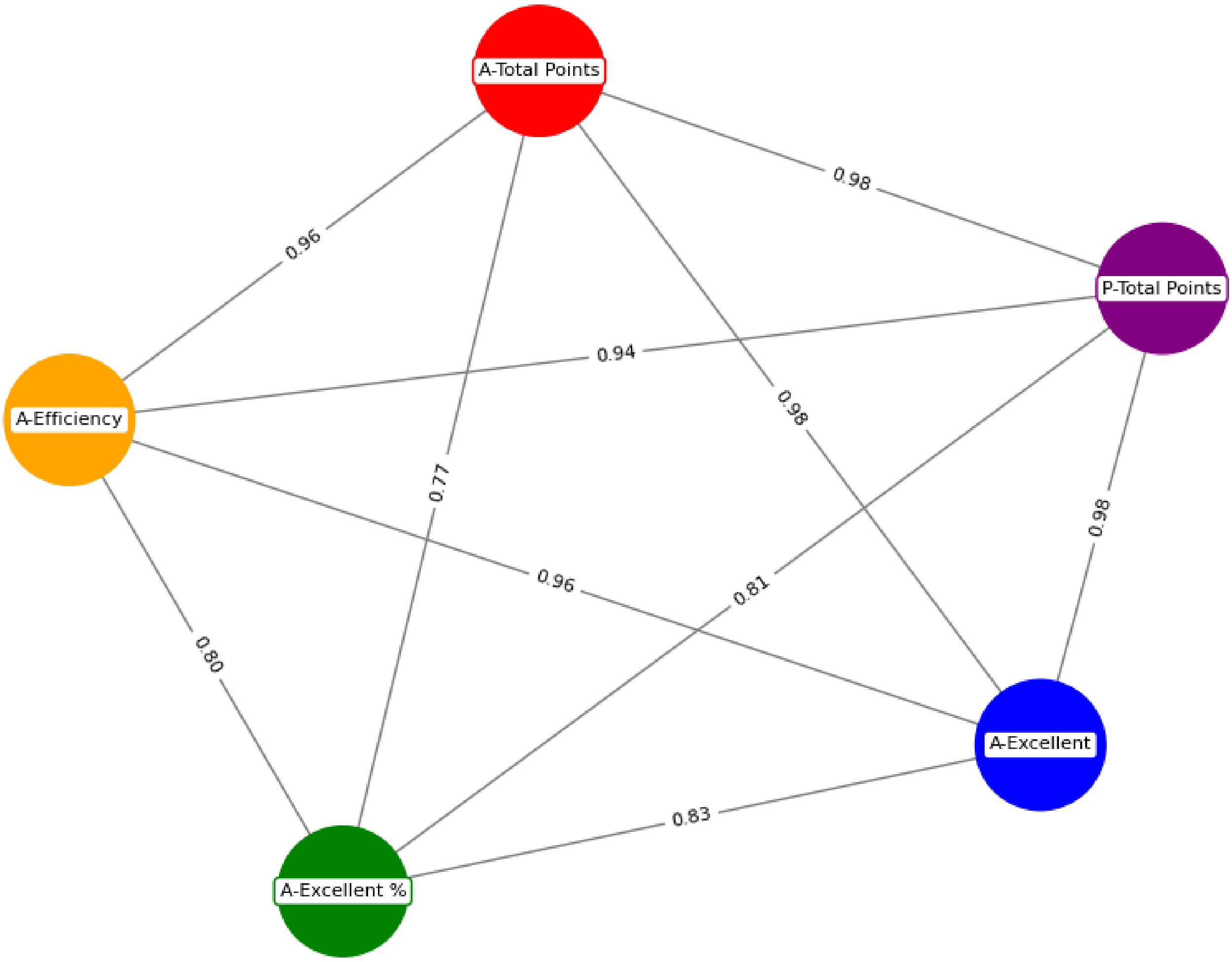

Figure 2. Correlation Network Graph for Opposite

when assessing each player's contribution to their team's success, most works [26, 29, 30] do not use normalized indicators. This leads to difficulties in comparing players with different levels of playing time.

In contrast, our study applies data normalization, ensuring a more objective evaluation of player contributions. This approach allows not only for ranking players within a single team but also for identifying patterns relevant to inter-team comparisons.

The validity of using normalized indicators is supported by several studies across different sports. In the study by Phatak et al. [36], it was shown that incorporating normalized variables contributes to a higher increase in information, improved performance, and enhanced model interpretability. Another study utilized normalized indicators of technical and tactical actions in football based on the effective playing time of each team in each match [37]. In volleyball, this approach enabled the identification of each player's contribution to team success, regardless of the number of sets played or their position [38].

Our study highlights the importance of applying normalized indicators for analyzing players' competitive performance. This aligns with the findings of Silva et al. [7, 8], who emphasized the significance of data systematization for identifying patterns in gameplay actions. Unlike their studies, our research focuses on integrating normalized data to provide a more objective assessment of each player's contribution, independent of the number of matches played.

Furthermore, the results of this study confirm the findings of previous research regarding the importance of normalized indicators in analyzing players' competitive performance. For example, the identified correlations between scoring actions, such as aces and total points, align with the data presented in studies [21, 22]. These works emphasize the importance of accurately assessing statistical metrics to determine players' contributions to overall team success.

Our data also support findings from studies on the development of game phases and scoring methods at different stages of competitions [23]. Player ranking based on normalized data aligns with approaches used in the analysis of matches from women's and men's teams at the Olympics

Table 4. Regression Equations for Different Volleyball Actions по средним значениям для каждого амплуа

Action	Regression Equation	Variables
Setter		
Action	**Regression Equation**	**Variables**
Serve	$y = -3.399 - 0.279x_1 + 0.134x_2 + 1.978x_3 - 1.828x_4$	x_1: Sets; x_2: S-Total Points; x_3: S-Ace; x_4: S-Error; y: S-Efficiency
Reception	$y = 0.270 - 0.056x_1 - 6.313x_2 - 27.558x_3 + 6.813x_4 + 42.128x_5$	x_1: Sets; x_2: R-Total; x_3: R-Error; x_4: R-Negative; x_5: R-Excellent; y: R-Efficiency
Attack	$y = 10.359 + 1.238x_1 - 2.434x_2 - 15.073x_3 - 16.234x_4 + 7.509x_5$	x_1: Sets; x_2: A-Total Points; x_3: A-Error; x_4: A-Blocked; x_5: A-Excellent; y: A-Efficiency
Block	$y = 0.011 + 0.039x_2$	x_2: B-Points; y: B-Points per Set
Middle Blocker		
Action	**Regression Equation**	**Variables**
Serve	$y = -5.218 - 1.360x_1 + 0.572x_2 + 1.241x_3 - 1.979x_4$	x_1: Sets; x_2: S-Total Points; x_3: S-Ace; x_4: S-Error; y: S-Efficiency
Reception	$y = 4.459 - 0.257x_1 - 0.814x_2 - 22.583x_3 - 4.550x_4 + 20.371x_5$	x_1: Sets; x_2: R-Total; x_3: R-Error; x_4: R-Negative; x_5: R-Excellent; y: R-Efficiency
Attack	$y = 16.007 + 1.844x_1 - 1.459x_2 + 0.074x_3 - 5.423x_4 + 2.664x_5$	x_1: Sets; x_2: A-Total Points; x_3: A-Error; x_4: A-Blocked; x_5: A-Excellent; y: A-Efficiency
Block	$y = 0.228 - 0.013x_1 + 0.049x_2$	x_1: Sets; x_2: B-Points; y: B-Points per Set
Opposite		
Action	**Regression Equation**	**Variables**
Serve	$y = -2.832 - 0.868x_1 + 0.252x_2 + 2.068x_3 - 1.430x_4$	x_1: Sets; x_2: S-Total Points; x_3: S-Ace; x_4: S-Error; y: S-Efficiency
Reception	$y = 0.952 - 0.339x_1 + 3.883x_2 - 31.013x_3 - 9.451x_4 + 14.850x_5$	x_1: Sets; x_2: R-Total; x_3: R-Error; x_4: R-Negative; x_5: R-Excellent; y: R-Efficiency
Attack	$y = -2.381 + 1.039x_1 - 0.124x_2 - 0.299x_3 - 0.172x_4 + 0.419x_5$	x_1: Sets; x_2: A-Total Points; x_3: A-Error; x_4: A-Blocked; x_5: A-Excellent; y: A-Efficiency
Block	$y = 0.029 + 0.036x_2$	x_2: B-Points; y: B-Points per Set
Outside Spiker		
Action	**Regression Equation**	**Variables**
Serve	$y = -10.366 - 1.839x_1 + 0.769x_2 + 2.203x_3 - 2.184x_4$	x_1: Sets; x_2: S-Total Points; x_3: S-Ace; x_4: S-Error; y: S-Efficiency
Reception	$y = 0.828 - 0.108x_1 - 0.026x_2 - 0.874x_3 - 0.092x_4 + 0.905x_5$	x_1: Sets; x_2: R-Total; x_3: R-Error; x_4: R-Negative; x_5: R-Excellent; y: R-Efficiency
Attack	$y = -0.052 + 1.152x_1 - 0.248x_2 - 0.071x_3 - 1.324x_4 + 0.843x_5$	x_1: Sets; x_2: A-Total Points; x_3: A-Error; x_4: A-Blocked; x_5: A-Excellent; y: A-Efficiency
Block	$y = 0.049 - 0.004x_1 + 0.051x_2$	x_1: Sets; x_2: B-Points; y: B-Points per Set
Libero		
Action	**Regression Equation**	**Variables**
Reception	$y = -0.916 - 1.225x_1 + 0.501x_2 - 1.943x_3 - 0.701x_4 + 0.487x_5$	x_1: Sets; x_2: R-Total; x_3: R-Error; x_4: R-Negative; x_5: R-Excellent; y: R-Efficiency

Table 5. Regression Equations for Various Volleyball Actions of Each Player in the Ukraine Team

Name	Position	Matches	Sets	P-Total Points	Serve Equation	Reception Equation	Attack Equation	Block Equation
Yurii SEMENIUK	Middle Blocker	8	29	76	$y = 1.133 - 0.954x_1 + 4.002x_2 + 0.760x_3 - 0.732x_4$	$y = 0.186 - 0.657x_1 + 0.221x_2$	$y = 1.396 - 2.382x_1 + 5.625x_2 + 0.231x_3 - 1.055x_4 + 1.422x_5$	$y = 0.228 - 0.384x_1 + 0.881x_2$
Dmytro YANCHUK	Outside Spiker	7	27	93	$y = 0.442 + 0.554x_1 + 3.129x_2 - 0.089x_3 - 0.751x_4$	$y = 1.201 - 1.206x_1 + 5.639x_2 + 0.191x_3 + 0.151x_4$	$y = 1.040 - 0.339x_1 + 4.633x_2 + 1.669x_3 - 0.329x_4 + 2.778x_5$	$y = 0.049 - 0.102x_1 + 0.257x_2$
Yevhenii KISILIUK	Outside Spiker	8	27	84	$y = 0.442 + 0.554x_1 + 3.129x_2 - 0.163x_3 - 0.930x_4$	$y = 1.201 - 1.206x_1 + 6.541x_2 + 0.273x_3 + 0.293x_4$	$y = 1.040 - 0.339x_1 + 4.121x_2 + 1.073x_3 - 0.476x_4 + 2.236x_5$	$y = 0.049 - 0.102x_1 + 0.360x_2$
Serhii YEVSTRATOV	Setter	8	29	16	$y = 0.386 - 0.142x_1 + 3.382x_2 - 0.599x_3 + 0.021x_4$	$y = 0.064 - 0.232x_1$	$y = 0.062 - 0.179x_1 + 0.442x_2 - 0.113x_3 + 0.007x_5$	$y = 0.011 - 0.010x_1 + 0.234x_2$
Maksym DROZD	Middle Blocker	6	20	40	$y = 1.133 - 0.658x_1 + 2.601x_2 + 0.570x_3 - 0.865x_4$	$y = 0.186 - 0.453x_1 + 0.553x_2 - 0.056x_4$	$y = 1.396 - 1.643x_1 + 2.779x_2 + 0.058x_3 + 0.739x_5$	$y = 0.228 - 0.265x_1 + 0.392x_2$
Danylo URYVKIN	Opposite	8	27	76	$y = 0.636 - 0.250x_1 + 2.652x_2 + 0.360x_3 - 0.571x_4$	$y = 0.290 - 0.439x_1$	$y = 1.484 - 2.053x_1 + 8.118x_2 - 0.780x_3 + 2.800x_4 - 1.762x_5$	$y = 0.029 - 0.009x_1 + 0.107x_2$
Mikola RUDNYTSKYI	Middle Blocker	6	12	25	$y = 1.133 - 0.395x_1 + 1.081x_2 + 0.190x_3 - 0.333x_4$	$y = 0.186 - 0.272x_1 + 0.111x_2$	$y = 1.396 - 0.986x_1 + 1.588x_2 + 0.173x_3 - 0.211x_4 + 0.427x_5$	$y = 0.228 - 0.159x_1 + 0.392x_2$
Dmytro DOLGOPOLOV	Setter	8	24	8	$y = 0.386 - 0.117x_1 + 1.127x_2 - 0.075x_3 + 0.010x_4$	$y = 0.064 - 0.192x_1$	$y = 0.062 - 0.148x_1 + 0.354x_2 + 0.011x_5$	$y = 0.011 - 0.008x_1 + 0.156x_2$
Viktor SHAPOVAL	Opposite	5	14	37	$y = 0.636 - 0.130x_1 + 1.520x_2 + 0.599x_3 - 0.303x_4$	$y = 0.290 - 0.228x_1 + 0.256x_2 - 0.922x_3$	$y = 1.484 - 1.064x_1 + 3.532x_2 - 0.780x_3 + 0.875x_4 - 0.631x_5$	$y = 0.029 - 0.005x_1 + 0.107x_2$
Denys VELETSKYI	Middle Blocker	2	5	10	$y = 1.133 - 0.164x_1 + 0.480x_2 - 0.133x_4$	$y = 0.186 - 0.113x_1$	$y = 1.396 - 0.411x_1 + 0.794x_2 + 0.058x_3 + 0.228x_5$	$y = 0.228 - 0.066x_1 + 0.098x_2$
Mykyta LUBAN	Outside Spiker	4	8	16	$y = 0.442 + 0.164x_1 + 0.707x_2 - 0.015x_3 - 0.179x_4$	$y = 1.201 - 0.357x_1 + 2.030x_2 + 0.027x_3 + 0.009x_4$	$y = 1.040 - 0.100x_1 + 0.602x_2 + 0.477x_3 - 0.037x_4 + 0.407x_5$	$y = 0.049 - 0.030x_1 + 0.154x_2$
Dmytro TERYOMENKO	Middle Blocker	1	3	7	$y = 1.133 - 0.099x_1 + 0.360x_2$	$y = 0.186 - 0.068x_1 + 0.995x_2 + 0.057x_3$	$y = 1.396 - 0.246x_1 + 0.926x_2 + 0.116x_3 + 0.171x_5$	$y = 0.228 - 0.040x_1 + 0.049x_2$
Oleksandr KOVAL	Middle Blocker	3	5	7	$y = 1.133 - 0.164x_1 + 0.600x_2 + 0.095x_3 - 0.200x_4$	$y = 0.186 - 0.113x_1$	$y = 1.396 - 0.411x_1 + 0.662x_2 - 0.211x_4 + 0.142x_5$	$y = 0.228 - 0.066x_1 + 0.049x_2$
Oleksandr NALOZHNYI	Outside Spiker	5	8	10	$y = 0.442 + 0.164x_1 + 0.336x_2 - 0.015x_3 - 0.036x_4$	$y = 1.201 - 0.357x_1 + 0.632x_2 + 0.082x_3 + 0.009x_4$	$y = 1.040 - 0.100x_1 + 0.602x_2 + 0.238x_3 - 0.037x_4 + 0.271x_5$	$y = 0.049 - 0.030x_1 + 0.051x_2$
Dmytro SHAPOVAL	Opposite	2	7	6	$y = 0.636 - 0.065x_1 + 0.259x_2 + 0.060x_3 - 0.034x_4$	$y = 0.290 - 0.114x_1$	$y = 1.484 - 0.532x_1 + 0.930x_2 - 0.195x_3 + 0.175x_4 - 0.132x_5$	$y = 0.029 - 0.002x_1$
Dmytro FEDORENKO	Outside Spiker	1	3	0	$y = 0.442 + 0.062x_1$	$y = 1.201 - 0.134x_1 + 0.947x_2 + 0.082x_3 + 0.009x_4$	$y = 1.040 - 0.038x_1$	$y = 0.049 - 0.011x_1$
Oleksandr BOIKO	Libero	6	21	0	$y = 0.011 - 0.023x_1$	$y = 1.144 - 1.542x_1 + 6.501x_2 + 0.307x_3 + 0.189x_4$	$y = 0.048x_2$	$y = 0.000$
Vitaliy SHCHYTKOV	Setter	1	4	0	$y = 0.386 - 0.020x_1$	$y = 0.064 - 0.032x_1 + 0.680x_2$	$y = 0.062 - 0.025x_1$	$y = 0.011 - 0.001x_1$
Yaroslav PAMPUSHKO	Libero	4	14	0	$y = 0.011 - 0.015x_1$	$y = 1.144 - 1.028x_1 + 2.444x_2 + 0.170x_3 + 0.024x_4$	$y = 0.000$	$y = 0.000$

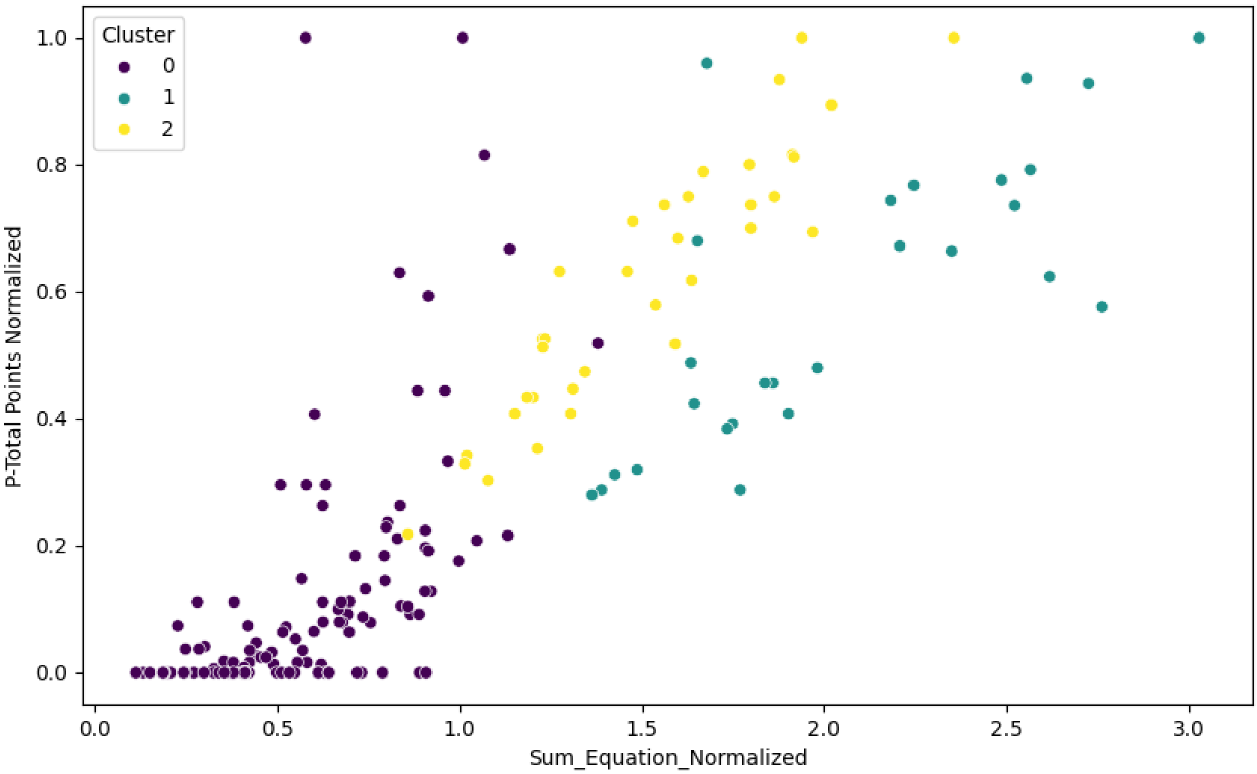

Figure 3. Cluster Analysis Results

and World Championships [32]. Additionally, the clustering of players helps identify groups similar to those defined in studies focused on analyzing attacking actions and player roles [24, 27].

It is particularly important to note that our study has deepened the understanding of the significance of player positions and their roles in competitive performance. For example, the identified high correlation between *P-Total Points* and *A-Total Points* (r = 0.976) for *Middle Blockers* expands on previous findings regarding the key role of these players in attacking actions, as presented in [26].

At the same time, the observed relationship between *S-Ace per Set* and *S-Ace* (r = 0.983) for *Setters* and *Outside Spikers* demonstrates how the effectiveness of gameplay actions varies depending on the player's role, adding further detail to the findings of Echeverría Carlos et al. [29] and Da Silva Luis et al. [30].

Our results differ from most existing studies in that top players are identified while considering the number of matches they participated in, whereas other works [24, 25, 27] disregard this factor. These studies overlook the importance of a player's involvement in more or fewer matches, which may distort performance evaluation.

Additionally, our findings support the conclusions of Fernandez-Echeverria et al. that match analysis can significantly enhance coaching effectiveness [10, 11]. However, our data provide a deeper understanding by applying cluster analysis, which categorizes players based on their contribution to team performance. This approach offers a more precise understanding of player roles, particularly in high-level competitions.

Studies examining the social interactions of players on the court, such as those by Martins et al. [12, 13], are of particular interest. Unlike the focus on interaction networks, our study highlights the significance of traditional indicators, such as *P-Total Points* and *A-Total Points*, in evaluating performance within the context of team strategies.

Overall, our results confirm and expand upon existing research, emphasizing the need for a comprehensive approach to analyzing competitive performance. They also underscore the practical value of normalized indicators for assessing player efficiency within team strategies.

Limitations of the Study

One of the main limitations is the use of data exclusively from teams in the *European Golden League*. This may restrict the generalizability of the findings to other tournaments or age categories. Additionally, the specific roles of *Libero* and *Setter* were not included in the analysis due to their unique characteristics, which should also be considered a limitation.

Future research could focus on expanding the methodology by incorporating data from other tournaments and exploring additional factors such as psychological resilience, game motivation, and team interaction dynamics.

Conclusions

This study highlights the importance of a comprehensive approach to volleyball match analysis, based on normalized data and the integration of various statistical analysis methods. The application of normalization allows for an objective assessment of players' contributions while considering the specifics of their roles and participation levels, leading to a deeper understanding of competitive performance.

The findings emphasize the importance of developing individualized tactical strategies and training programs based on an objective evaluation of gameplay efficiency. The use of such approaches can significantly enhance both individual player performance and overall team effectiveness.

Conflict of interests

The authors declare that there is no conflict of interests.

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