

# Statistical match reports of the 2022 volleyball World Championship in the context of network analysis with Gephi

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## Abstract

**Background and Study Aim** Modern volleyball teams participating in tournaments provide extensive statistical data about their actions. These data are available for analysis and represent a valuable source for assessing the potential and future success of both individual athletes and teams as a whole. In this context, tools such as Gephi become particularly valuable for visualizing and analyzing events at high-level tournaments. Our study aims to create and analyze network models of interaction among men's volleyball teams during the qualifying matches of the 2022 World Championship using the Gephi software.

**Material and Methods** For the research, data were obtained from a volleyball statistics website renowned for its extensive database. The study centered on Group C, comprising the teams: Poland, USA, Mexico, and Bulgaria. Data from six matches were extracted into Microsoft Excel tables and then converted into CSV format. The data from these tables were processed using the PyCharm programming environment and Python code. Visualization and analysis of the data were conducted using Gephi.

**Results** The results of the data processing highlight the professional expertise of the teams. The average values for all primary metrics underscore the teams' proficiency in executing fundamental actions at an elevated level. Eigenvector centrality helps determine the significance of nodes in the graph. The graph's density is 0.601, suggesting a relatively dense network of connections within the team. This indicates that volleyball players frequently engage with one another and share information on the court. Such extensive interaction can lead to enhanced coordination and efficiency in team actions. The parameter  $\epsilon$  has a value of 1.0E-4, denoting high computational precision. The average interaction degree among volleyball players stands at 46.244. This measure denotes the interaction intensity among team members, hinting at the overall court activity. The modularity measure is 0.483, which signals the structural organization of the graph rooted in modularity. The graph comprises 5 modular communities, hinting at shared characteristics and cohesion among players within these groups. The HITS (Hyperlink-Induced Topic Search) metric assesses the node significance in the graph in terms of hubs and authorities. High HITS values pinpoint pivotal players acting as hubs, signifying their numerous connections with fellow teammates. Such players are crucial for facilitating information flow and coordination within the squad.

**Conclusions** Utilizing statistical match reports in volleyball, combined with the Gephi software, offers a deeper insight into the dynamics of player interactions. This aids in pinpointing key players, refining team strategies, and enhancing court coordination. Coaches are advised to leverage these tools for an in-depth evaluation of gameplay instances and to make informed decisions. Network analysis methodologies might soon be indispensable tools in the contemporary coaching toolkit.

**Keywords:** Gephi, volleyball, statistics, network, model

## Introduction

Sports analytics is becoming increasingly crucial in deciphering team dynamics and evaluating the performance of top-tier volleyball players and teams. By delving into statistical match reports in volleyball using network analysis, one can unearth concealed patterns and relationships, leading to improved coaching tactics and a more profound comprehension of the game.

Several researches [1, 2, 3] have pinpointed numerous prospects for implementing network analysis in the realm of sports. Employing network

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models to assess sports performance enables the identification of shifts in sports strategies and lays the groundwork for understanding sports-related social networks from an ecological standpoint [4, 5, 6]. Concurrently, other studies hone in on discerning the preferences and engagements of fans on social media platforms [7, 8].

When evaluating network models in team sports, certain studies stand out. Korte et al. [9], for example, undertook a comparative study of network models across diverse team sports. The authors contend that this methodology offers a more profound insight into the significance of various tactical positions within each sport. In the research conducted by

Borges et al. [10], handball is the focal sport, with an emphasis on analyzing the distribution of players' positions during offensive maneuvers.

Several studies adopt a technical and algorithmic perspective when analyzing sports data [11, 12]. The authors emphasize the creation and utilization of novel methods aimed at optimizing interaction and leadership within volleyball squads. In research by Laporta et al. [13], analysis covered seven matches from the 2020 Brazilian Women's Cup playoffs. They discerned a recurring sequence of volleyball maneuvers, classifying them into six distinct gameplay complexes. Each of these complexes showcased its unique dynamics, highlighting the efficacy of network analysis in unraveling the intricate nature of volleyball encounters.

Rocha et al. [14] undertook an examination of the attacking phase among men's volleyball teams during the 2018 World Volleyball Championship. The observed variability both within and among teams highlighted the imperative of recognizing each team's distinct traits and the necessity of adopting diverse strategies towards gameplay and achievement. In separate studies, network analysis was employed to pinpoint the paramount parameters governing player interactions in volleyball [15, 16], with some incorporating the use of Gephi software [17].

The findings underscore the efficacy of deploying network analysis techniques within the realm of volleyball statistics. Such evaluations play a pivotal role in augmenting the existing knowledge in volleyball analytics. Through network analysis, obscured patterns and connections in the performance metrics of premier players and teams can be revealed. Consequently, volleyball match statistical reports can be depicted as networks. The configuration of such networks mirrors the rivalry among players occupying identical roles. Herein, a team's triumph hinges on the collective efforts of players across all positions. Given this backdrop, the objective of this research is to dissect and illustrate the performance metrics of elite volleyball players and squads utilizing the Gephi software.

## Materials and Methods

### *Data Sources*

Multiple volleyball statistics websites were considered for data collection. The preference was given to a site offering the most exhaustive statistical information on the 2022 Men's World Volleyball Championship [18]. Preliminary matches from Group C, featuring 4 teams – Poland, USA, Mexico, and Bulgaria – were chosen. Each team consisted of 14 players, identified by their positions and jersey numbers.

### *Procedure*

### *Data Extraction*

Data from all six matches was harvested from the [championat.com] website and imported into Excel. The site offers a total of 12 tables showcasing performance metrics for every player. For each match, metrics are laid out in two tables for each participating team. Additionally, comprehensive team performance metrics for each game are also available.

The data tables corresponding to each team were then transitioned into CSV format.

### *Data Preprocessing*

For a thorough analysis of the data from all matches, it was imperative to depict them as a network prior to undertaking the analysis. The Gephi 0.10 for Mac software [19] was employed for this purpose. Two CSV files were readied: one for nodes and another for edges. The data transformation unfolded in the subsequent manner.

#### *Step 1. Normalization Method*

Performance metrics in statistical match reports are influenced by multiple factors such as the athletes' proficiency, the collective team performance, and more. Consequently, drawing parallels between a specific metric from one game to that in another might not always provide accurate insights. Given this scenario, the normalization technique ensured an apt comparison of congruent team performance metrics.

#### *Objective of the Method*

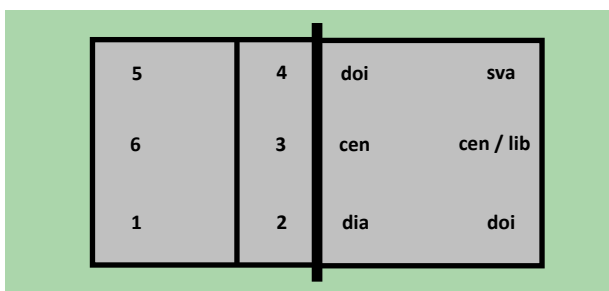
The objective of this method is to standardize the metrics from all matches to fit within a specific range, namely 0 to 1, via a linear transformation. This adjustment can, for instance, be executed in Excel. We've devised a specialized converter, articulated through HTML code, to process CSV files. Consequently, post Min-Max normalization, all game metrics will be confined within the 0 to 1 spectrum. It's paramount to highlight that certain metrics, such as Serve aces, Attack points, and Block points, will possess the most significant values (or weights). If these metric values initially lay within the specified range, the normalization process wouldn't alter them. Subsequent to this, all data across the 12 tables get supplanted with normalized figures. For illustrative purposes, Tables 1 and 2 display normalized metrics for the Poland vs. USA match. Concurrently, Table 3 exhibits normalized performance metrics for each squad in every game, whereas Table 4 illustrates normalized metrics for teams throughout the six matches.

*Step 2.* An interaction framework for players of identical positions must be established. The conventional layout for categorizing volleyball players based on their position is depicted in Figure 1.

**Table 1.** Normalized performance indicators of the Polish team in the match against the United States

ID	Label	Role	Country	Total points	Serve total	Serve aces	Receiving total	Attack total	Attack Points	Attack %total	Block points
1	PLplayer3lib	lib	Poland	0.01676	0.00000	0.01500	0.00000	0.00000	0.00088	0.00000	0.00088
2	PLplayer5dia	dia	Poland	0.06719	0.01333	0.01500	0.00000	0.02000	0.01765	0.00033	0.00088
3	PLplayer6dia	dia	Poland	0.72017	0.15333	0.03529	0.01333	0.20000	0.30000	0.00057	0.01765
4	PLplayer7cen	cen	Poland	0.01676	0.00000	0.01500	0.00000	0.00000	0.00088	0.00000	0.00088
5	PLplayer12sva	sva	Poland	0.02343	0.00000	0.01500	0.00667	0.00000	0.00088	0.00000	0.00088
6	PLplayer14doi	doi	Poland	0.33777	0.02667	0.01500	0.10000	0.10667	0.08824	0.00031	0.00088
7	PLplayer15cen	cen	Poland	0.23058	0.08667	0.01500	0.00000	0.04000	0.07059	0.00067	0.01765
8	PLplayer16doi	doi	Poland	0.55012	0.10667	0.03529	0.12000	0.09333	0.17647	0.00071	0.01765
9	PLplayer17lib	lib	Poland	0.11676	0.00000	0.01500	0.10000	0.00000	0.00088	0.00000	0.00088
10	PLplayer18doi	doi	Poland	0.01676	0.00000	0.01500	0.00000	0.00000	0.00088	0.00000	0.00088
11	PLplayer19sva	sva	Poland	0.11530	0.08000	0.01765	0.00000	0.00000	0.00000	0.00000	0.01765
12	PLplayer20cen	cen	Poland	0.40135	0.11333	0.01765	0.00000	0.09333	0.14118	0.00057	0.03529
13	PLplayer21doi	doi	Poland	0.30910	0.04667	0.01500	0.08000	0.06000	0.10588	0.00067	0.00088
14	PLplayer72cen	cen	Poland	0.01676	0.00000	0.01500	0.00000	0.00000	0.00088	0.00000	0.00088
Mean				0.20992	0.04476	0.01828	0.03	0.04381	0.06466	0.00027	0.00813
Std Deviation				0.22555	0.0531	0.00727	0.04676	0.06047	0.09065	0.0003	0.011

NOTE: ID - Player’s serial number or identifier; Label - Player’s name or alternate label; Role - Player’s designated role or position on the team; Country - Player’s representing country; Total Points - Cumulative number of points scored by the player; Serve Total - Total number of serves by the player; Serve Aces - Number of serves that resulted in aces; Receiving Total - Total number of receptions by the player; Attack Total - Total number of attacks initiated by the player; Attack Points - Number of points scored through attacks; Attack %total - Percentage representation of successful attacks; Block Points - Number of points scored through blocks.



**Figure 1.** Six primary volleyball positions based on starting zone designations: Zone 1: Setter (sva); Zone 2: Right-side hitter - HitterR (doi); Zone 3: Middle blocker (cen); Zone 4: Opposite (dia); Zone 5: Outside hitter - HitterO (doi); Zone 6: Central blocker - Middle blocker/Libero (cen or lib). Note: Conditional abbreviations are provided in parentheses.

For the normalized data from the Poland-USA match (as presented in Tables 1 and 2), we have

pinpointed the jersey numbers corresponding to the “doi” position as follows:

- Poland Team: Athlete Numbers (from Table 1): 6, 8, 10, 13;
- USA Team: Athlete Numbers (from Table 2): 15, 16, 19, 23, 28.

A new Table 5 enumerates the sequential athlete numbers for both teams. Similar structures have been curated for the other games, covering all six matches in total.

Constructing a diagram for the potential interactions among all players in the “doi” position. We postulate that performance metrics of a player in the “doi” role from the Poland team are juxtaposed with metrics of players occupying the identical “doi” role in the USA team. The hypothetical interaction diagram for all athletes in the “doi” position during the Poland-USA game is as follows (Note: Each numeral duo is delineated with a “hyphen”; the premier numeral corresponds to the player from

**Table 2.** Normalized performance indicators of the U.S. team in the match against the Polish team

ID	Label	Role	Country	Total points	Serve total	Serve aces	Receiving total	Attack total	Attack Points	Attack %total	Block points
15	USAplayer1doi	doi	USA	0.27703	0.04375	0.01500	0.03125	0.10000	0.08571	0.00025	0.00107
16	USAplayer2doi	doi	USA	0.70682	0.07500	0.02143	0.20000	0.13125	0.25714	0.00057	0.02143
17	USAplayer4cen	cen	USA	0.19230	0.06875	0.02143	0.00000	0.03750	0.04286	0.00033	0.02143
18	USAplayer5dia	dia	USA	0.21777	0.03750	0.02143	0.00000	0.05000	0.10714	0.00063	0.00107
19	USAplayer8doi	doi	USA	0.77459	0.08750	0.02143	0.16250	0.18125	0.30000	0.00048	0.02143
20	USAplayer11sva	sva	USA	0.01714	0.00000	0.01500	0.00000	0.00000	0.00107	0.00000	0.00107
21	USAplayer15dia	dia	USA	0.08143	0.03750	0.04286	0.00000	0.00000	0.00000	0.00000	0.00107
22	USAplayer16sva	sva	USA	0.14493	0.09375	0.02143	0.00000	0.00625	0.02143	0.00100	0.00107
23	USAplayer18doi	doi	USA	0.01714	0.00000	0.01500	0.00000	0.00000	0.00107	0.00000	0.00107
24	USAplayer19cen	cen	USA	0.10368	0.03125	0.01500	0.00000	0.01250	0.04286	0.00100	0.00107
25	USAplayer20cen	cen	USA	0.26568	0.05000	0.02143	0.00625	0.03750	0.06429	0.00050	0.08571
26	USAplayer21lib	lib	USA	0.01714	0.00000	0.01500	0.00000	0.00000	0.00107	0.00000	0.00107
27	USAplayer22lib	lib	USA	0.08589	0.00000	0.01500	0.06875	0.00000	0.00107	0.00000	0.00107
28	USAplayer23doi	doi	USA	0.01714	0.00000	0.01500	0.00000	0.00000	0.00107	0.00000	0.00107
Mean				0.20848	0.0375	0.01975	0.03348	0.03973	0.0662	0.00034	0.01148
Std Deviation				0.24334	0.03432	0.00738	0.0659	0.05784	0.09682	0.00037	0.02302

NOTE. Similarly to Table 1.

**Table 3.** Normalized total performance metrics for each team in every match

Game Number	Country	Total points	Serve total	Serve aces	Receiving total	Attack total	Attack points	Attack %total	Block points	Result sets
1	Poland	0.64447	0.14186	0.02459	0.06977	0.13721	0.24590	0.00055	0.02459	3
1	USA	0.61748	0.11860	0.03443	0.09767	0.13023	0.20656	0.00048	0.02951	1
2	Poland	0.39945	0.09302	0.01475	0.01163	0.05814	0.16721	0.00060	0.05410	3
2	MEX	0.32180	0.04419	0.00984	0.05116	0.08837	0.12295	0.00037	0.00492	0
3	Poland	0.47627	0.09535	0.05902	0.02093	0.07907	0.18689	0.00058	0.03443	3
3	Bulgaria	0.37256	0.04651	0.00984	0.07442	0.07907	0.13770	0.00043	0.02459	0
4	USA	0.35454	0.07674	0.01475	0.00000	0.05581	0.18689	0.00068	0.01967	3
4	Mexico	0.30147	0.02791	0.00000	0.05581	0.06977	0.13279	0.00044	0.01475	0
5	USA	0.50480	0.09767	0.02951	0.04419	0.11163	0.18689	0.00048	0.03443	3
5	Bulgaria	0.50084	0.08140	0.00984	0.07442	0.12326	0.18197	0.00044	0.02951	0
6	Mexico	0.80468	0.17442	0.04426	0.11860	0.17674	0.26557	0.00050	0.02459	3
6	Bulgaria	0.87840	0.17442	0.02459	0.13953	0.20000	0.30000	0.00052	0.03934	2
Mean		0.51473	0.09767	0.02295	0.06318	0.10911	0.19344	0.00051	0.02787	
Std Deviation		0.18765	0.04791	0.01682	0.04197	0.04622	0.05409	9E-05	0.01247	

NOTE. Similarly to Table 1.

**Table 4.** Normalized total performance metrics for teams in the 6 matches

Country team	Total points	Serve total	Serve aces	Receiving total	Attack total	Attack points	Attack %total	Block points	Sets	Winning
Poland	1.52019	0.33023	0.09836	0.10233	0.27442	0.6	0.00173	0.11312	9	3
USA	1.47682	0.29301	0.07869	0.14186	0.29767	0.58034	0.00164	0.08361	7	2
Mexico	1.42795	0.24652	0.0541	0.22557	0.33488	0.52131	0.00131	0.04426	3	1
Bulgaria	1.7518	0.30233	0.04427	0.28837	0.40233	0.61967	0.00139	0.09344	2	0

NOTE. Similar to Table 1. Sets - sets won; Winning - matches won.

the Poland squad, whereas the subsequent numeral relates to the player from the USA squad:

6-15; 6-16; 6-19; 6-23; 6-28; 8-15; 8-16; 8-19; 8-23; 8-28; 10-15; 10-16; 10-19; 10-23; 10-28; 13-15; 13-16; 13-19; 13-23; 13-28

**Table 5.** Scheme of team ordinal numbers.

Team 1	Team 2	Team 3	Team 4
POL	USA	MEX	BUL
1	15	29	43
2	16	30	44
3	17	31	45
4	18	32	46
5	19	33	47
6	20	34	48
7	21	35	49
8	22	36	50
9	23	37	51
10	24	38	52
11	25	39	53
12	26	40	54
13	27	41	55
14	28	42	56

A new Table 6 is formulated, where the athlete numbers in the diagram are replaced with their performance metrics from Tables 1 and 2. This table is then converted into a CSV format.

Equivalent data is acquired for the remaining five games. The culmination of processing all six games in this manner is encapsulated in a solitary CSV document. This final CSV file serves as the “edges” input for the Gephi software.

Data conversion from one format to another can be facilitated using software like Excel. Special converters, represented by HTML codes, have been developed for processing CSV files. The procedure is outlined below:

- Import the table in CSV format, such as Table 1 (CSV format).
- Manipulate the data from Table 1.
- Output the results in a fresh CSV file.

**Table 6.** Scheme of conditional interaction of athletes (for example, 2 athletes: numbers 6-15) of the same position (“doi”) in the match between Poland and the USA teams.

Source	Target	Weight	Attribute	Game_N
6	15	0.33777	Total points	1_POL-USA
6	15	0.02667	Serve total	1_POL-USA
6	15	0.01500	Serve aces	1_POL-USA
6	15	0.10000	Receiving total	1_POL-USA
6	15	0.10667	Attack total	1_POL-USA
6	15	0.08824	Attack points	1_POL-USA
6	15	0.00031	Attack %total	1_POL-USA
6	15	0.00088	Block points	1_POL-USA
15	6	0.27703	Total points	1_USA-POL
15	6	0.04375	Serve total	1_USA-POL
15	6	0.01500	Serve aces	1_USA-POL
15	6	0.03125	Receiving total	1_USA-POL
15	6	0.10000	Attack total	1_USA-POL
15	6	0.08571	Attack points	1_USA-POL
15	6	0.00025	Attack %total	1_USA-POL
15	6	0.00107	Block points	1_USA-POL

NOTE. Source - athlete’s number; Target - athlete’s number; Weight - indicator; Attribute - athlete’s action type; Game\_N - match number.

Employing this method streamlines the task of transforming data from the tables of all six matches into the concluding file, which is used as the “edges” input for the Gephi software.

The subsequent step involves crafting a “nodes” table for additional processing in the Gephi software (Table 7). This table comprises five columns: ID, Label, Role, and Country. The cell data are sourced from each team’s tables. There are a collective 56

ordinal numbers for athletes (column ID). Attributes and labels for the four teams (ID numbers 57-60) and six matches (ID numbers 61-78) are appended to this information.

**Table 7.** Characteristics and Symbols of Athletes, Teams, and Matches («Nodes»)

ID	Label	Role	Country
1	POL3lib	lib	Poland
...	...	...	...
56	BUL23doi	doi	Bulgaria
57	POL	Poland	team1
58	USA	USA	team2
59	MEX	Mexico	team3
60	BUL	Bulgaria	team4
61	1_POL-USA	POL-USA	Match1
62	1_USA-POL	USA-POL	Match1
...	...	...	...
72	6_BUL-MEX	BUL-MEX	Match6
73	Match1	POL-USA	POLUSA
...	...	...	...
78	Match6	MEX-BUL	MEXBUL

To interpret the gathered data (Tables 6, 7), the Gephi software is utilized to construct a graph. After importing both the “Nodes” and “Edges” files into Gephi, a corresponding graph is generated (Figure 2, 3). Distinct communities or groups of volleyball players have been identified (Figure 4, 5, 6).

Figures 2-6 represent the visualization of team and volleyball player interactions. Various manipulations with the graph allow highlighting: individual countries (Figure 2) and volleyball player positions (Figure 3); communities or groups of volleyball players (Figure 4). They also allow highlighting and calculating metrics (Figure 5, 6) and presenting the results of the “Statistics” section in the form of graphs (Figure 7). As an example, Figure 7 displays the “Eigenvector Centrality Report “ statistics with comments. The “Eigenvector Centrality Report “ is also presented as an html file. Eigenvector centrality: measures the importance of a node based on the importance of its neighbors. Nodes connected to other important nodes are considered more important in the network.

#### *Digital Data and Data Analysis*

Data from four teams were selected for analysis: Poland, USA, Mexico, and Bulgaria. Each team was represented by 14 athletes.

The results of athletes’ actions in the 6 matches of Group C are presented in 12 tables (only 2 tables are shown as an example). Based on the data from these tables, 2 resulting tables were prepared for the Gephi program. The size of the “Nodes” table is 4x78 cells, and the size of the “Edges” table is 5x4553 cells. Two additional tables contain the summary statistics of the actions of all 56 athletes and 4 teams in all 6 matches (Table 3, 4).

#### *Statistical Analysis*

The data tables were processed using the PyCharm programming environment with Python code. Calculations were made for mean and standard deviation.

## **Results**

Tables 1-3 represent the normalized performance indicators of the teams in the Poland-USA match. The obtained results show that there were no statistically significant differences between the teams for all the metrics considered (Table 3, 4).

The data processing results (Table 3) confirm the high professional skills of the teams. The average values for all key metrics (Total points, Serve total, Serve aces, Receiving total, Attack total, Attack points, Attack % total, Block points) indicate the teams’ ability to perform fundamental actions at a high level. Although there is a small standard deviation, it suggests some variability in the results, which may be related to changes in the game strategy. The overall impression of the teams’ level can be characterized as high professionalism and the ability to perform various actions in volleyball. All four teams demonstrated good preparation and teamwork. These statistical data emphasize that the matches between these teams were intense and of high quality, indicating matches at the highest level.

To analyze the structure of the volleyball action graph involving players with the same positions and teams, the following key metrics were obtained:

#### *Graph Metrics*

1.1. Average Clustering Coefficient: The average clustering coefficient was 0.515, indicating a moderate degree of clustering in the graph. This suggests the presence of some structure in the interactions among volleyball players.

1.2. Eigenvale Centrality: The sum of changes in the algorithm was 0.0118, which may indicate the presence of key players among the volleyball players who have a significant influence on the team.

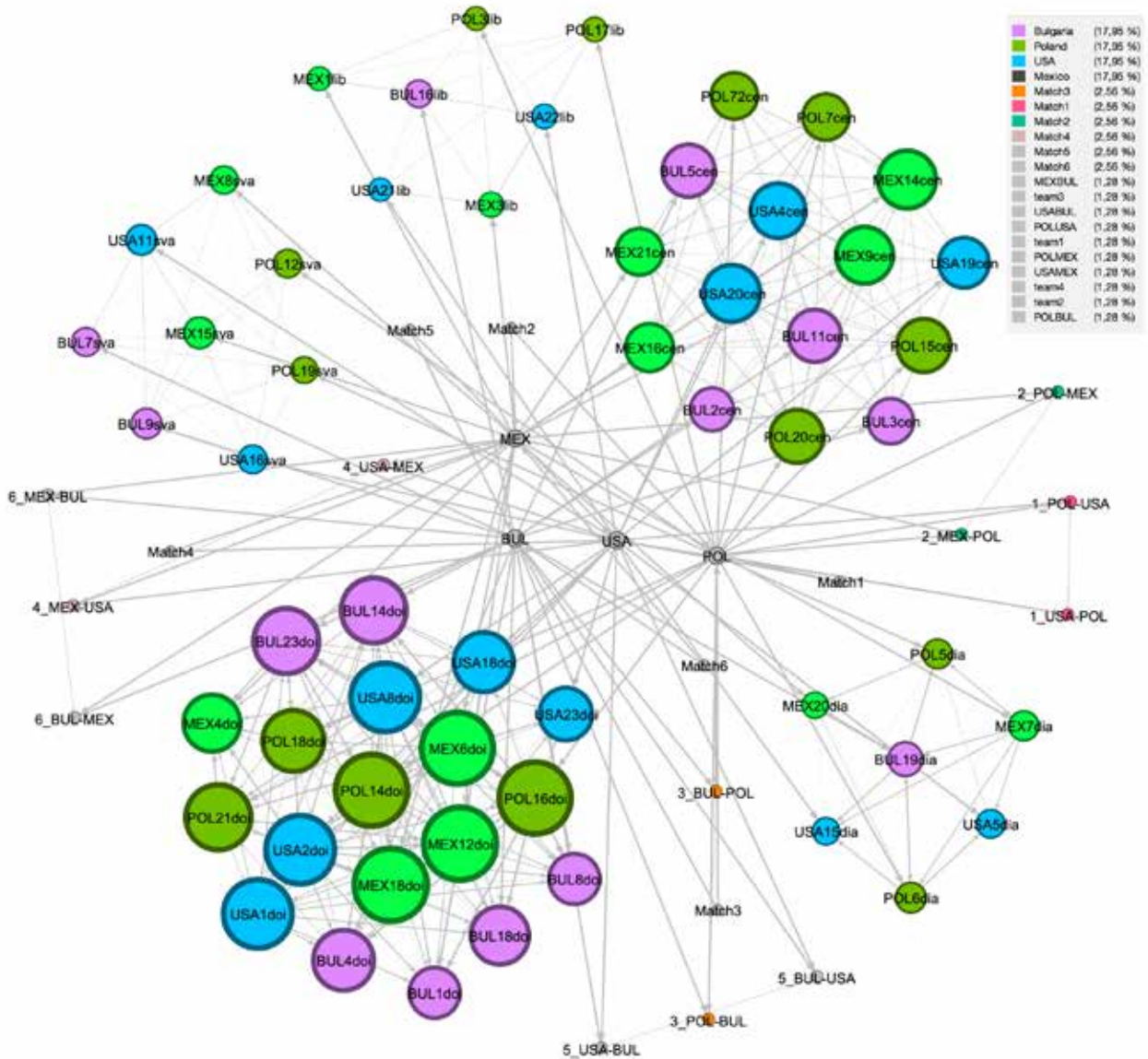
#### 1.3. Graph Structure Metrics:

- Graph Diameter: 3.
- Graph Radius: 1.
- Average Path Length: 1.638.
- Graph Density: 0.601.

The high density of the graph indicates intense interactions among volleyball players and active information exchange, which contributes to better coordination and effectiveness of team actions.

1.4. HITS Metric (Hyperlink-Induced Topic Search): The parameter  $\epsilon$  value of 1.0E-4 indicates high calculation accuracy. Analyzing the HITS metric can help identify the roles of volleyball players within the team, determine hubs (players with numerous connections), and leaders (players influencing interactions).

#### *2. Weighted Metrics*



**Figure 2.** Match graph involving teams from Poland (POL), USA (USA), Mexico (MEX), and Bulgaria (BUL) (distribution by countries).

2.1. Average Degree: The average degree of interaction among volleyball players was 46.244, reflecting the intensity of interactions among players within the team.

2.2. Average Weighted Degree: The average weighted degree was 4.885 and takes into account the weights of connections, which is useful for determining the intensity of specific types of interactions.

### 3. Algorithm Results

3.1. PageRank: The PageRank algorithm helped determine the importance of nodes in the graph, revealing the significance of each volleyball player in the team in terms of their influence on interactions.

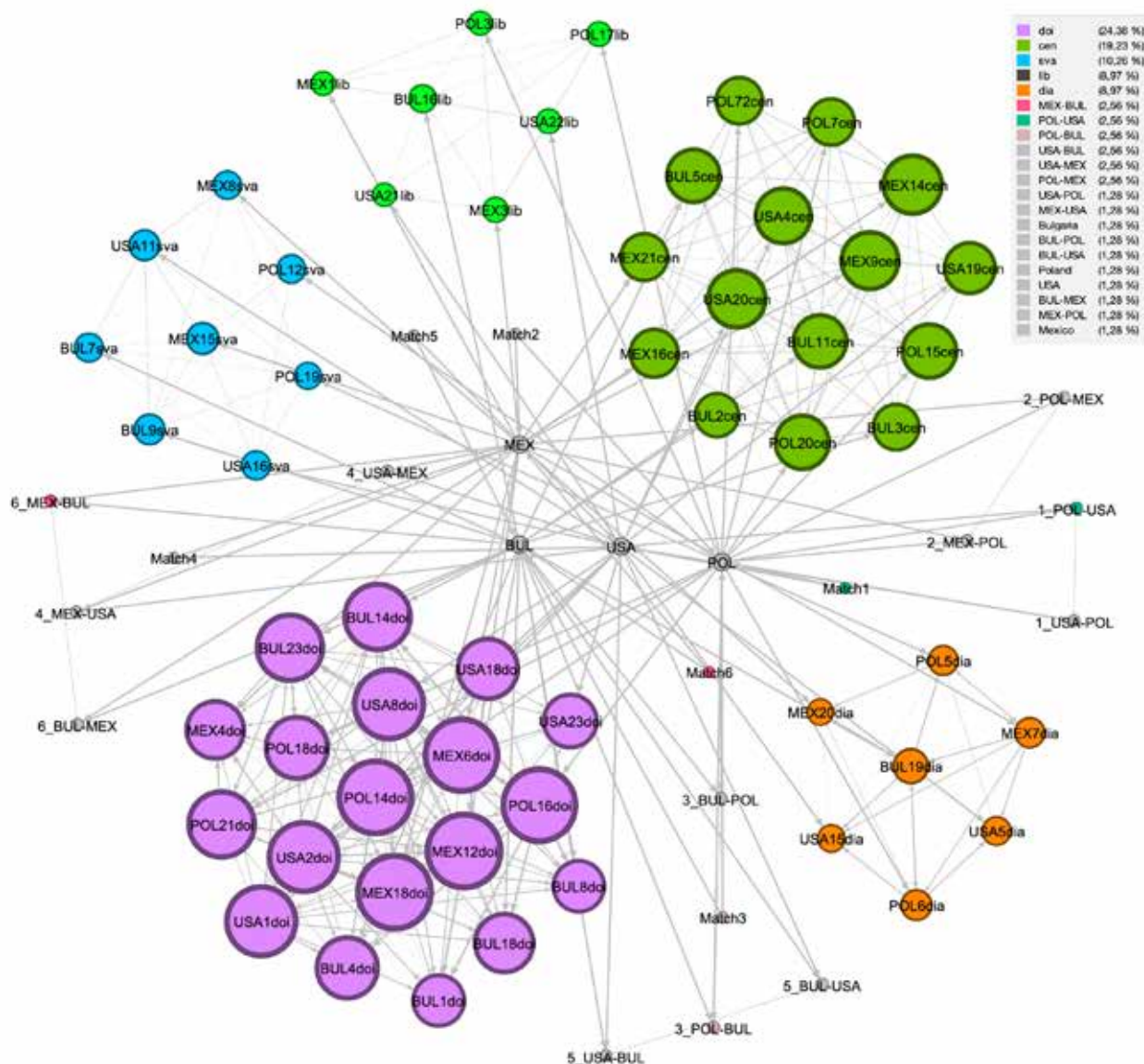
3.2. Modularity: The modularity value was 0.483, indicating the structural organization of the graph based on modularity and the division of the graph

into 4 communities. This suggests similarities and cohesion among volleyball players within these groups.

Analyzing the metrics and graph parameters allows us to gain a deeper understanding of the structure and interactions among volleyball players in the team. Special attention should be given to the HITS metric, which helps identify key players influencing the team. The combination of a high graph density and high HITS metric values underscores the intensity and importance of interactions among volleyball players in the team.

These results can serve as a starting point for further research and strategic analysis aimed at improving the effectiveness of team actions and achieving success on the volleyball court.

*Results for the 'Filters' section in the Gephi program.*



**Figure 3.** Match graph involving teams from Poland (POL), USA (USA), Mexico (MEX), and Bulgaria (BUL) (distribution by volleyball player positions).

#### *'Ego Network' Filter*

The graph represents interactions among 56 volleyball players. In the graph, five of the most characteristic player groups were identified, organized according to their positions (see screenshot\_amplua.png). For the convenience of identifying players in the groups, symbolic notations were used. The first three characters represent the player's country (e.g., POL for Poland, USA for the United States, MEX for Mexico, BUL for Bulgaria), followed by the player's number, and the last three characters indicate the player's position (e.g., doi for outside (right side) hitter, cen for middle blocker, dia for opposite, sva for setter, lib for libero).

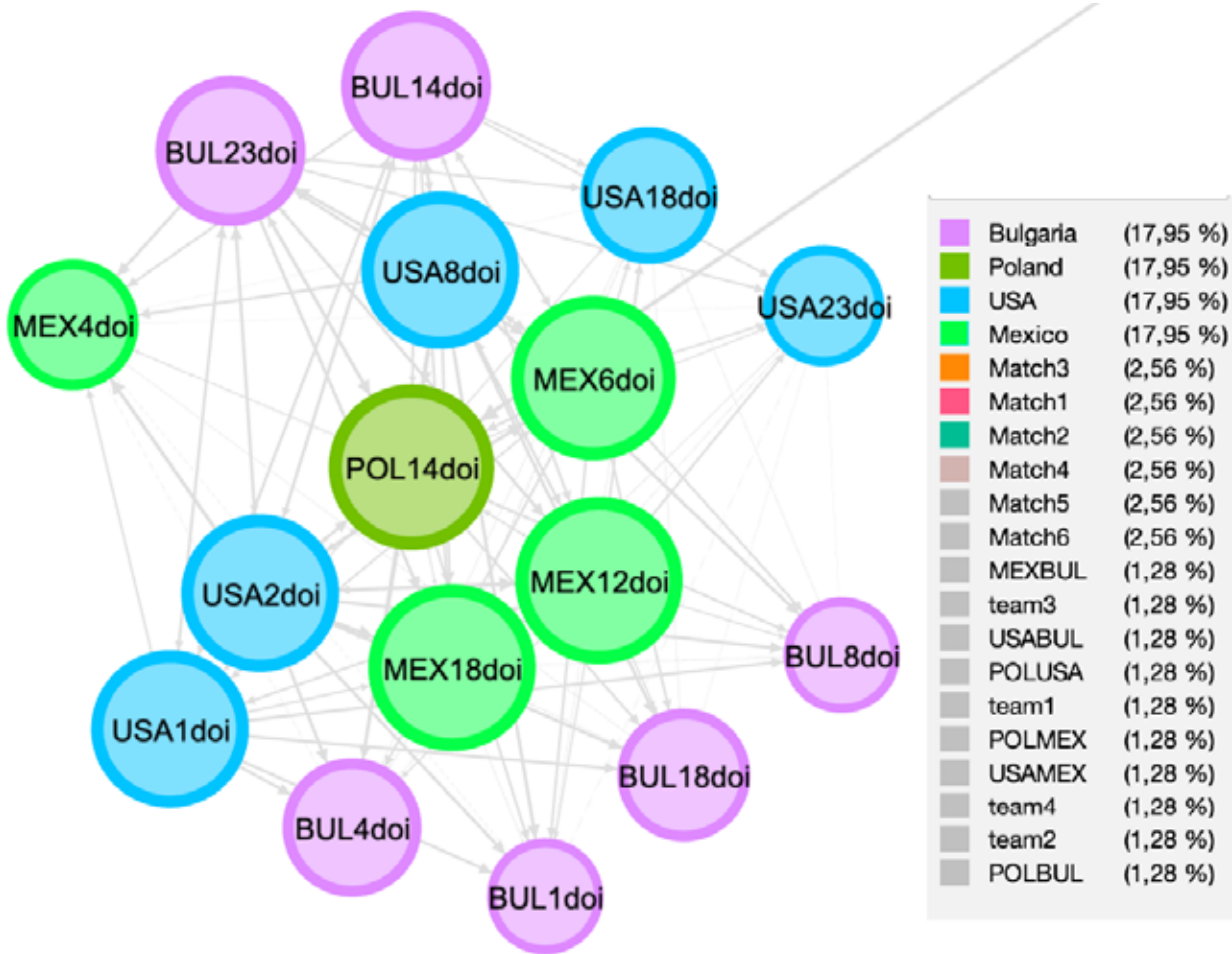
In each of these groups, volleyball players representing different countries were highlighted with different colors (Figure 2). This allows for an easy visualization of the diversity of countries

within the group.

For a deeper analysis of player interactions and the identification of key players, the 'Ego Network' filter was used. This filter allows you to extract the network around a specific node (ego) selected as the central node. In our case, as an example, the network around the node 'POL14doi' with an ID of 6 was extracted (Figure 4). Similarly, you can analyze and extract networks around other nodes. This enables a more detailed exploration of the relationships and roles of individual volleyball players within the team.

#### *'Power Range' Filter*

Using the 'Power Range' filter, the nodes in the graph were distributed into four quartiles based on their degree of mutual power. Each of the quartiles has its own range of values. This allows for the classification of volleyball players based on the



**Figure 4.** Community (group) graph 'doi'

intensity of their interactions within the team.

*Quartile 4:*

In this quartile, volleyball players whose degree of mutual power is the lowest (not exceeding 50) are represented. These players may have more limited connections with other team members.

*Quartile 3:*

In this quartile, volleyball players with a higher degree of mutual power, ranging from 51 to 100, are located. This quartile includes all players with the roles 'dia - opposite' and 'sva - setter', indicating their more active interaction within the team.

*Quartile 2 (Figure 5):*

In this quartile, there are players with a higher degree of mutual power, within the range of 101 to 150. This quartile includes:

- 3 athletes with the role 'doi - opposite' (BUL1doi, BUL8doi, USA23doi).

- 9 athletes with the role 'cen - middle blocker' (BUL2cen, BUL3cen, BUL5cen, BUL11cen, USA19cen, MEX18cen, MEX21cen, POL7cen, POL72cen). This group of volleyball players has a higher degree of mutual power, indicating their significant role within the team.

*Quartile 1 (Figure 6):*

- In this quartile, there are players with the

highest degree of mutual power, within the range of 151 to 221. This quartile includes:

- 16 athletes with the role 'doi - hitter' (excluding athletes BUL1doi, BUL8doi, USA23doi).

- 2 athletes each from the teams of Poland (POL15cen, POL20cen), USA (USA4cen, USA20cen), and Mexico (MEX9cen, MEX14cen). These volleyball players exhibit a high degree of mutual power and can play a significant role in their respective teams.

This quartile distribution helps us better understand the structure of interactions among volleyball players and identify key players with a high degree of interaction within the team.

**Discussion**

In recent years, the active use of sports analytics for network analysis has proven its significance in various team sports: basketball [20, 21], football [22, 23], rugby [24], hockey [25], and volleyball [14]. Based on the research results, important aspects and conclusions have been identified during the analysis of statistical reports on matches using network analysis.

The primary goal of network analysis is to uncover hidden patterns and relationships within

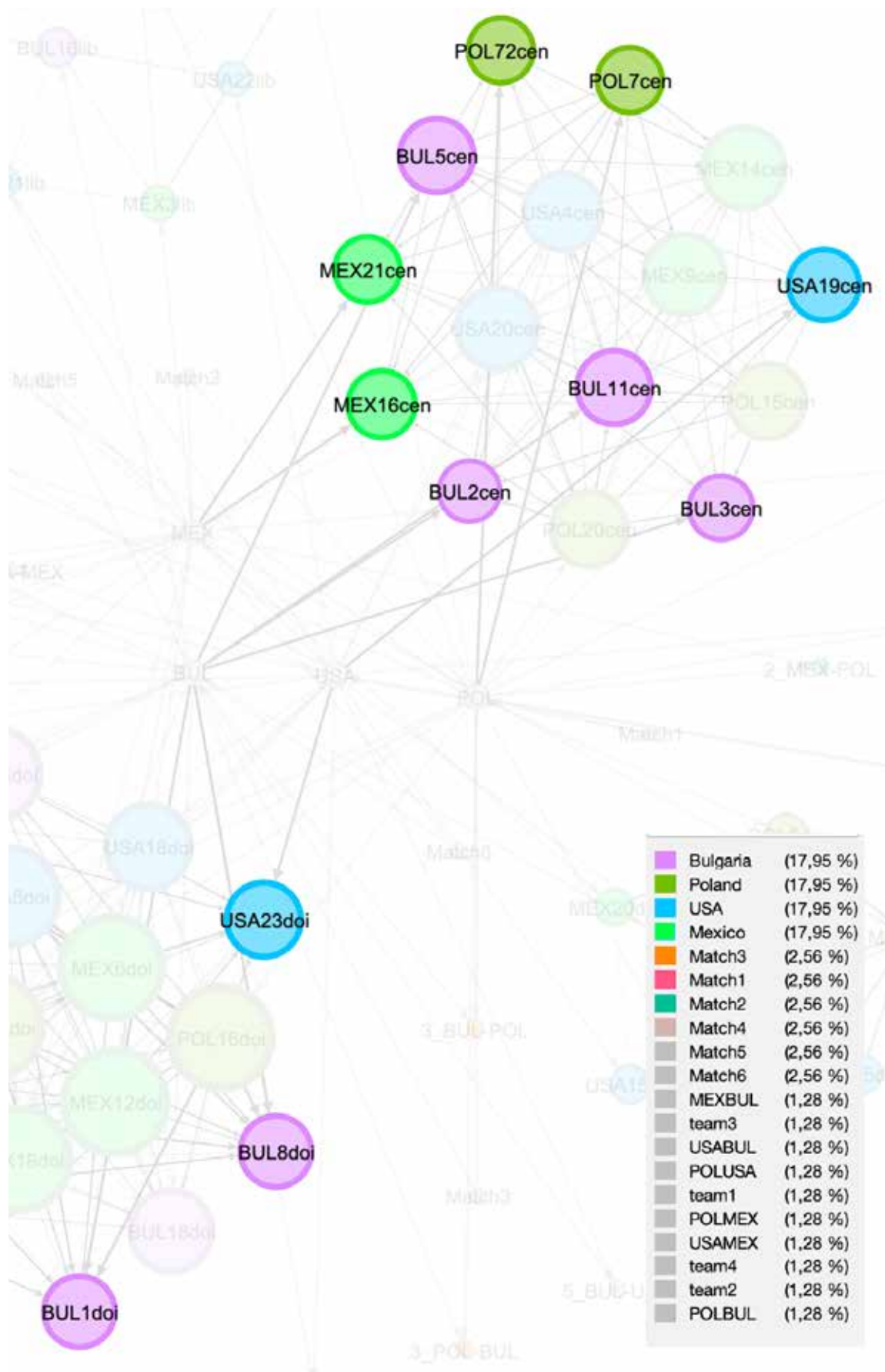
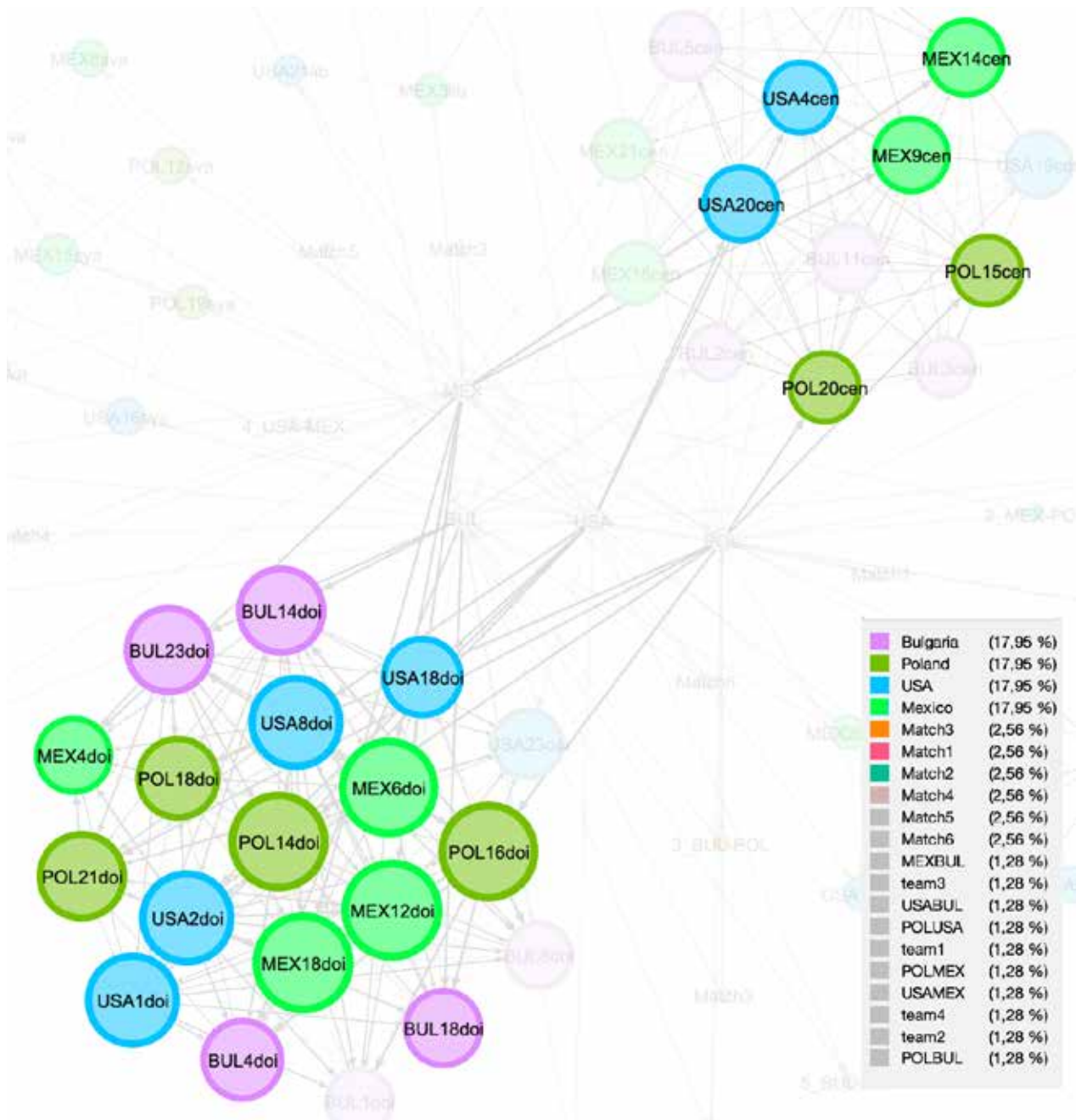


Figure 5. Community (group) graph of volleyball players assigned to quartile 2



**Figure 6.** Community (group) graph of volleyball players assigned to quartile 1

data. As demonstrated in several studies [1, 2, 3], network analysis can provide valuable insights in sports, helping to better understand tactical positions and the roles of players on the field. Korte et al. [9] emphasized that this approach provides a deep understanding of the roles of different positions in various sports.

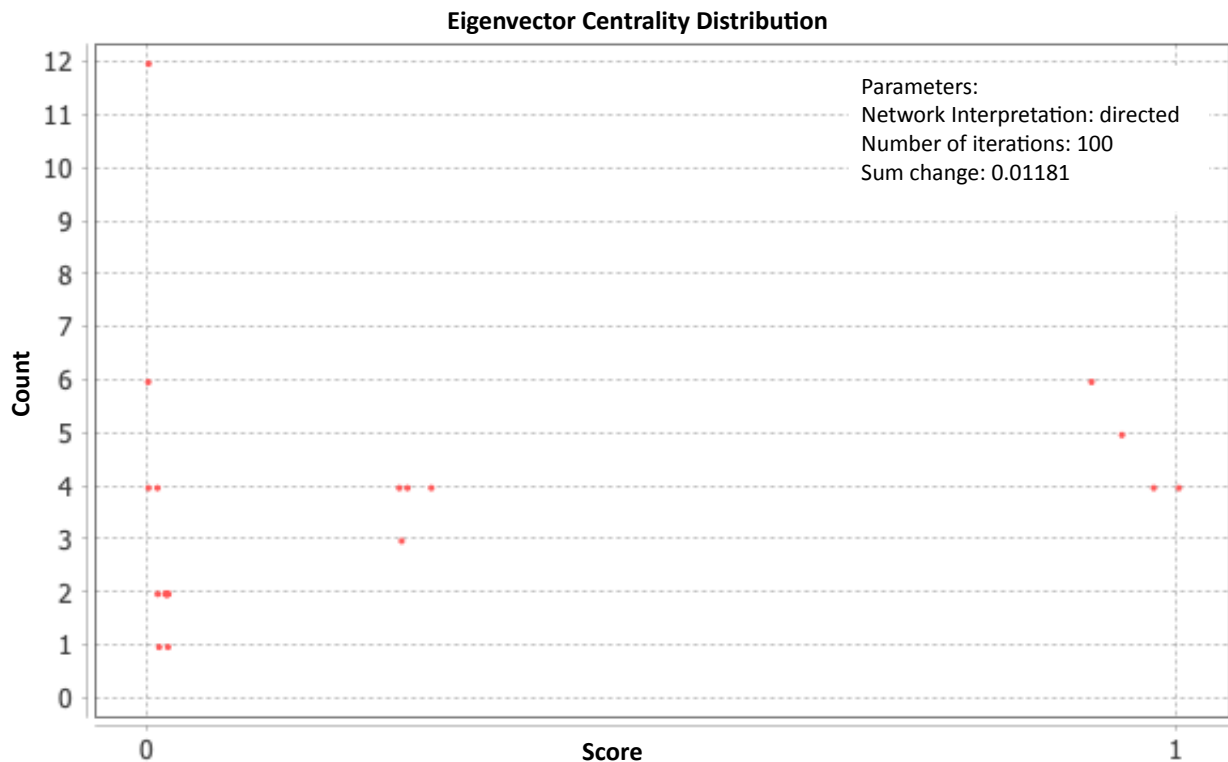
However, it's important to note that each team possesses its unique characteristics, and as emphasized in Rocha's study [14], the variability in team play should be taken into account when devising strategies. This is particularly relevant in volleyball, where the dynamics and tactics of the game can vary significantly from one match to another. The findings of Laporta et al.'s research [13]

suggest that volleyball matches exhibit a certain structure, and players' actions can be systematized. This underscores the potential of network analysis in deciphering complex game moments and selecting optimal strategies.

In this context, research on volleyball issues using network analysis can be categorized into the following directions:

*1. Analysis of game patterns and effectiveness in volleyball using social network analysis:*

Studies in this category focus on the application of social network analysis to examine game patterns and assess effectiveness in volleyball. Authors explore various aspects of the game, including the



**Figure 7.** “Eigenvector Centrality Report” statistics

use of eigenvector centrality methods to analyze patterns and develop models of game effectiveness. These studies also emphasize the importance of in-depth analysis of volleyball matches to gain a better understanding of game dynamics and formulate optimal strategies [13, 26, 27, 28, 29].

*2. Exploring variability in game scenarios and positional differences in volleyball through social network analysis:*

Research in this category focuses on studying the variability in game scenarios and positional differences among players and teams. Authors analyze how different teams and players adapt their strategies in various game scenarios. The primary emphasis is on positional disparities between players, as well as inter-team and intra-team variability. The goal is to gain a better understanding of how specific scenarios influence the choice of strategy and player behavior on the field [14, 29, 30, 31, 32, 33].

*3. Application of artificial neural networks in analyzing volleyball match results:*

Research in this area focuses on the use of artificial neural networks for predicting and analyzing the outcomes of volleyball matches. Authors explore how neural network-based models can be effective in predicting match results based on historical data and gameplay statistics. These studies demonstrate the potential of applying modern technologies in sports data analysis [34, 35, 36].

The use of Gephi software not only allows for visualizing but also for analyzing data in a more intuitive manner. Given the points mentioned above, network analysis emerges as a vital tool for coaches and analysts. It aids them in gaining a deeper understanding of game processes and in optimizing their strategies for both training and matches.

In our study, we visualized and analyzed interactions among volleyball players in Group C of the 2022 World Championship. This graphical analysis underscores the dynamic nature of interactions between players and facilitates the identification of pivotal figures within each team.

When comparing our results to previous research [27], it becomes evident that visualizing data with Gephi software enables coaches and analysts to analyze gameplay processes both swiftly and effectively. This methodology offers a significant tool for enhancing the understanding of gameplay dynamics and refining strategies for training and matches.

Both our study and Laporta et al.’s research [27] utilized network analysis to dissect volleyball data and pinpoint predominant game patterns. However, our research primarily focuses on the holistic team characteristics and quantitative metrics. In contrast, Laporta et al.’s paper [27] leans more towards distinguishing team differences and accentuating the variability in gameplay patterns.

Eigenvector Centrality stands out as a pivotal

metric in Gephi analysis. In this regard, our study resonates with other scholarly works. For instance, Martins et al.'s research [37] delves into an Eigenvector Centrality network consisting of 420 nodes and 7367 edges. Their primary objective was to decipher the influence of volleyball player actions during attacks.

Similarly, Laporta et al.'s study [28] incorporates Eigenvector Centrality. However, their research diverges in its aim, focusing on evaluating the amalgamation of direct and indirect connections amidst gameplay actions.

Nascimento et al.'s research [38] presents an analysis of 132 games from the qualifying rounds involving 12 teams in the 2021-2022 Brazilian Men's Volleyball Super League. While they too employ Eigenvector Centrality, their research is geared towards understanding the decision-making processes of setters during flank attacks.

In our research, we also harness the power of Eigenvector Centrality. This metric underscores the prominence of nodes within the network. With a sum of changes amounting to 0.0118, it can be inferred that certain volleyball players wield more significance or sway within the team. This observation might suggest the presence of key players or leaders within the squad.

It's worth highlighting that network analysis, grounded in statistical data from volleyball matches, offers a robust mechanism for delving deep into team dynamics. Our findings underscore the potency of this methodology. Moving forward, this approach could set a benchmark in volleyball analytics, equipping teams with a strategic edge en route to triumph.

## Conclusions

From the analysis of statistical reports derived from the 2022 Volleyball World Championship matches, utilizing network analysis methods within the Gephi software, we can deduce the following:

*1. High Level of Professional Preparation of Teams:* The results from data processing unequivocally affirm the exceptional professional prowess of the volleyball teams participating in the tournament. The mean values of pivotal metrics reflect the teams' adeptness in executing fundamental actions at an elite standard.

*2. Active Player Interaction:* A notable graph density of 0.601 in player interactions underscores the active collaboration and extensive information exchange among volleyball players on the field. Such active engagement fosters enhanced coordination and synchronization of team maneuvers.

*3. Significance of Key Players:* Utilizing the HITS metric, we identified players who function as both hubs and authorities within the team. These individuals, with their myriad connections

to fellow team members, are pivotal in facilitating information exchange and ensuring seamless coordination across the squad.

*4. Structural Organization of the Graph:* A modularity score of 0.483 signifies a well-defined structural organization of the graph based on modularity principles. The segmentation of the graph into five distinct modular communities highlights the inherent connectivity and similarities among volleyball players within these groupings.

In conclusion, these insights accentuate the indispensable role of network analysis in deciphering player interactions in elite volleyball tournaments. Harnessing statistical data in tandem with the Gephi software empowers coaches and analysts to delve deeper into game dynamics, pinpoint pivotal players, and refine team tactics. Such an approach can pave the way for enhanced competitive performances.

## Prospects

*1. Technological Aspect:* The rapid progression in technologies, such as real-time player tracking and comprehensive data collection of every player's court movements, is broadening the horizons for network analysis. Such data can offer a more nuanced comprehension of game mechanics and player interplay.

*2. Psychological Aspect:* Beyond tactics and strategy, player interactions are also influenced by interpersonal dynamics, leadership attributes, and psychological fortitude. While network analysis can spotlight these interrelations, a holistic understanding necessitates delving into the game's psychological facets.

*3. Application in Other Sports:* Drawing parallels between volleyball and other team sports could be enlightening, revealing whether interaction patterns are consistent across disciplines. Such a comparison could shed light on the method's universality and its adaptability across diverse sports arenas.

## Recommendations

Drawing from the analysis of statistical reports from the 2022 World Volleyball Championship matches, using network analysis methods in the Gephi software, we propose the following recommendations tailored to distinct segments within the volleyball community:

*For Coaches and Athletes:*

*1. Enhancing Coordination and Interaction:* The essence of success lies in active player interaction. Coaches are advised to orchestrate training drills and exercises that accentuate collaboration and foster seamless information exchange on the court.

*2. Identification and Nurturing of Key Players:* Players spotlighted as hubs and authorities via the HITS metric can be game-changers. It's imperative

for coaches to channel resources into their growth and to integrate them actively in tactical deliberations.

3. Analysis of Team Structure: Grasping the team's graph structural organization can empower coaches to fine-tune player placements and strategies, drawing from the graph's modularity. This strategic insight can lead to a more judicious allocation of team assets.

#### For Future Research:

A deeper dive into specific gameplay segments, such as passing sequences, receptions, and libero dynamics, can unravel intricate tactical nuances of volleyball matches.

In summation, when combined with the Gephi software, network analysis of statistical volleyball match data emerges as a formidable asset for coaches, athletes, and scholars. This synergy can catalyze enhanced team outcomes and a profound grasp of the game's intricacies.

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