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# Social Network Analysis: Mathematical Models for Understanding Professional Football in Game Critical Moments—An Exploratory Study

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**Abstract:** Considering the Social Network Analysis approach and based on the creation of mathematical models, the aim of this study is to analyze the players' interactions of professional football teams in critical moments of the game. The sample consists in the analysis of a 2019/2020 season UEFA Champions League match. The mathematical models adopted in the analysis of the players (micro analysis) and the game (macro analysis) were obtained through the uPATO software. The results of the networks indicated a performance pattern trend more robust in terms of the mathematical model: Network Density. As far as it concerned, we found that the Centroid Players had a decisive role in the level of connectivity and interaction of the team. Regarding the main critical moments of the game, the results showed that these were preceded by periods of great instability, obtaining a differentiated performance in the following mathematical models: Centrality, Degree Centrality, Closeness Centrality, and Degree Prestige. We concluded that the networks approach, in concomitance with the dynamic properties of mathematical models, and the critical moments of the game, can help coaches to better evaluate the level of interaction and connectivity of their players toward the actions imposed by opponents.

**Keywords:** football; match critical events; mathematical models; network analysis

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## 1. Introduction

The Social Network Analysis approach, also known as human network analysis, is mostly based on "Graph Theory", that is, on a mathematical model [1] related to a set of vertices interconnected by nodes. As such, taking the dynamic and synergy that happens in-game into account, it is possible to consider football as a cooperation-opposition game, which depends on various interactions. This dynamic may be analyzed through the usage of techniques and methods based on the analysis of human social networks. In this case, a human network or a superorganism like a football team, is, in most cases, composed by vertexes (also designated as nodes), in which they are represented by the number of players on the team [2–4]. Furthermore, Medina et al. [5], upon analyzing the usefulness of the social network approach in terms of a methodology to determine the statistical role of the passing network in the performance of a team in a soccer match, questioned the following "Is a social network approach relevant to football results?" The authors concluded that some network measures could cover relevant information about player performance describers, such as betweenness centrality, connectivity, among others. Although in a different sport, another recent study [6] stated that personal social network mapping, or egocentric network analysis, is a valuable proxy for various social factors, including social support.

### 1.1. Mathematic Models Applied to Professional Football and to the Centroid Player

The Network Approach allows the observation of patterns that emerge from the interaction and connectivity between players from a team in a given space and time [7]. The analysis of human networks has proven useful in football at different levels: (i) Micro analysis-individual player performance and (ii) Macro analysis-referring to the global interaction of the team [8]. Finally, to understand the teams' performance, it is important to characterize each player's contribution through dynamic, non-linear and chaotic analysis, which characterize the football game [9]. In this sense, as later reported, Mathematical Models applied to Professional Football, as well as the centroid player methodology can be useful in this subject.

Martins et al. [10], upon applying a mathematical model to a case study in football in the Champions League Finals, through the Bayesian approach to the study of passing sequence, realized that the winning team presented greater values for both individual and team transition entropies, which showed that greater levels of unpredictability could bring teams closer to the win. On the other hand, the number of links between players tend to display a power law distribution, with a few players concentrating more actions [11], pointing that the centroid player should be considered in the match performance analysis. Considering this, Clemente et al. [12] performed a revision to the Centroid Player methodology (that is, the athlete who contributes the most for the connectivity levels of the team), concluding that the inclusion of both the players' and ball's positions allowed for a greater comprehension of the team's behaviors, improving the game's analysis and making fast decision-making possible in the middle of games. Additionally, Gama et al. [13] analyzed the network of interactions resulting from the collective behavior of professional football teams through the centroid player and networks connections, concluding that the interaction of the centroid players, in the offensive phase of the game happened through the formation of vertices that were connected by links, which were mainly "orchestrated" by the action of centroid players. Therefore, taking into account the match key moments, the region where players' interactions occur and the relationships established are crucial for a better understanding of the game [11,13,14].

### 1.2. Critical Events and Moments in a Football Game

In football, critical game moments, such as scoring attempts, can be preceded by periods of instability in the balance of both team's behavior [15]. These critical events may be characterized as game-changing moments, such as shots on target, disciplinary actions and substitutions [16] and have been analyzed in match performance analysis [17]. Importantly, knowing the timespan that influences this critical event is difficult to determine. Memmert et al. [18] defined the 30 s prior to a critical event as the critical period, whereas Janetzko et al. [19] analyzed issues exclusively related to the players and what happened with the team in specific time frames before critical moments (2, 5, and 10 s).

Concomitantly to the previously described critical game moments, the literature also indicates that the area of analysis of individual and collective tactical performance is of great importance for both coaches and football players [20–22]. Transferability of this information to them is an issue, as most practitioners usually rely on simpler metrics such as possession, or passing accuracy [23].

Considering what has been stated, taking the Social Network Analysis approach into account and having the creation of mathematical models as a basis, this study's main objective was to analyze the interactions of professional football teams' players in critical game moments. Specifically, this work aims to identify a tendency both in the connectivity pattern, and interaction of specific centroid players (micro level) and of the team (macro level) in critical game moments.

## 2. Materials and Methods

### 2.1. Participants

This study's sample consisted in the analysis of a UEFA Champions League game in the 2019/2020 season, played by two teams who were in this competition: Benfica (SLB) and Olympique Lyon (OL).

### 2.2. Ethical Clearance

This study followed the code of ethics of the Polytechnic Institute of Coimbra, and the assumptions of the Declaration of Helsinki in human research.

### 2.3. Design and Procedures

Prior to the viewing of the television transmission of a game selected for data collecting, it was stipulated that this study would encompass two data analysis strands (micro-players and macro–team). Following this perspective, the following technical gestures were selected: (i) shot on target; (ii) goal; (iii) corner; (iv) substitution; and (v) free kick [7].

Three types of critical game moments were also defined, based on Memmert et al. [18]: (i) goal, (ii) shot, and (iii) shot on target; the considered time frame of analysis prior and subsequent to the event was 15 s. Taking the networks approach into account, there was another technical gesture analyzed: the pass [3,23], which was usually followed by events.

### 2.4. Data Analysis

Following the selection of critical game moments, the data were treated using the uPATO software [24]. This scientifically validated program [2] enables the codification of interactions between players in any team sport. Prior to the match analysis, the observers were trained in the usage of uPATO to analyze matches. The intraobserver and interobserver analysis was done with the validation of two expert observers in observation and analysis of team sports. Both of these experts are Professors in public Higher Teaching Institutes in Portugal and graduated in Sports Science. The values of concordance, above 80%—Bellack formula—were achieved after the training process. From this moment onward, the autonomy of the investigator was assumed to develop this study [25].

In order to calculate the mathematical models of player performance evaluation (cf. Table 1) and to analyze the previously described player interaction metrics on both teams, various adjacency matrixes had to be developed, where the number of interactions a player recorded during a game would be registered using the uPATO program. Through the usage of the matrixes, it was possible to have a greater understanding of each player and how many times they interacted (networks) with their teammates [10,26].

**Table 1.** Mathematical models which support the players' performance evaluation metrics (adapted from [8,11,27]).

| Mathematical Models | Abbreviation | Analysis Type |
|---|---|---|
| Betweenness Centrality | BC | Micro |
| Closeness Centrality | CC | |
| Degree Centrality | DC | |
| Degree Prestige | DP | Macro |
| Eigenvector Centrality | EC | |
| Assortativity Coefficient | AC | |
| Network Density | ND | |
| Network Heterogeneity | NH | |
| Reciprocity | R | |

Legend: Betweenness Centrality—related to the many times a given player is necessary for completing the routes connecting any other two players of its team; Closeness Centrality—related to the connection distance from a player to the rest of the team; Degree Centrality—reveals how central and important a player is in the game; Degree Prestige—measures the player who got the most of connections from other players; Eigenvector Centrality—related to the importance obtained from the eigenvectors of the adjacency matrix; Assortativity Coefficient—related to the tendency of players to connect with players with similar properties; Network Density—measures the overall cooperation among athletes; Network Heterogeneity—measures the variation of connectivity among athletes; Reciprocity—calculates the bidirectional connection between players.

Based on Memmert et al. [18], matrixes were created, one for each part (1st and 2nd halves) and one for the whole game. Moreover, matrixes were created to analyze the critical moments 15 s before and after they happened for each team. After the development of the essential adjacency matrixes, the values of the mathematical models of choice were calculated using the uPATO software. Taking the player performance evaluation mathematical models into account (Table 1), in order to analyze the player interactions for both teams from an individual point of view (micro analysis) and from a team point of view (macro analysis), the following metrics were adopted.

## 3. Results

Each team's Micro and Macro analysis, regarding player and team performance respectively, are presented in Tables A1–A12, which may be found in the Appendix A.

### *3.1. Micro Analysis*

The detailed results of the micro analysis that emerged from the analysis of Tables A1–A10 are presented below (Table 2), where the best performers for each mathematical model are highlighted.

**Table 2.** Best performers according to mathematical model.

| Mathematical Model | Player Performance |
|---|---|
| Team A's Degree Centrality (DC): | Player 3 obtained higher DC values in two critical game moments (B4 e B5) and also in $\Sigma_R$. |
| Team B's Degree Centrality (DC): | Player 14 reached the highest value on $\Sigma_{R,}$ and on critical event: L3. |
| Team A's Closeness Centrality (CC): | Players 97 and 3 reached their highest values of CC, in critical events B3 and B5. |
| Team B's Closeness Centrality (CC): | Players 14, 5 and 6 obtained the highest levels of CC. Even though players 5 and 6 were the most relevant on field, they did not participate in the previously established critical events. |
| Team A's Betweenness Centrality (BC): | Player 3′s values for the previously stated critical events were all inferior to those obtained in the global analysis of results. |
| Team B's Betweenness Centrality (BC): | The analysis of critical events did not translate into concrete values for mathematical model BC. |
| Team A's Degree Prestige (DP): | Player 3 achieved his highest EC values in critical events B4, B5 and in $\Sigma_R$ |
| Team B's Degree Prestige (DP): | Regardless of how essential for the team's performance players 5 and 6 were, they did not take part in the critical events. Besides, only players 11, 27 and 9 obtained higher DP values in $\Sigma_{R,}$ than in the complete analysis of the game. |
| Team A's Eigenvector Centrality (EC): | Players 27, 61, 11 and 14 reached better values in $\Sigma_G$ analysis. |
| Team B's Eigenvector Centrality (EC): | In a global analysis, athletes 14, 5 and 6 were the team's centroid players and the ones who interacted the most with their teammates. |

Legend: $\Sigma_G$ = Sum of goals scored by team A; $\Sigma_{Ra}$: Sum of all of team A's shots; B3: Shot made by team A; B4: shot made by team A; B5: shot on target by team A; $\Sigma_{Rb}$ = Sum of all of team B's shots; L3: Goal by team B; L5: Shot on target by team B.

Results from Table 2 show that the mathematical models do not clearly agree as to who was the best performer in the critical moments. Team B presents greater values of centrality for players 5 and 6. However, they did not show any relevance in the critical moments of the game. As for team A, player 3 had greater numbers of centrality in almost all mathematical models, assuming an important role in the critical moments of the game.

### 3.2. Macro Analysis

Below, both teams' performance is presented in Table 3. The analysis is made under the scope of the mathematical models used in the macro analysis presented in Tables A11 and A12.

**Table 3.** Team performance according to each mathematical model.

| Mathematical Model | Team Performance |
|---|---|
| Team A's Network Density (ND): | The team's highest ND value was achieved in $\Sigma_R$. |
| Team B's Network Density (ND): | Team B achieved a higher ND value in the ΣR than team A did in both ΣR and ΣG. The critical event analysis was very close to 0. |
| Team A's Network Heterogeneity: | In critical event B2, team A obtained the highest NH value. This team displayed a lesser degree of cooperation between players in the critical event analysis. |
| Team B's Network Heterogeneity: | This team presented a great degree of deviance in the number of interactions each player was involved in when in critical moments, more specifically in the L1 moment, where they obtained their highest value of NH. |
| Team A's Reciprocity: | Regarding critical event analysis, it was observed that, for moments B2, B3, B1, B6, and $\Sigma_G$ there was no calculation result, which may indicate a limitation in this model for this specific metric. |
| Team A's in—Assortativity Coefficient Matrix of Values: | The in-AC model values calculated for team A were, for the most part, negative. However, this team also reached the most positive value (in the first half) and also the most negative ($\Sigma_G$). |
| Team B's in—Assortativity Coefficient Matrix of Values | The value calculated for critical event L1 was the lowest in this regard, which means that the players who received the ball the most, did not pass it to the players which passed it the most. The values obtained in the analysis of both halves and of the full game presented the values closest to 0, this team in particular kept their values very close to 0. |
| Team A's out—Assortativity Coefficient Matrixes of values | This team obtained the closest value to the very worst value possible in the $\Sigma_R$, whereas team B achieved their best value for this model in the second half. Because team A's value was so close to 0, it ended up as not being relevant to the graphical representation of the mathematical model. |
| Team B's out—Assortativity Coefficient Matrix of values: | For the out-AC model, team B reached their highest value in the 2nd half of the game, that is, the players responsible for the most passes were interconnected between each other. However, the same did not occur during event L1. |

**Table 3.** *Cont.*

| Mathematical Model | Team Performance |
|---|---|
| Team A's (out-in)—Assortativity Coefficient values: | Values were not calculated for moments B1, B6 and $\Sigma_G$, as such it is assumed that this model possesses some limitations for this metric's calculation. |
| Team B's (out-in)—Assortativity Coefficient values: | Team B obtained the highest (out-in)-AC value in the $\Sigma_R$ analysis, that is, in the sum of the shots they took. It was in both $\Sigma_R$ and $\Sigma_G$ analysis that the lowest values were achieved. It is important to stress that team B obtained the most consistent (out-in) value. |
| Team A's (in-out)—Assortativity Coefficient Matrix of values: | Out of both teams, team A was the one who achieved the most positive value (in the 1st half of the game) but also the most negative value ($\Sigma_R$). Besides, B1, B6 and $\Sigma_G$ did not obtain a value due to the possible limitation this mathematical value possesses to this performance metric's calculation. |
| Team B's (in-out)—Assortativity Coefficient Matrix of values: | In the both halves of the game, this team achieved (in-out)—AC values very close to 0, which means that the players did not achieve a strong connection with the players they interacted with in the game. It was in events L2 and L4, that the players who received the most passes displayed the lowest values of connection with the players who had the most passes. |

Legend: $\Sigma_R$: Sum of all of the shots taken by the team; $\Sigma_G$: Sum of all goals scored by the team; B1: First goal scored by Team A; B2: Shot made by team A; B3: Shot made by team A; B6: second goal scored by team A; L1: Shot made by team B; L2: Shot made by team B; L4: Shot on target by team B.

The majority of the group metrics presented in Table 3 present results very close to 0, which indicate that little connections were found during these events.

### 3.3. Centroid Players' Interaction Networks of Both Teams

Figures 1–4 present a graphical representation of the network display of each team, divided in each half of game. Each player is represented as a ball with his jersey number in it. The size of the ball depicts the number of interactions (passes) that player had with the remaining network. The increased size of each ball represent a greater number of passes the player was involved in. Finally, the arrows show the direction of the passing, with the increase in the arrow thickness showing a greater number of passes to and from that player.

As it may be observed in Figure 1, the Centroid player for team A was player 3, as it may be confirmed in Tables A1, A3, A5, A7 and A9. He played as Left Wing, effecting 28 interactions in the first half, most of them with player 8.

Figure 2 presents the network display of team A in critical event B4. Here, Centroid Player remained Player 3. He kept his playing position, having interacted two times, once with player 84, and another with player 14, during this event.

For Team B, Figure 3 shows that the Centroid Player was Player 5 (Tables A2, A4, A6, A8 and A10). He played as center-back, effecting 48 interactions in the first half, most of them with player 6.

Lastly, Figure 4 presents the network display in critical event L3. The Centroid Player in this event was Player 14. He played as right wing, completing 2 interactions during this event, once with Player 17 and another with 11. Note that Player 17 does not match any player in the analysis tables due to the fact that he was substituted in, and therefore not included in the analysis.

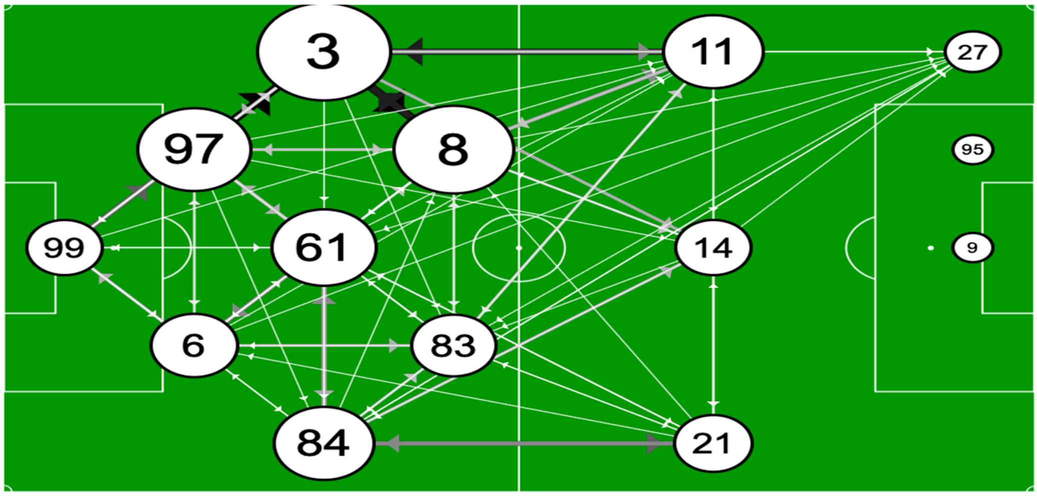


**Figure 1.** Network display results from team A in first half of game.

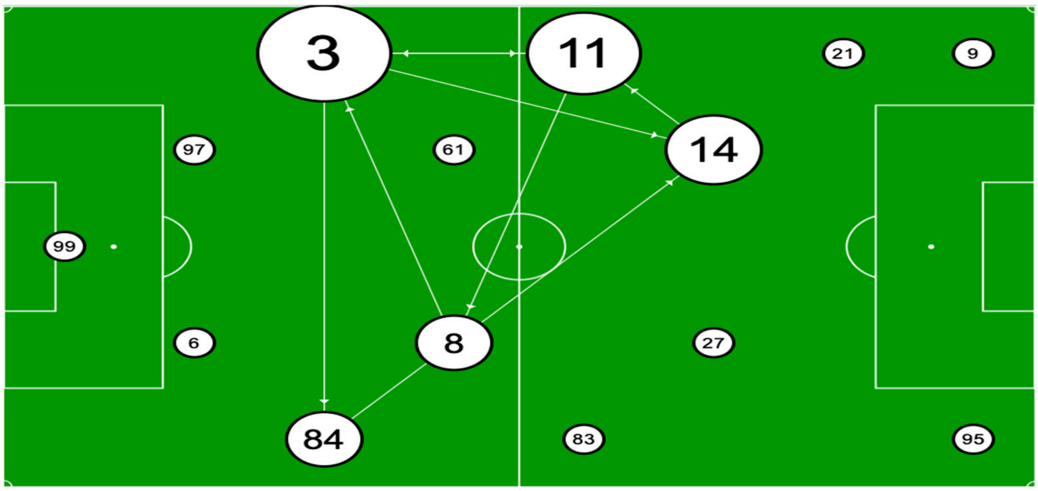


**Figure 2.** Network display results from team A in the critical event B4.

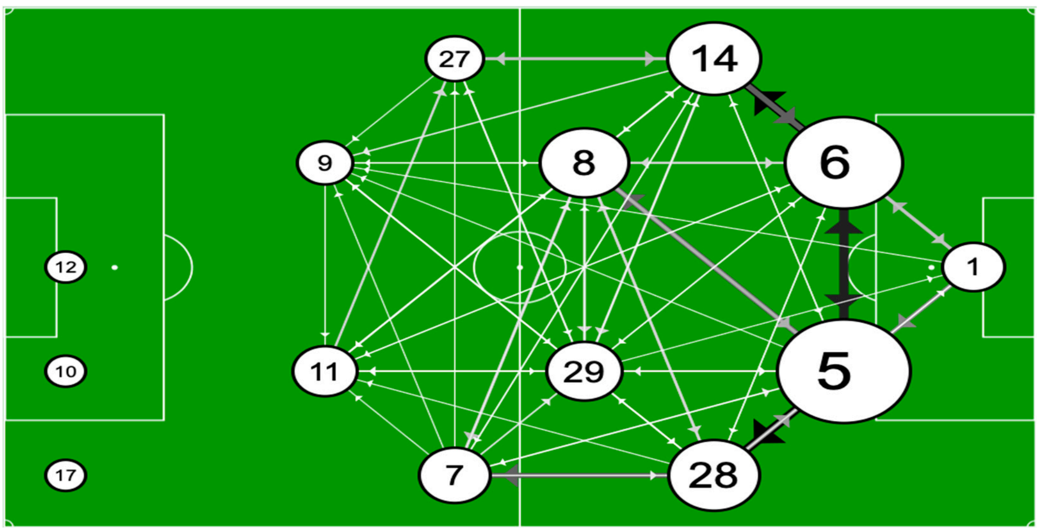


**Figure 3.** Network display results from team B in the first half of game.

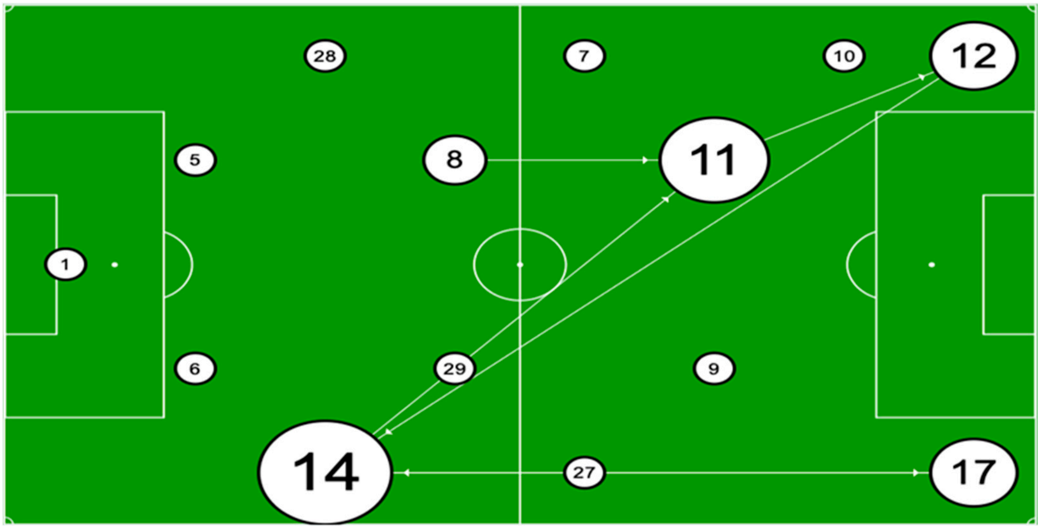


**Figure 4.** Network display results from team B in the critical event L3.

## 4. Discussion

This study's main objective was to analyze the interactions made by professional football players in critical game moments. Considering this, the players' performance analysis tends to focus on the observation of patterns that may emerge along the game. As such, it is essential that this approach allows the coach, coaching staff, and players to quickly recognize their opponents' interaction behavioral patterns (e.g., through networks), in order to overcome their weaknesses with tactical arguments derived from their opponents' current on-field positioning [12]. These aspects are in line with our results, confirming that the centroid player tends to be the greater contributor to the team's connectivity level, allowing for greater team interaction during the game. On the other hand, [13] indicated that the interaction of centroid players in the offensive phase of the game occurred by creating vertices that were connected by links, which were mainly "orchestrated" by the action of centroid players.

The interaction networks of both 1st and 2nd halves of the game depicted in Figures 1–4 showed that the wing players had a great level of importance in the team's connectivity, followed by the midfielders and, finally, the forward players, who had a relevant role in the team's finishing process and in the final result of the game. These data are in line with Gama et al. [3], where similar results were achieved. This may allow us to assume that this type of approach, centered on the mathematical models presented, tends to be relevant for the identification of interaction patterns and player connectivity in relation to both their in-field positioning and their roles. Based on the results of this study, the mathematical models which assumed the highest degree of importance were Network Density; Network Heterogeneity and Reciprocity. These data are in line with Medina et al. [5], which upon analyzing the Social Network Approach to verify if this model was truly useful in terms of methodology to determine the statistical role of the passing network in the performance of a team in a soccer match, concluded that some network measures could cover relevant information about player performance indicators. Our results follow the same idea as Dhand et al. [6] when they verified that the personal social network mapping, or egocentric network analysis, is a useful proxy for multiple factors. Regarding critical game moments, these can be preceded by periods of instability in the team's behavior, which tend to have a differentiated tactical performance [28].

On the other hand, after analyzing an entire Portuguese Premier League season, Pratas et al. [16] verified that performance indicators such as shots on target, disciplinary actions, and substitutions are predictors of the first goal. Taking this into account, our results show that, for team A's Centrality (CD), higher DC levels were reached in two critical or key [29] game moments (B4 and B5) but also in $\sum$R. The identification of these types of moments is considered as a relevant task for game analysis [28] and team performance [30]. Through critical game moments, which can be preceded by periods of instability in the behavioral balance of both teams, the impact in the collective tactical performance can be measured [28]. Following this method, team A's Network Density (ND) values were the highest in the second half. However, all critical event analysis values were very close to 0. Similarly, team B's Network Density (ND) values in critical events were also close to zero. Upon analyzing team B's (NH) values, it was observed that it was also involved in a number of critical events, more specifically in moment L1, where it reached its highest NH values. This data is in line with Ribeiro et al. [4], when the authors displayed some tendencies that this type of collective team performance is relevant to identify game patterns.

## 5. Conclusions

In summary, and considering the present study's main aim, a tendency can be identified in the connectivity patterns and in the interaction of centroid players, at a micro level, and of the team, at a macro level, in critical game moments such as shots or goals.

The present study showed that it is possible to break critical game moments down into specific key events. Understanding how the opposing team reacts to what occurs in critical moments may be important to block their centroid players and those who contribute the most to the success of collective plays. From another point of view, the properties of the mathematical models emerge as a tool capable of helping coaches further understand their team and take better tactical and technical decisions in a more in-depth way.

Therefore, the networks approach is a useful tool for analyzing player and team interactions, helping further the understanding of its defense and attack mechanisms and of the game's main dynamic properties. It provides coaches and analysts with valuable information regarding the connections and relationships between players, allowing for tactical adaptations in order to overcome the opposing team.

## 6. Limitations

This exploratory study analyzed the networks that occurred before critical game events. It is still unclear the duration that this period of time should have. Shorter periods may produce very small networks, which may reduce the feasibility of this analysis. Therefore, it should be taken into account that 15 s can be a relatively short time frame to analyze the critical moment/event. As such we recommend that future investigations should analyze more critical moments and with longer time frames. Future studies should also analyze more games in order to identify more robust behavioral patterns from a micro (players) and macro (team) point of view, through the usage of new mathematical models.

**Author Contributions:** D.A., I.P., R.M. and G.D. designed the research study; D.A., R.M., F.M. and J.F. conceived the data collection; D.A., I.P., R.M. and F.M. performed analysis and interpretation the data; D.A., J.F., R.G. and G.D. performed the drafting the article and/or its critical revision. All authors contributed to editorial changes in the manuscript. All authors have read and agreed to the published version of the manuscript.

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**Institutional Review Board Statement:** The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Polytechnic institute review board [CEPC 32018].

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data presented in this study are available on request by the corresponding authors.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

Micro analysis comparing individual player performance based on mathematical models.

**Table A1.** Team A's Degree Centrality Matrix of values.

| Player | 1st | 2nd | G | B2 | B3 | B4 | $\Sigma_R$ | B5 | B1 | B6 | $\Sigma_G$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 84 | 0.109 | 0.104 | 0.107 | 0.000 | 0.000 | 0.077 | 0.091 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.078 | 0.104 | 0.090 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 99 | 0.078 | 0.067 | 0.073 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 97 | 0.124 | 0.141 | 0.132 | 0.000 | 0.077 | 0.000 | 0.091 | 0.167 | 0.000 | 0.000 | 0.000 |
| 3 | 0.140 | 0.117 | 0.129 | 0.000 | 0.077 | 0.231 | 0.364 | 0.333 | 0.000 | 0.000 | 0.000 |
| 27 | 0.016 | 0.000 | 0.008 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.077 | 0.000 | 0.077 |
| 61 | 0.098 | 0.086 | 0.093 | 0.000 | 0.000 | 0.000 | 0.000 | 0.167 | 0.000 | 0.000 | 0.000 |
| 83 | 0.047 | 0.086 | 0.065 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.077 | 0.000 | 0.077 |
| 8 | 0.124 | 0.086 | 0.107 | 0.000 | 0.000 | 0.077 | 0.091 | 0.000 | 0.000 | 0.000 | 0.000 |
| 11 | 0.093 | 0.018 | 0.059 | 0.077 | 0.000 | 0.154 | 0.273 | 0.000 | 0.077 | 0.000 | 0.077 |
| 14 | 0.036 | 0.025 | 0.031 | 0.000 | 0.000 | 0.077 | 0.091 | 0.000 | 0.077 | 0.000 | 0.077 |

**Table A2.** Team B's Degree Centrality Matrix of values.

| Player | 1st | 2nd | G | L1 | L2 | L5 | $\Sigma_P$ | L4 | L3 |
|---|---|---|---|---|---|---|---|---|---|
| 14 | 0.110 | 0.123 | 0.116 | 0.000 | 0.077 | 0.077 | 0.154 | 0.000 | 0.154 |
| 5 | 0.205 | 0.145 | 0.178 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.175 | 0.141 | 0.159 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1 | 0.065 | 0.048 | 0.057 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 28 | 0.110 | 0.097 | 0.104 | 0.000 | 0.000 | 0.077 | 0.077 | 0.000 | 0.000 |
| 11 | 0.049 | 0.070 | 0.059 | 0.000 | 0.000 | 0.077 | 0.077 | 0.000 | 0.077 |
| 7 | 0.065 | 0.022 | 0.045 | 0.077 | 0.000 | 0.000 | 0.077 | 0.000 | 0.000 |
| 8 | 0.099 | 0.066 | 0.084 | 0.000 | 0.000 | 0.000 | 0.000 | 0.077 | 0.077 |
| 29 | 0.065 | 0.101 | 0.082 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 27 | 0.030 | 0.040 | 0.035 | 0.000 | 0.077 | 0.000 | 0.077 | 0.000 | 0.000 |
| 9 | 0.027 | 0.018 | 0.022 | 0.000 | 0.077 | 0.000 | 0.077 | 0.077 | 0.000 |

**Table A3.** Team A's Closeness Centrality Matrix of values.

| Player | 1st | 2nd | G | B2 | B3 | B4 | $\Sigma_P$ | B5 | B1 | B6 | $\Sigma_\Gamma$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 84 | 2.495 | 1.747 | 2.363 | 0.000 | 0.000 | 1.444 | 1.083 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 1.966 | 1.863 | 2.427 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 99 | 2.203 | 1.877 | 2.656 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 97 | 2.662 | 2.198 | 2.972 | 0.000 | 4.333 | 0.000 | 1.040 | 5.200 | 0.000 | 0.000 | 0.000 |
| 3 | 2.272 | 1.797 | 2.801 | 0.000 | 13.000 | 2.600 | 2.000 | 6.500 | 0.000 | 0.000 | 0.000 |
| 27 | 0.974 | 0.000 | 0.806 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 4.333 | 0.000 | 4.333 |
| 61 | 2.721 | 1.646 | 2.605 | 0.000 | 0.000 | 0.000 | 0.000 | 2.600 | 0.000 | 0.000 | 0.000 |
| 83 | 1.515 | 1.500 | 2.023 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 4.333 | 0.000 | 4.333 |
| 8 | 2.122 | 1.569 | 2.478 | 0.000 | 0.000 | 1.857 | 1.368 | 0.000 | 0.000 | 0.000 | 0.000 |
| 11 | 2.228 | 1.008 | 2.325 | 13.000 | 0.000 | 2.167 | 2.000 | 0.000 | 4.333 | 0.000 | 4.333 |
| 14 | 1.201 | 0.969 | 1.328 | 0.000 | 0.000 | 1.625 | 1.300 | 0.000 | 2.167 | 0.000 | 2.167 |

**Table A4.** Team B's Closeness Centrality Matrix of values.

| Player | 1st | 2nd | G | L1 | L2 | L5 | $\Sigma_P$ | L4 | L3 |
|---|---|---|---|---|---|---|---|---|---|
| 14 | 5.027 | 2.172 | 4.197 | 0.000 | 2.167 | 13.000 | 1.857 | 0.000 | 3.250 |
| 5 | 5.884 | 2.506 | 4.410 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 5.950 | 2.416 | 4.426 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1 | 4.461 | 1.650 | 3.478 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 28 | 4.085 | 2.130 | 3.742 | 0.000 | 0.000 | 1.300 | 0.520 | 0.000 | 0.000 |
| 11 | 2.568 | 1.374 | 2.558 | 0.000 | 0.000 | 4.333 | 1.083 | 0.000 | 2.167 |
| 7 | 2.648 | 1.149 | 2.170 | 13.000 | 0.000 | 0.000 | 2.167 | 0.000 | 0.000 |
| 8 | 3.803 | 1.704 | 3.153 | 0.000 | 0.000 | 0.000 | 0.000 | 2.167 | 1.300 |
| 29 | 2.938 | 1.963 | 3.140 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 27 | 3.208 | 1.584 | 3.111 | 0.000 | 4.333 | 0.000 | 4.333 | 0.000 | 0.000 |
| 9 | 1.911 | 0.896 | 1.837 | 0.000 | 13.000 | 0.000 | 13.000 | 4.333 | 0.000 |

**Table A5.** Team A's Betweenness Centrality Matrix of values.

| Player | 1st | 2nd | G | B2 | B3 | B4 | $\Sigma_P$ | B5 | B1 | B6 | $\Sigma_\Gamma$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 84 | 0.135 | 0.125 | 0.166 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.071 | 0.050 | 0.077 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 99 | 0.026 | 0.013 | 0.013 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 97 | 0.179 | 0.074 | 0.192 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 3 | 0.122 | 0.163 | 0.263 | 0.000 | 0.006 | 0.038 | 0.077 | 0.006 | 0.000 | 0.000 | 0.000 |
| 27 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.019 | 0.000 | 0.019 |
| 61 | 0.218 | 0.008 | 0.119 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 83 | 0.026 | 0.111 | 0.068 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.013 | 0.000 | 0.013 |
| 8 | 0.022 | 0.059 | 0.054 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 11 | 0.087 | 0.000 | 0.119 | 0.000 | 0.000 | 0.038 | 0.077 | 0.000 | 0.006 | 0.000 | 0.006 |
| 14 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.019 | 0.026 | 0.000 | 0.000 | 0.000 | 0.000 |

**Table A6.** Team B's Betweenness Centrality Matrix of values.

| Player | 1st | 2nd | G | L1 | L2 | L5 | $\Sigma_P$ | L4 | L3 |
|---|---|---|---|---|---|---|---|---|---|
| 14 | 0.186 | 0.269 | 0.343 | 0.000 | 0.000 | 0.019 | 0.077 | 0.000 | 0.038 |
| 5 | 0.311 | 0.295 | 0.314 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.250 | 0.321 | 0.288 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 28 | 0.045 | 0.301 | 0.131 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 11 | 0.006 | 0.103 | 0.109 | 0.000 | 0.000 | 0.026 | 0.064 | 0.000 | 0.032 |
| 7 | 0.006 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 8 | 0.038 | 0.179 | 0.103 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 29 | 0.000 | 0.013 | 0.038 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 27 | 0.000 | 0.013 | 0.000 | 0.000 | 0.013 | 0.000 | 0.064 | 0.000 | 0.000 |
| 9 | 0.000 | 0.000 | 0.000 | 0.000 | 0.013 | 0.000 | 0.038 | 0.013 | 0.000 |

**Table A7.** Team A's Degree Prestige Matrix of values.

| Player | 1st | 2nd | G | B2 | B3 | B4 | $\Sigma_P$ | B5 | B1 | B6 | $\Sigma_\Gamma$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 84 | 0.078 | 0.104 | 0.090 | 0.000 | 0.000 | 0.077 | 0.091 | 0.000 | 0.000 | N/A | 0.000 |
| 6 | 0.067 | 0.067 | 0.067 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | N/A | 0.000 |
| 99 | 0.036 | 0.037 | 0.037 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | N/A | 0.000 |
| 97 | 0.098 | 0.092 | 0.096 | 0.000 | 0.000 | 0.000 | 0.000 | 0.167 | 0.000 | N/A | 0.000 |
| 3 | 0.145 | 0.123 | 0.135 | 0.000 | 0.077 | 0.154 | 0.273 | 0.333 | 0.000 | N/A | 0.000 |
| 27 | 0.036 | 0.000 | 0.020 | 0.077 | 0.000 | 0.000 | 0.091 | 0.000 | 0.154 | N/A | 0.154 |
| 61 | 0.098 | 0.055 | 0.079 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | N/A | 0.000 |
| 83 | 0.088 | 0.117 | 0.101 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.077 | N/A | 0.077 |
| 8 | 0.124 | 0.080 | 0.104 | 0.000 | 0.000 | 0.077 | 0.091 | 0.000 | 0.000 | N/A | 0.000 |
| 11 | 0.093 | 0.055 | 0.076 | 0.000 | 0.000 | 0.154 | 0.182 | 0.000 | 0.077 | N/A | 0.077 |
| 14 | 0.073 | 0.031 | 0.053 | 0.000 | 0.077 | 0.154 | 0.273 | 0.000 | 0.000 | N/A | 0.000 |

**Table A8.** Team B's Degree Prestige Matrix of values.

| Player | 1st | 2nd | G | L1 | L2 | L5 | $\Sigma_P$ | L4 | L3 |
|---|---|---|---|---|---|---|---|---|---|
| 14 | 0.118 | 0.123 | 0.120 | 0.000 | 0.000 | 0.077 | 0.077 | 0.000 | 0.154 |
| 5 | 0.183 | 0.115 | 0.151 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.152 | 0.128 | 0.141 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1 | 0.034 | 0.026 | 0.031 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 28 | 0.106 | 0.093 | 0.100 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 11 | 0.053 | 0.088 | 0.069 | 0.000 | 0.000 | 0.077 | 0.077 | 0.077 | 0.154 |
| 7 | 0.068 | 0.022 | 0.047 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 8 | 0.110 | 0.084 | 0.098 | 0.000 | 0.000 | 0.077 | 0.077 | 0.000 | 0.000 |
| 29 | 0.084 | 0.075 | 0.080 | 0.000 | 0.077 | 0.000 | 0.077 | 0.000 | 0.000 |
| 27 | 0.049 | 0.044 | 0.047 | 0.077 | 0.077 | 0.000 | 0.154 | 0.000 | 0.000 |
| 9 | 0.042 | 0.031 | 0.037 | 0.000 | 0.077 | 0.000 | 0.077 | 0.077 | 0.000 |

**Table A9.** Team A's Eigenvector Centrality Matrix of values.

| Player | 1st | 2nd | G | B2 | B3 | B4 | $\Sigma_P$ | B5 | B1 | B6 | $\Sigma_\Gamma$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 84 | 0.206 | 0.327 | 0.280 | −1.000 | 0.000 | 0.190 | 0.145 | 0.000 | 0.000 | −1.000 | 0.000 |
| 6 | 0.222 | 0.390 | 0.300 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | −1.000 | 0.000 |
| 99 | 0.307 | 0.255 | 0.297 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | −1.000 | 0.000 |
| 97 | 0.447 | 0.455 | 0.472 | −1.000 | −1.000 | 0.000 | 0.338 | 0.369 | 0.000 | −1.000 | 0.000 |
| 3 | 0.455 | 0.325 | 0.381 | −1.000 | 0.000 | 0.629 | 0.639 | 0.652 | 0.000 | −1.000 | 0.000 |
| 27 | 0.036 | 0.000 | 0.026 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.471 | −1.000 | 0.471 |
| 61 | 0.312 | 0.291 | 0.319 | −1.000 | 0.000 | 0.000 | 0.000 | 0.326 | 0.000 | −1.000 | 0.000 |
| 83 | 0.143 | 0.290 | 0.203 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.673 | −1.000 | 0.673 |
| 8 | 0.414 | 0.228 | 0.336 | −1.000 | 0.000 | 0.363 | 0.338 | 0.000 | 0.000 | −1.000 | 0.000 |
| 11 | 0.305 | 0.059 | 0.199 | −1.000 | 0.000 | 0.572 | 0.517 | 0.000 | 0.404 | −1.000 | 0.404 |
| 14 | 0.075 | 0.063 | 0.080 | −1.000 | 0.000 | 0.330 | 0.273 | 0.000 | 0.404 | −1.000 | 0.404 |

**Table A10.** Team B's Eigenvector Centrality Matrix of values.

| Player | 1st | 2nd | G | L1 | L2 | L5 | $\Sigma_P$ | L4 | L3 |
|---|---|---|---|---|---|---|---|---|---|
| 14 | 0.285 | 0.340 | 0.309 | −1.000 | −0.707 | 0.000 | −0.333 | 0.000 | 0.614 |
| 5 | 0.572 | 0.460 | 0.536 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 6 | 0.546 | 0.502 | 0.530 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1 | 0.291 | 0.196 | 0.265 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 28 | 0.276 | 0.272 | 0.280 | −1.000 | 0.000 | −0.577 | −0.333 | 0.000 | 0.000 |
| 11 | 0.112 | 0.148 | 0.135 | −1.000 | 0.000 | −0.577 | −0.667 | 0.000 | 0.350 |
| 7 | 0.148 | 0.036 | 0.116 | −1.000 | 0.000 | 0.000 | −0.333 | 0.000 | 0.000 |
| 8 | 0.268 | 0.197 | 0.252 | −1.000 | 0.000 | 0.000 | 0.000 | 1.000 | 0.264 |
| 29 | 0.143 | 0.355 | 0.251 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 27 | 0.061 | 0.104 | 0.083 | −1.000 | −0.707 | 0.000 | −0.333 | 0.000 | 0.000 |
| 9 | 0.043 | 0.032 | 0.042 | −1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Macro Analysis comparing individual team performance based on mathematical models.

**Table A11.** Team A's Matrix of values of the macro analysis mathematical models.

| Mathematical Model | 1st | 2nd | G | B2 | B3 | B4 | ∑R | B5 | B1 | B6 | ∑G |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Network Density | 0.118 | 0.128 | 0.122 | 0.005 | 0.011 | 0.044 | 0.030 | 0.016 | 0.022 | N/A | 0.022 |
| Network Heterogeneity | 0.630 | 0.606 | 0.574 | 3.606 | 2.449 | 1.581 | 1.535 | 1.700 | 1.581 | inf | 1.581 |
| Reciprocity | 0.622 | 0.491 | 0.635 | N/A | N/A | 0.250 | 0.182 | 0.333 | N/A | N/A | N/A |
| (out-in)-Assortativity Coefficient | 0.166 | 0.045 | 0.028 | inf | inf | −0.290 | −0.311 | −0.333 | −0.333 | inf | −0.333 |
| (in-out)-Assortativity Coefficient | 0.049 | −0.056 | −0.076 | inf | −1.000 | −0.143 | −0.360 | −0.304 | N/A | N/A | N/A |
| in-Assortativity Coefficient | 0.136 | −0.007 | 0.022 | −1.000 | −0.333 | −0.333 | −0.349 | −0.557 | −0.714 | N/A | −0.714 |
| out-Assortativity Coefficient | 0.061 | 0.046 | −0.001 | −1.000 | −0.333 | −0.362 | −0.485 | −0.333 | inf | N/A | inf |

**Table A12.** Team B's Matrix of values of the macro analysis mathematical models.

| Mathematical Model. | 1st | 2nd | G | L1 | L2 | L5 | ∑R | L4 | L3 |
|---|---|---|---|---|---|---|---|---|---|
| Network Density | 0.085 | 0.113 | 0.096 | 0.005 | 0.016 | 0.022 | 0.044 | 0.016 | 0.033 |
| Network Heterogeneity | 0.853 | 0.630 | 0.711 | 3.606 | 1.915 | 1.581 | 1.09 | 1.915 | 1.453 |
| Reciprocity | 0.700 | 0.687 | 0.735 | N/A | N/A | N/A | N/A | N/A | 0.333 |
| (out-in)-Assortativity Coefficient | 0.037 | 0.017 | 0.013 | inf | inf | inf | 0.333 | inf | −0.333 |
| (in-out)-Assortativity Coefficient | 0.001 | 0.037 | −0.008 | inf | −0.500 | −0.333 | −0.043 | −0.500 | −0.286 |
| in-Assortativity Coefficient | −0.024 | −0.021 | −0.032 | −1.000 | −0.200 | −0.143 | −0.418 | −0.200 | −0.600 |
| out-Assortativity Coefficient | 0.071 | 0.100 | 0.045 | −1.000 | −0.200 | −0.143 | −0.418 | −0.200 | −0.500 |

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