Social Network Analysis applied to Marvel Crisis Protocol

Igor Magno Silva[1], Rodrigo Colnago Contreras[2]

[1]Universidade Estadual de Feira de Santana - Uefs
Feira de Santana - BA, 44036-900, Brazil

igor.magn@gmail.com

[2]Universidade Federal de São Paulo - Unifesp
Departamento de Ciência e Tecnologia
São José dos Campos - SP , CEP: 12247-014

contreras@unifesp.br

***Abstract. Introduction**: Social Network Analysis (SNA) based on Graph Theory has proven to be a powerful tool for modeling and understanding interactions in various contexts. In this study, we apply SNA to examine the connections and synergies between characters in the Marvel Crisis Protocol (MCP) miniatures game, a tabletop miniatures game where players form teams of Marvel heroes and villains based on abilities, affiliations, and strategic synergies. **Objective:** This study aims to analyze the undefeated lists of the tournaments in the first quarter of 2025 and verify if there is any competitive advantage in using the most influential characters according to the centrality measures of Graph Theory. **Methodology or Steps**: For this purpose, a simulation of a Social Network Analysis was carried out using the characters' Affiliations as a basis using five centrality measures. **Results:** After identifying the influential characters, a comparison was made with the undefeated lists to verify whether such characters make up the winning rosters and if using a team with two Affiliations is a good strategy. Unfortunately, single Affiliations roosters performed better in the championships analyzed.*
***Keywords** Social Network Analysis, Graph Theory, Centrality, Marvel Crisis Protocol, Tabletop Game*

1. Introduction

The modern Graph Theory emerged in the 18th century with the famous Konigsberg Bridge problem proposed by Euler. About 300 years later, this theory has made significant advances and currently finds applications in various areas of knowledge [Barnett 2005].

Specific areas that heavily utilize Graph Theory are Computer Science, Artificial Intelligence and Social Network Analysis (SNA), graphs can be used for analyzing complex networks, explaining the relationships between entities within the network, thus addressing questions such as: which entities have the best connections, are more centralized, have greater influence in the network, how information flows within it, or which are the existing clusters [Majeed e Rauf 2020]?

Social networks are structures built upon the links between individuals [Alamsyah et al. 2021], which can be diverse, such as users of a webpage, companies, clients, computers, among others. For an effective application of SNA it is necessary to possess an extensive knowledge of the analyzed network and the characteristics of Graphs [Kostić et al. 2020], which can be studied through metrics such as density, size, degree, and other measures. The study [Alamsyah et al. 2021] divides Graph Theory metrics into Centrality-based Metrics and Non-Centrality-based Metrics.

Marvel Crisis Protocol™ (MCP) can be classified as a Tabletop Game, Miniature Game, or Wargame, as the definition of this type of game is difficult to precisely pin down and may vary from author to author [Harrop et al. 2013]. One of the attractive aspects of this type of game is the greater social interaction among players compared to digital games [Carter et al. 2014]. Additionally, non-digital games have immersive elements that transcend fiction into reality through miniatures, scenery, rules, and other elements that replicate a battle between armies. In a way, more traditional games like Chess, Shogi or Go can be considered wargames as they simulate a military battle using miniatures [Buthaud 2022].

This article aims to conduct a SNA of the MCP miniature game based on the relationship between characters and their Affiliations utilizing Graph Theory. For this purpose, five centrality measures were employed: Degree Centrality, Closeness Centrality, Betweenness Centrality, Eigenvector, and PageRank. By the end of the study, the undefeated tournament lists from the first quarter of 2025 will be analyzed to assess if MCP characters in influential positions are used on these lists.

2. Material and Methods

2.1. Marvel Crisis Protocol

MCP is a miniature game produced by Atomic Mass Games since 2019 [Atomic Mass 2019], one of the best-selling in the sector according to [ICv2 2023], as shown in the Table 1. Its rules and other important documents, such as the list of Affiliations used in this study, can be found on its website. As of the date of this study, the game is composed of 198 characters and 28 Affiliations [Atomic Mass 2025a], where each character belongs to at least one of them.

Table 1. Tabletop miniatures– Fall 2023.

Rank	Miniature Game	Publisher
1	Warhammer 40.000	Games Workshop
2	Nolzur's Marvelous Miniatures	Wizkids
3	BattleTech	Catalyst Game Labs
4	Star Wars: Shatterpoint	Atomic Mass Games
5	Marvel Crisis Protocol	Atomic Mass Games

In a match, as shown in Figure 1, a player must have a roster with 10 different characters and can choose any number of characters from their roster as long as the sum of the team's threat level is less than or equal to the mission threat [Atomic Mass 2025b]. To gain the bonuses related to Affiliation, your team needs to have a leader character and more than half of the team's characters must belong to that Affiliation, as shown in the example in Figure 2, hence, choosing more centralized characters can mean a better roster or allow the creation of a roster with more than one affiliation, offering more versatility to the team.

Figure 1. Match of Marvel Crisis Protocol, X-Men against Criminal Syndicate.

A character can have more than one Affiliation, such as Black Panther (Avenger, Wakanda), Killmonger (Wakanda, Cabal, Criminal Syndicate), and Okoye (A-Force, Wakanda). For this study, it was considered that two or more characters have a relationship if they share at least one common Affiliation. In this case, the three mentioned characters are connected through the Affiliation "Wakanda," even though the other Affiliations may be different.

It's important to highlight another crucial point: characters with different names represent different versions of the same hero/villain. For instance, Black Widow, The Black Widow, and Black Widow Agent of S.H.I.E.L.D represent three different versions of Natasha Romanoff.

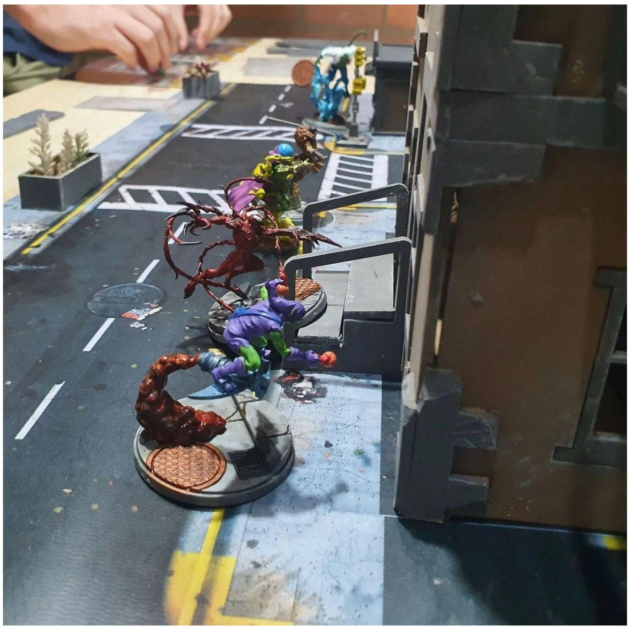

Figure 2. Spider-Foes team with Green Goblin (Leadership), Carnage, Mysterio, Kraven the Hunter, and Lizard.

2.2. Database

This article aims to analyze the relationship between characters in the MCP miniature game by simulating a Social Network, using Graph Theory as the analytical tool. For this purpose, each character was considered a node, and an edge was created for each other character that shares an Affiliation with it, forming a complete subgraph within each Affiliation, as shown in Figure 3. A complete graph is one in which every vertex has all possible edges [dos Santos Simões-Pereira 2013].

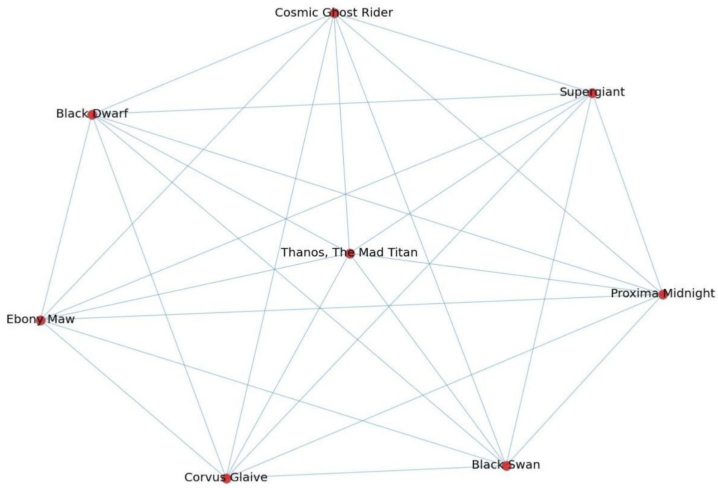

Figure 3. Representation of the Affiliation Black Order Subgraph.

The list of characters and their respective affiliations is available on the Atomic Mass website [Atomic Mass 2025a]. However, for this study, the data was obtained through the MCPDB website[1], because it provides the data in tabular format and allows extraction via the Python programming language. A cleaning process was performed to distinguish different characters with identical names and remove duplicate characters. After that, a dictionary was generated with each character and their Affiliations to create the nodes, followed by a list with pairs of characters that share Affiliations to form the edges. According to [Pachayappan et al. 2018], from a social network perspective, nodes can represent various actors, while ties can represent different relationships and connections. The graph and all centrality calculations were performed using the Python library NetworkX [Hagberg et al. 2008].

For the MCP tournament data, it was obtained from the Longshanks website[2], an online platform that allows the organizers to easily publicize events and collect tournament data. For this study, 83 undefeated rosters from 57 championships in the first quarter of 2025 were selected. In addition, a separation of undefeated tournament list with two Affiliations rosters was carried out, and the data on the top 10 most popular characters used was also included for comparison.

2.3. Graph and Centrality

According to [dos Santos Simões-Pereira 2013], a graph $G = (N, E)$ is a system composed of a set N of elements called nodes and a set E of unordered pairs of

[1] http://www.mcpdb.com/
[2] https://www.longshanks.org/

nodes called edges. These two basic elements can describe various phenomena, such as social connections [Goldenberg 2021]. A graph can be directed, or a digraph, when its edges have a single direction, or undirected when they have both directions [dos Santos Simões-Pereira 2013]. In this study, only undirected graphs were considered.

Since the character Dormammu is only part of the Dark Dimension and has no relation to any other character, it was excluded from this study. As a result, there were 197 nodes and 3446 edges obtained in the end, which can be seen in the graph in Figure 4.

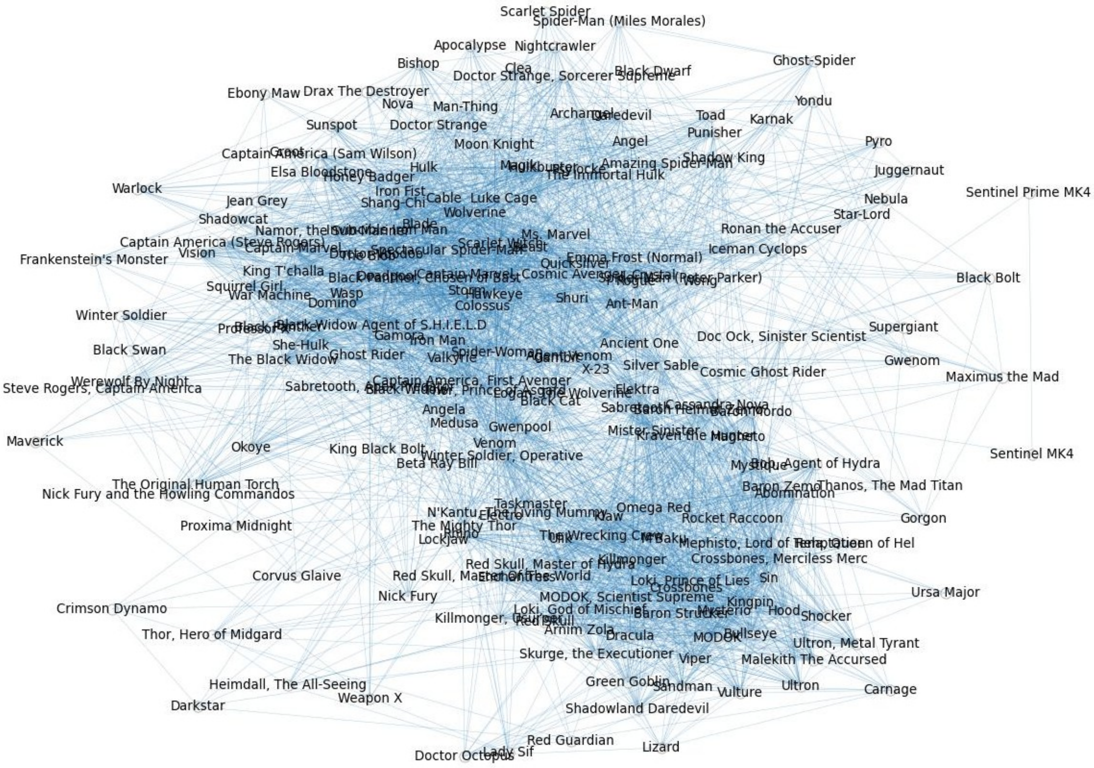

Figure 4. MCP Social Network Graph.

Other important points to highlight are the distribution of the node degrees, as shown in the histogram of the nodes in Figure 5. It is possible to note that this is an irregular distribution with asymmetry to the right, which implies the existence of many agents interacting with few individuals and few agents interacting with many.

Many social networks have community structures, and the analysis of communities and their forms are natural questions [Campbell et al. 2013]. Affiliations are the communities within MCP, which share common characters. An important indicator in Graph Theory is Centrality; it indicates which nodes hold critical positions in the Social Network [Latora e Marchiori 2007]. Central nodes play a key role in the Network, serving as connectors [Goldenberg 2021]. Therefore, this study utilized five centrality measures: Degree Centrality, Closeness Centrality, Betweenness Centrality, Eigenvector, and PageRank to identify key nodes among the characters of MCP.

The degree centrality of a node i in a graph G is the first and simplest measure of centrality used. It is essentially the number of edges that the node has, a value that can be

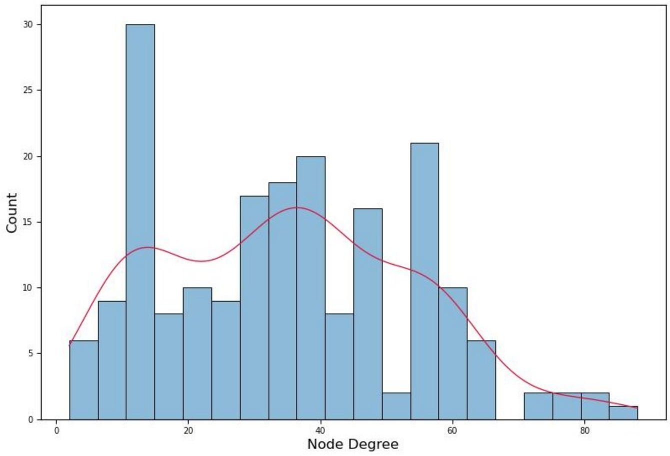

Figure 5. Node Degree Histogram.

obtained through the Equation (1):

$$C_i = \frac{\sum_{j=1}^{n} X_{ij}}{n-1}(i \neq j), \tag{1}$$

where:

- C_i is the node i Degree Centrality,
- degree n is the number of node's i edges,
- is the total number of nodes in the graph (excluding the node i).

The formula for Closeness Centrality is the value of the distance from a node to the other nodes through the geodesic path, given by Equation (2):

$$C_i = \frac{1}{n-1}\sum_{j\neq i}\frac{1}{d_{ij}}, \tag{2}$$

where:

- C_i is the node i Closeness Centrality ,
- d_{ij} is the shortest distance between the nodes i and j.

Betweenness Centrality is the shortest path between two different nodes s and t that passes through node i, generated by the Equation (3):

$$C_i = \sum_{s\neq i\neq t}\frac{\sigma_{st}(i)}{\sigma_{st}}, \tag{3}$$

where:

- $C_b(i)$ is the node i Betweenness Centrality,
- σ_{st} is the number of shortest paths to s from t,
- $\sigma_{st}(i)$ is the number of shortest paths to s from t that pass through the node i.

Eigenvector centrality of node i corresponds to the proportional value of the centralities of its neighbors j, such that important neighbors provide a higher weight in the calculation than less important neighbors, obtained through the Equation (4)

$$x_i = \frac{1}{\lambda} \sum_j A_{ij} x_j, \tag{4}$$

where:

- x_i is the node i eigenvector value,
- λ is the eigenvalue corresponding to the eigenvector x,
- A_{ij} is the correspondent value on matrix adjacency.

A ranking algorithm for websites, PageRank is a metric where each node i receives a score based on the centrality of its neighbors j, similar to Eigenvector, generated by the Equation (5)

$$x_i = \alpha \sum_j A_{ij} \frac{x_j}{k_j^{\text{out}}} + \beta, \tag{5}$$

where:

- x_i is the node i PageRank score,
- α and β are positive constants,
- A_{ij} is the correspondent value on matrix adjacency,
- k_j^{out} is the out-degree.

3. Results and Discussion

The results obtained from the SNA applied to MCP revealed interesting patterns regarding the importance of characters within the game. Through the centrality metrics used, it was possible to identify which characters occupy strategic positions in the network, reflecting their potential impact on building winning teams.

Table 2 presents the characters with the highest Degree Centrality, indicating those with the most connections to other characters through affiliations. These characters exhibit higher connectivity within the network, which can be a strategic factor in assembling versatile and synergistic teams. In Table 3, we observe Closeness Centrality, which measures a character's accessibility within the network. The presence of these characters suggests that having multiple affiliations may be advantageous by offering quick connections to different groups.

Betweenness Centrality (Table 4) highlights which characters emerge as key intermediaries between different communities in the graph. This result suggests that these characters play fundamental roles in connecting different segments of the network, potentially facilitating synergy strategies between less-connected characters.

The results for Eigenvector Centrality (Table 5) and PageRank (Table 6) highlight the characters that are favored within the network due to their prominent position in the global structure of connections.

When comparing the most central characters with those most used in tournaments (Table 7), a discrepancy between structural influence and popularity is evident. This finding suggests that player choices may be more associated with individual abilities or specific synergies within the game's mechanics rather than the characters' positions in the social network.

Table 2. Degree Centrality.

Character	Degree
Winter Soldier, Operative	0,4489
Wolverine	0,4234
Spider-Woman	0,4132
Scarlet Witch	0,4030
Gwenpool	0,3979
Black Cat	0,3826
Beast	0,3673
Omega Red	0,3367
Black Panther, Chosen of Bast	0,3367
Cable	0,3316

Table 3. Closeness Centrality.

Character	Closeness
Winter Soldier, Operative	0,6302
Spider-Woman	0,6125
Gwenpool	0,6068
Scarlet Witch	0,6012
Black Cat	0,5993
Beast	0,5921
Wolverine	0,5850
Hawkeye	0,5747
Black Widow	0,5714
Silver Sable	0,5697

Table 4. Betweenness Centrality.

Character	Betweenness
Cosmic Ghost Rider	0,0692
Winter Soldier, Operative	0,0581
Agent Venom	0,0505
Black Cat	0,0466
Angela	0,0445
Spider-Woman	0,0425
Beast	0,0391
Gwenpool	0,0368
Wolverine	0,0326
Cassandra Nova	0,0322

Table 5. Eigenvector Centrality.

Character	Eigenvector
Winter Soldier, Operative	0,1660
Gwenpool	0,1557
Spider-Woman	0,1441
Scarlet Witch	0,1368
Wolverine	0,1348
Black Panther, Chosen	0,1244
Black Cat	0,1237
Hawkeye	0,1192
Blade	0,1151
Iron Fist	0,1151

Additionally, in the analysis of Undefeated tournament rosters (Table 8), only Beast and Black Cat appear both among the most influential characters and the most frequently used in competitions, this data are highlighted in Table 10 where it is possible to identify repetition of characters among the Centralities and another repetition the between the tournament lists, suggesting that centrality may play an important role in competitiveness but is not the sole determining factor.

Regarding teams that used two affiliations in Table 9, we observed that this strategy was not widely adopted, with only 13.25% of undefeated rosters exhibiting this characteristic (11 of the 83), and even among these rosters, out of the 70 characters that made up these lists, only 8 characters were in the Top 10 ranking of some centrality. This suggests that, despite offering greater strategic flexibility, maintaining a team focused on a single affiliation may be more effective in most cases.

One way to assess the similarity between the obtained centralities and the Top 10 tables is through hierarchical clustering. This method allows the creation of groups based on their similarity by calculating the Euclidean distance between them [Provost e Fawcett 2013]. As observed in the dendrogram in Figure 6, there was first a cluster between centralities mensures, then, there was another cluster with the tournament

Table 6. PageRank Centrality.

Character	PageRank
Winter Soldier, Operative	0,0113
Wolverine	0,0107
Spider-Woman	0,0103
Scarlet Witch	0,0101
Beast	0,0099
Black Cat	0,0097
Gwenpool	0,0096
Omega Red	0,0088
Black Widow	0,0086
Cable	0,0085

Table 7. Popular Character Roster.

Character	Frequency
Baron Zemo	2443
Toad	2046
Wong	1951
Black Cat	1939
Beta Ray Bill	1835
Bullseye	1734
Hulk	1688
Rhino	1544
Shang-Chi	1399
Namor, the Sub-Mariner	1321

Table 8. Undefeated Tournament Lists.

Character	Frequency
Shang-Chi	28
Baron Zemo	24
Toad	22
Namor, the Sub-Mariner	21
Hulk	20
Beta Ray Bill	20
Bullseye	18
Okoye	16
Wong	16
Beast	15

Table 9. Undefeated 2 Affiliations Lists.

Character	Frequency
Beta Ray Bill	5
The Mighty Thor	4
She-Hulk	4
Nick Fury	3
Toad	3
Okoye	3
Black Cat	3
Bullseye	3
Kingpin	3
Namor, the Sub-Mariner	2

lists. This Reinforce the idea that factors external to network structure—such as individual abilities and specific in-game interactions—influence competitors' strategic decisions. These results indicate that while SNA is a valuable tool for understanding interactions within MCP, other aspects, such as character-specific abilities and tactical synergies, should be considered for a more comprehensive analysis.

4. Final Considerations

Normally, Social Network Analysis (SNA) deals with large volumes of data, which was not the case with this study, where 198 nodes and 3446 edges were analyzed. For comparison, in 2024, X (former Twitter) had 335.7 million users[3]. However, because this study focused on analyzing centralities in a smaller context, this fact did not hinder the study. On the contrary, working with large volumes of data requires significant computational power, and visualizing the graph can become very heavy or visually challenging.

Despite the differences in the calculations of centralities measures, in the Social

[3]https://shorturl.at/aghv3

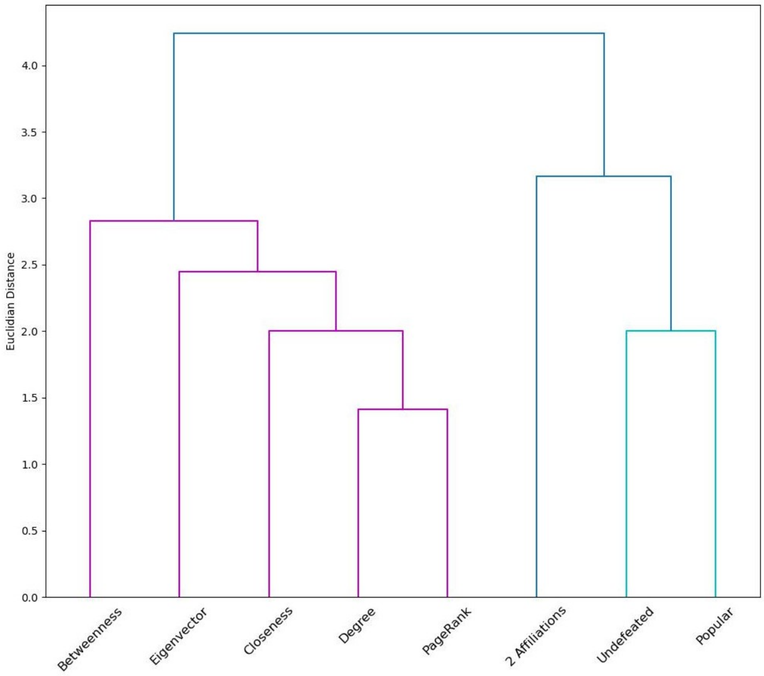

Figure 6. Hierarchical clustering of Centralities and Top 10 ranking

Table 10. Similarity of Centralities and Tournament lists.

	Degree	Close	Between	Eigen	Page	Undefeated	Popular
Closeness	7						
Betweenness	6	6					
Eigenvector	7	7	6				
PageRank	9	8	6	6			
Undefeated	1	1	1	0	1		
Popular	1	1	1	1	1	8	
2 Affiliations	1	1	1	1	1	5	5

Network Analysis conducted in this study, there was no significant difference between their Top 10 character.

Contrary to expectations, using a roster with 2 Affiliations did not imply an advantage in the game with the scenario discussed in this article. There are probably many more factors that should be analyzed in a game of this complexity, such as synergy between characters, abilities, Team Tactics cards and other variables that make this game much more dynamic and one of the best-selling in the sector.

For future work, these variables can be considered, in addition to enriching the database with more tournaments, since the website from which the lists were taken does not have information on tournaments prior to 2025. In addition, an exploratory analysis based on Affiliations may be a viable study alternative.

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