Clustering Player Performance in Pokémon TCG Tournaments: A K-means Approach to Identifying Performance Groups Based on Wins, Losses, and Tournament Statistics

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ABSTRACT

This study applies K-means clustering to analyze player performance in competitive Pokémon TCG tournaments, categorizing players into four distinct performance groups based on metrics such as wins, losses, and ties. Using a dataset comprising over 186,000 players, the study identifies key clusters representing varying levels of success in the game. The data was preprocessed by handling missing values and standardizing features to ensure uniform contribution across metrics. MiniBatchKMeans was employed to optimize clustering for large datasets, resulting in a model that groups players into low, moderate, and high-performance categories. The clustering results provide valuable insights into the distribution of player performance and help identify trends in competitive dynamics. A Silhouette Score of 0.4582 indicates that the clustering is moderately effective, with some overlap between clusters, suggesting that further refinement may be needed. Visualizations, including scatter plots, box plots, and heatmaps, were used to interpret the cluster characteristics, showing that top-performing players cluster into smaller groups, while a large majority of players exhibit moderate performance. The findings offer important implications for both players and tournament organizers: players can refine strategies based on their cluster profiles, while organizers can use clustering insights to design more balanced and engaging tournament formats. Future research could explore alternative clustering methods and incorporate additional performance features to further optimize player segmentation and enhance tournament design.

Keywords Pokémon TCG, K-Means Clustering, Player Performance, Tournament Analysis, Competitive Gaming

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INTRODUCTION

The competitive Pokémon Trading Card Game (TCG) has experienced a significant rise in popularity, transforming from a casual hobby into a core component of global gaming culture. Once regarded mainly as a children's pastime, it has now grown into a competitive arena that attracts players of all ages, driven by its intellectual challenge and strategic depth. This shift from a simple card game to a high-stakes competitive environment has had a profound impact on the gaming community, both by influencing how people

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engage with the game and by contributing to the broader cultural development of gaming. The competitive Pokémon TCG scene not only fosters social bonds and shared cultural identity but also highlights the mental health challenges faced by players who participate in such intense competitions [1]. As the game continues to evolve, players must refine their strategies to adapt to an ever-changing landscape, ensuring its continued relevance in both physical and digital gaming communities. This evolution has given rise to community-driven strategies, the sharing of cultural practices, and the development of an ecosystem that transcends the game itself.

The structure of competitive Pokémon TCG tournaments plays a pivotal role in shaping the strategies that underpin successful gameplay. These tournaments typically follow formats such as the Swiss-system or single-elimination structures, which ensure that players compete in multiple rounds before final placements are determined. These formats not only provide a fair competition but also generate valuable data, including match outcomes, player performance statistics, and deck selection trends. These datasets are crucial for analyzing competitive dynamics and player behavior, offering insights into the factors that contribute to success [2]. By examining tournament data, researchers can uncover patterns in player performance, deck composition, and strategic decision-making, providing players with actionable insights and informing game designers on potential improvements to game mechanics.

Data collection in Pokémon TCG tournaments is diverse and includes both traditional over-the-table event results and digital gameplay metrics. Platforms like Pokémon TCG Live offer detailed, quantifiable gameplay data, providing a complementary perspective to the more traditional data gathered from physical tournaments. The combination of these data sources enriches the analysis of competitive dynamics, revealing the cyclical strategic interactions that define the Pokémon TCG ecosystem [3], [4]. For instance, analyses using principal trade-off methods have successfully identified strategic clusters within tournament data, uncovering patterns similar to the rock-paper-scissors dynamics that define competitive play in the TCG. The integration of diverse datasets from both digital and physical platforms enables a more comprehensive understanding of the strategic nuances that contribute to competitive success.

Understanding player performance in these competitive settings is crucial for modeling the strategies that lead to victory. By systematically evaluating tournament outcomes, player rankings, deck selection, and in-game decision-making, researchers can gain insights into the most effective strategies and help players optimize their approach. Quantitative analyses of player behavior and match statistics reveal important trends that can inform both competitive optimization and game design improvements. Performance metrics such as win-loss records, match duration, and player rankings provide a solid foundation for refining the Pokémon TCG experience, ensuring that the game remains engaging for players of all skill levels. These insights are invaluable not only for enhancing player performance but also for ensuring that the game remains balanced and fair, fostering an environment where both new and experienced players can thrive.

Optimal tournament design and dynamic pairing algorithms have also been explored to enhance fairness in Pokémon TCG competitions. Research into knockout tournament structures has provided theoretical frameworks that can be applied to Pokémon TCG event organization. These algorithms ensure that top-performing players are more likely to face each other in the later stages of the tournament, contributing to a more competitive and exciting experience. These insights from mathematical modeling and algorithmic design help tournament organizers create structures that better reflect player performance and contribute to the overall fairness of the competitive scene [2]. By integrating algorithmic modeling with tournament data, organizers can refine the structure and scheduling of events, ensuring that the competitive integrity of Pokémon TCG tournaments is upheld.

The competitive Pokémon TCG serves as a model of strategic gameplay and community development within the broader gaming ecosystem. The game's ability to foster both competitive and collaborative dynamics has contributed to its success and sustained popularity. By analyzing player performance, tournament outcomes, and strategic trends, researchers can provide valuable insights into the mechanics that contribute to the game's competitiveness. These insights not only enhance player strategies but also inform game developers and tournament organizers on how to improve the Pokémon TCG experience. Furthermore, the integration of diverse data sources, such as digital platform metrics and traditional tournament results, enhances our understanding of the competitive dynamics at play, making Pokémon TCG a model for analyzing and optimizing competitive gaming strategies [4]. Ultimately, this research underscores the importance of performance analysis in sustaining the dynamic evolution of gaming communities and optimizing gameplay strategies for the future of the Pokémon TCG and beyond.

The objective of this research is to identify different performance groups among players in the competitive Pokémon Trading Card Game (TCG) using clustering techniques. By analyzing player performance data from various tournaments, the goal is to classify players into distinct groups based on their gameplay behavior and performance metrics. This will allow for a deeper understanding of the strategic variations across different player types and highlight key factors that contribute to success in competitive play. A significant gap exists in understanding the patterns of player performance across various Pokémon TCG tournaments. While tournament data is widely available, there is limited analysis focused on categorizing players based on their performance in a way that could reveal hidden strategic trends or performance discrepancies. Without a comprehensive analysis of these performance patterns, players may miss opportunities to refine their strategies, and tournament organizers may lack the necessary insights to optimize tournament formats for competitive fairness and engagement.

The insights derived from clustering player performance into distinct groups can have several valuable applications. For players, understanding their performance profile can lead to more targeted strategy improvements, enabling them to identify areas where they need to focus more or adjust their approach. For tournament organizers, these insights can inform the development of more balanced tournament formats by recognizing different player types and designing structures that foster fairness and competition. This research can ultimately contribute to enhancing the overall competitive experience in Pokémon TCG tournaments. This paper proposes the use of K-means clustering to analyze and group players based on their performance metrics. By applying this machine learning algorithm to tournament data, we aim to uncover patterns in player performance, which will allow for a more nuanced understanding of competitive dynamics in the Pokémon TCG. The clustering approach provides a way to identify different player types and explore the characteristics that distinguish successful players from others, contributing to both player strategy optimization and tournament design improvement.

Literature Review

Player Performance Metrics in Tournaments

Evaluating player performance in tournament settings frequently centers around quantifiable metrics such as wins, losses, and ties, which serve as the foundation for assessing competitive success. In many competitive environments—including digital card games like the Pokémon TCG—these metrics provide a clear, outcome-oriented measure of a player's effectiveness during tournaments [5]. By analyzing win percentages and tie frequencies, researchers and event organizers can derive composite performance scores that reflect both strategic prowess and execution consistency. Such performance metrics offer a simple evaluative framework for ranking players and allow for the identification of key strategic inflection points that differentiate high-performing participants from their peers.

Furthermore, modern analytical approaches extend beyond mere outcome-based statistics by incorporating granular action-level data that inform the subtleties behind each win, loss, or tie. For instance, embedding techniques have been developed to quantify individual player actions and aggregate these into comprehensive performance scores [6], [7]. These models effectively bridge the gap between raw outcome metrics and the tactical decisions that lead to these results, thereby refining our understanding of player performance in competitive settings [6]. The integration of such detailed analyses is important in the context of the Pokémon TCG, where the complexity of deck compositions and in-game decision pathways requires wins, losses, and ties to be considered alongside more nuanced performance indicators [5].

Additionally, point-based predictive models have been employed to forecast match outcomes by leveraging historical win-loss data. This approach underscores the predictive power of traditional outcome metrics while enhancing them with probabilistic assessments that account for variability in performance across different tournaments or game phases [8]. Such models illustrate that even in environments where external factors might influence results—such as the dynamic meta-game of Pokémon TCG tournaments—

fundamental performance metrics remain robust indicators of success [8]. Consequently, by combining these aggregated metrics with experimental and computational techniques, researchers gain a more comprehensive understanding of player performance, allowing for both predictive analytics and strategic assessments to coexist in a mutually informative manner.

Clustering in Game Analytics

Research in game analytics has increasingly leveraged clustering techniques to uncover hidden structures and patterns in competitive gaming environments, including esports and digital card games. Clustering methods have been applied to differentiate player roles, segment gamers based on habits and preferences, and extract latent features from rapidly changing game design elements.

For instance, [9] demonstrate the use of clustering to capture patch-agnostic features by analyzing game design parameters derived from patch notes. Their work addresses the challenge posed by frequent rule changes in esports and illustrates how clustering can be used to derive stable character representations that remain robust even when game dynamics shift. This approach allows analysts to bypass the short lifespan often associated with esports analytics models that rely solely on static parameters, thus offering a more adaptive method for character and strategy analysis.

Additionally, clustering has been effectively applied to segment the gamer population based on behavioral patterns and preferences. Research [10] propose an instrument that classifies players into distinct clusters using a Game Preferences Questionnaire. Such segmentation provides valuable insights into gamer behavior that can drive customization in game design and targeted engagement strategies. By grouping players into clusters ranging from casual to highly competitive profiles, the study contributes to a nuanced understanding of player diversity within gaming communities and offers practical implications for both developers and educators in creating more engaging gaming environments.

Furthermore, ensemble clustering techniques have been utilized in esports to differentiate roles among participants. Research [11] applied ensemble clustering to classify and accurately label the roles of individual heroes in Dota 2, a popular esports title. This method accommodates the inherent complexity of assigning roles in a dynamic team setting, particularly when traditional performance metrics are insufficient. Their work underscores the importance of using clustering to capture the multi-dimensional aspects of gameplay, such as strategic positioning and role-specific contributions, thereby enhancing the precision of performance analytics in esports.

Application of Clustering in Esports and Other Games

Clustering techniques have proven instrumental in unveiling latent patterns within large-scale gameplay data, particularly in segmenting player performance in both esports and traditional competitive games. In esports, for instance, machine learning pipelines have been employed to classify players by skill level in Dota 2 tournaments. Research [12] detail an approach that integrates various performance metrics through a clustering framework, effectively segmenting players into distinct skill groups. This segmentation not only supports talent identification but also facilitates strategic alignment by coaching staff and team managers, as it provides granular insights into individual player strengths and weaknesses.

Similar applications can be observed in traditional sports, where clustering has been used to reveal different performance profiles, offering a refined perspective on competitive dynamics. In badminton tournaments, [13], [14] implemented cluster analysis to discern distinct performance groups among professional players. The study identified that top-ranked players tend to balance tournament participation frequency with recovery intervals compared to their lower-ranked counterparts, thereby highlighting the value of clustering for performance-based segmentation. In basketball, continuous-time stochastic block models have been utilized to classify players based on playing style and in-game performance metrics [15]. This approach distinguishes different types of player roles within team structures and provides cluster-specific estimates of key performance metrics, such as scoring and rebounding efficiency. Furthermore, [16] applied a two-step clustering process to extensive individual game performance records in European basketball competitions. Their analysis delineated multiple performance clusters that corresponded to variations in players' roles and contextual factors, enhancing understanding of the factors affecting player performance.

Method

The methodology for this study follows a structured and systematic approach, beginning with data collection and preprocessing, followed by K-means clustering, and concluding with performance evaluation and interpretation. This multistage process ensures that the competitive performance of players in the Pokémon Trading Card Game (TCG) is categorized into meaningful clusters, providing deeper insights into player behavior and tournament dynamics. The overall workflow of the methodology is illustrated in figure 1, which outlines the sequential steps from data preparation to clustering evaluation and visualization.

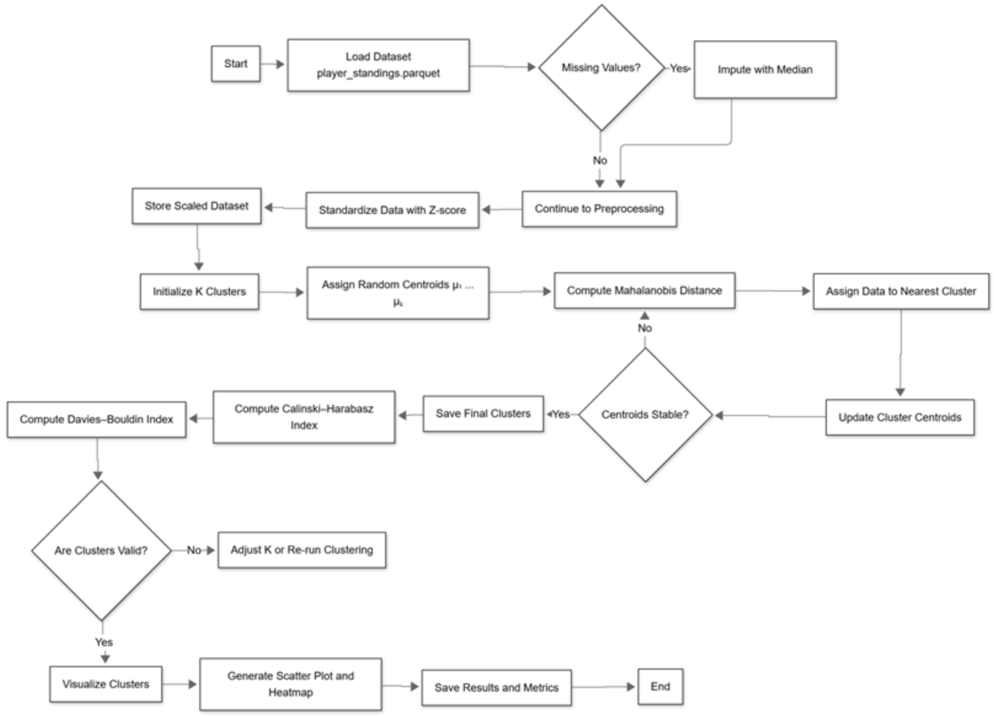

Figure 1 Research Flow

Data Collection and Preprocessing

The dataset for this study is derived from official Pokémon Trading Card Game (TCG) tournament records, stored in Parquet format (player_standings.parquet). It contains essential indicators of player performance, including the number of wins, losses, and ties, complemented by additional metadata that describes each competitor. In cases where the original dataset is inaccessible, a dummy dataset is generated to preserve the reproducibility of the analysis and maintain the integrity of the experimental workflow [17], [18].

Exploratory Data Analysis (EDA) is conducted to understand the dataset's internal structure. Descriptive statistics are used to assess the distribution of numerical and categorical features, while visualizations such as histograms, box plots, and scatter plots provide insight into performance patterns and potential outliers. A correlation heatmap is employed to identify interdependencies among performance metrics, ensuring that the most informative variables are retained for clustering.

Data preprocessing ensures that the clustering process operates on consistent and unbiased input features. Missing values in wins, losses, or ties are imputed using median substitution to avoid distortion caused by extreme values. The dataset is then normalized using z-score standardization to ensure that all features contribute equally to distance-based computations. This standardized dataset is stored for further use in the clustering and evaluation stages.

K-means Clustering

K-means clustering is applied to group players into performance-based categories, with the number of clusters ($K = 4$) determined according to the study's hypothesis of four distinct performance groups. The algorithm minimizes the within-cluster variance by iteratively updating cluster centroids until convergence [19], [20].

However, to increase robustness against correlations among features and non-spherical data distributions, this study adopts an advanced distance metric—the Mahalanobis distance—as an alternative to the standard Euclidean distance. This modification allows the model to capture complex relationships among the input variables. The Mahalanobis distance between a point $x$and a cluster centroid $\mu_k$is defined as:

$$D_M(x, \mu_k) = \sqrt{(x - \mu_k)^T S_k^{-1} (x - \mu_k)} \quad (1)$$

$S_k$represents the covariance matrix of cluster k. This formulation takes into account feature correlations, effectively adjusting the shape of clusters to better reflect the underlying data distribution.

The clustering process continues iteratively, assigning each data point to the cluster with the smallest distance measure until the centroids stabilize. This ensures that the partitioning of players into groups reflects consistent and statistically meaningful distinctions in performance characteristics.

Evaluation of Clustering Performance

Evaluating the quality of the clustering is critical to ensure the interpretability and validity of the results. Beyond visual inspection, quantitative indices are used to assess the compactness and separability of the formed clusters. One of the advanced measures employed in this study is the Calinski–Harabasz Index (CHI), which evaluates the ratio between the between-cluster dispersion and the within-cluster dispersion [21], [22]. It is expressed as:

$$CH = \frac{Tr(B_k)/(K-1)}{Tr(W_k)/(N-K)} \quad (2)$$

$Tr(B_k)$is the trace of the between-cluster dispersion matrix, $Tr(W_k)$is the trace of the within-cluster dispersion matrix, $K$is the number of clusters, and $N$is the number of observations. Higher values of CHindicate more distinct and well-separated clusters.

To complement this metric, the Davies–Bouldin Index (DBI) is also used as a secondary evaluation criterion. This index measures the average similarity between each cluster and its most similar counterpart, balancing intra-cluster cohesion and inter-cluster separation. The DBI is defined as:

$$DBI = \frac{1}{K} \sum_{i=1}^{K} \max_{j \neq i} \left(\frac{s_i + s_j}{d_{ij}}\right) \quad (3)$$

$s_i$and $s_j$are the average intra-cluster distances for clusters $i$and j, and $d_{ij}$is the distance between the centroids of clusters $i$and j. Lower DBI values correspond to better clustering outcomes, indicating compact and well-separated groups.

These indices together provide a more nuanced understanding of clustering quality than a single silhouette score. They offer complementary perspectives—one emphasizing the ratio of dispersions (Calinski–Harabasz) and the other emphasizing relative distances (Davies–Bouldin)—allowing for a multi-criteria evaluation of the clustering structure.

Visualization and Interpretation of Clusters

After the clustering model is trained and evaluated, the results are visualized to facilitate interpretation. Scatter plots are generated to show the relationship between pairs of performance metrics, such as wins vs. losses. Each point in the scatter plot is colored according to the cluster label, helping to visually distinguish between the different player groups. The cluster centroids are also plotted to show the center of each cluster, providing a reference point for understanding the typical performance of players in each group.

Box plots are created for each performance feature across the clusters. These plots help visualize the distribution of metrics like wins, losses, and ties within each cluster, revealing any significant differences between the clusters in terms of player performance. Heatmaps of the cluster centroids are also generated to summarize the central tendency of each cluster across all features. This visualization provides a clear picture of the average performance of players in each group and helps interpret the characteristics of each cluster.

Cluster Summary and Analysis

The final step in the analysis is to generate a cluster summary, which includes the mean values of performance metrics for each cluster. This summary provides a detailed view of the average performance of players in each cluster and helps to distinguish between high-performing and low-performing groups. Additionally, the size of each cluster is recorded to determine how many players belong to each group.

The cluster summary is saved as a CSV file, which can be used for further analysis or reporting. The centroids of each cluster are also analyzed to provide a more detailed understanding of the groupings. A heatmap of the centroids is generated to visualize the central performance values of each cluster across all features. This allows for an easy comparison of the performance patterns within each cluster and provides insights into the overall structure of the competitive player pool.

Algorithm 1 Player Performance Clustering and Evaluation

Step 1: Input and Initialization

Input:
Dataset $X = \{x_1, x_2, \ldots, x_N\}$, containing features {wins, losses, ties}
Number of clusters K

Output:

Cluster assignments $C = \{C_1, C_2, \dots, C_K\}$,
Evaluation metrics: Calinski–Harabasz Index (CH), and Davies–Bouldin Index (DBI)

Process:

1. Load dataset $X$from player_standings.parquet.
2. Check for missing values in all columns.
3. If any value is missing, replace it with the **median** of that feature:

$$x_i' = \begin{cases} x_i & \text{if } x_i \neq \text{NaN} \\ \text{median}(x_i) & \text{otherwise} \end{cases}$$

4. Standardize all features using z-score normalization:

$$z_i = \frac{x_i - \mu_i}{\sigma_i}$$

5. Store the standardized dataset as $Z = \{z_1, z_2, \dots, z_N\}$.

Step 2: Initialize K-means Parameters

1. Randomly initialize Kcluster centroids:

$$\mu_1, \mu_2, \dots, \mu_K$$

2. Set convergence threshold $\epsilon = 10^{-4}$.
3. Set iteration counter $t = 0$.

Step 3: Assign Points to Clusters (Using Mahalanobis Distance)

1. For each data point z_i, compute the **Mahalanobis Distance** to each centroid:

$$D_M(z_i, \mu_k) = \sqrt{(z_i - \mu_k)^T S_k^{-1} (z_i - \mu_k)}$$

where $S_k$is the covariance matrix of cluster k.

2. Assign each point $z_i$to the cluster $C_k$that minimizes the distance:

$$C_k = \{z_i : D_M(z_i, \mu_k) \leq D_M(z_i, \mu_j), \forall j \neq k\}$$

Step 4: Update Cluster Centroids

1. After all points have been assigned, recompute each centroid μ_k:

$$\mu_k = \frac{1}{\mid C_k \mid} \sum_{z_i \in C_k} z_i$$

2. Calculate the centroid shift:

$$\Delta = \max_k \parallel \mu_k^{(t)} - \mu_k^{(t-1)} \parallel$$

3. If $\Delta < \epsilon$, stop iteration. Otherwise, set $t = t + 1$and repeat Steps 3–4.

Step 5: Evaluate Clustering Results

After convergence, evaluate clustering quality using two advanced internal metrics.

(a) Calinski–Harabasz Index (CH)

This index measures the ratio of between-cluster dispersion to within-cluster dispersion:

$$Tr(B_k) = \sum_{k=1}^{K} \mid C_k \mu \parallel^2$$

$$CH = \frac{Tr(B_k)/(K-1)}{Tr(W_k)/(N-K)}$$

Higher CH values indicate better-defined clusters.

(b) Davies–Bouldin Index (DBI)

This index quantifies the average similarity between each cluster and its most similar counterpart:

$$s_i = \frac{1}{\mid C_i \mid} \sum_{z_j \in C_i} \parallel z_j - \mu_i \parallel$$

$$R_{ij} = \frac{s_i + s_j}{d_{ij}}, d_{ij} = \parallel \mu_i - \mu_j \parallel$$

$$DBI = \frac{1}{K} \sum_{i=1}^{K} \max_{j \neq i} R_{ij}$$

Lower DBI values indicate more compact and distinct clusters.

Step 6: Output and Visualization

1. Assign the final cluster label to each data point z_i.
2. Store the cluster assignments, centroids, and evaluation metrics (CH, DBI).
3. Generate visualizations to interpret cluster characteristics:
   - Scatter plot of wins vs. losses with color-coded clusters.
   - Box plot of performance metrics per cluster.
   - Heatmap of cluster centroids to show feature intensity patterns.
4. Save all results and plots for reporting and further analysis.

Step 7: End of Algorithm

Return:
Final cluster labels $C = \{C_1, C_2, \ldots, C_K\}$,
Calinski–Harabasz Index CH, and Davies–Bouldin Index DBI.

Result and Discussion

Data Overview

The data for this analysis was successfully loaded from the player_standings.parquet file, which contains a total of 186,961 entries and 11 columns. The dataset is rich with information, providing insights into player performance, tournament participation, and various other features such as wins, losses, ties, placing, and drop. It was clear from the initial inspection of the dataset that there were some missing values, particularly in the country, placing, and drop columns. Despite this, critical features like wins, losses, and ties were fully populated, allowing for clustering based on these performance metrics. The dataset's large size and rich feature set made it suitable for the purpose of this analysis, providing enough data to generate meaningful insights into player performance and clustering dynamics.

Upon performing an Exploratory Data Analysis (EDA), it became evident that several important metrics required attention. The country feature had 19,756 missing values, and the placing feature had 41,031 missing values, while the drop feature contained 76,263 missing values. These missing values were addressed during preprocessing, as detailed in the methodology. In addition, the summary statistics for the numerical features revealed that players' performance varied significantly across the dataset. For instance, the wins feature had a mean of 2.41, while losses averaged 2.76, and ties were relatively rare with a mean of 0.04. The data showed that while some players excelled in tournaments, most performed at a more moderate level, with a wide range of values for each feature. The correlation analysis indicated a moderate relationship between wins and losses, with a correlation coefficient of 0.47, which suggested that players who won more often also experienced more losses, perhaps indicating more competitive matches.

Figure 2 reveals the geographical distribution of players, showing that the United States (US) has the highest number of players, followed by Brazil (BR), Japan (JP), and Indonesia (ID). This suggests that certain countries have larger player bases, with the US having the most significant concentration. The data on player distribution across countries can be useful for tournament organizers to target specific regions for future events and tailor formats based on regional player engagement and skill levels.

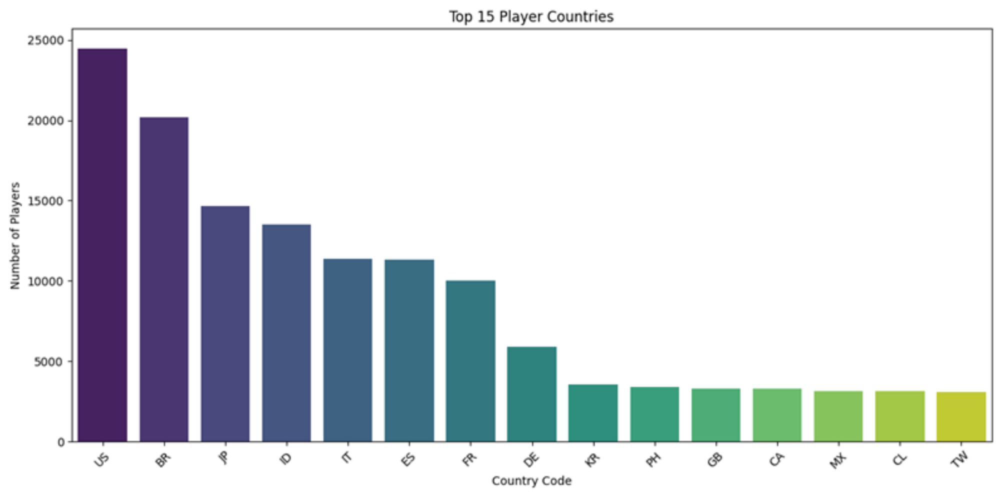

Figure 2 Top 15 Player Countries

In figure 3, we observe that most players tend to perform moderately, with a few players exhibiting exceptional results. The wins distribution shows that while many players have a small number of wins, there is a long tail indicating a small group of players who achieve high win counts. Similarly, the losses distribution indicates that most players experience only a few losses, with a sharp decrease in frequency as the number of losses increases. This suggests that players typically have a balanced performance but few players rack up a large number of losses. The ties distribution is dominated by zero ties, reflecting that ties are a rare event in competitive play. The placing distribution further emphasizes that most players rank lower, with a significant portion of players placing between positions 1 to 250, and very few achieving higher ranks. These findings indicate that the competitive environment in Pokémon TCG tournaments is skewed towards a large pool of players with moderate performance, with only a small group excelling.

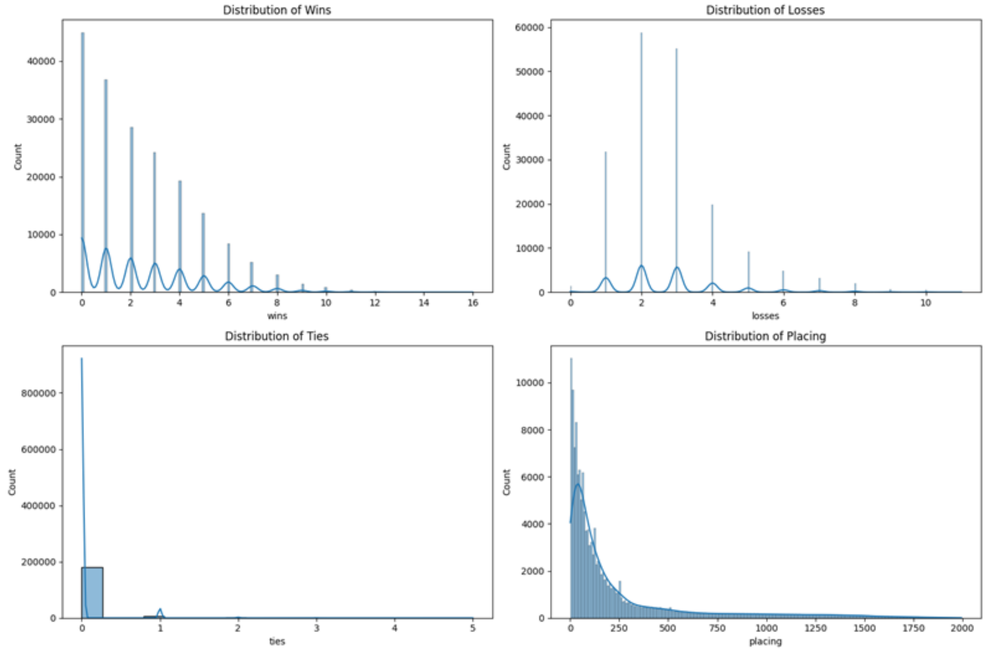

Figure 3 Distribution of Wins, Losses, Ties, and Placing

Figure 4 indicates that a significant proportion of players, 59.21%, dropped out of the tournament at some point, while the remaining players continued. This high dropout rate is an interesting finding, suggesting potential areas for improvement in player engagement or tournament design. Future analyses could investigate the reasons behind the dropout, such as the tournament's length, match difficulty, or the overall competitiveness, all of which could provide insights into how to retain players and enhance their experience in future events.

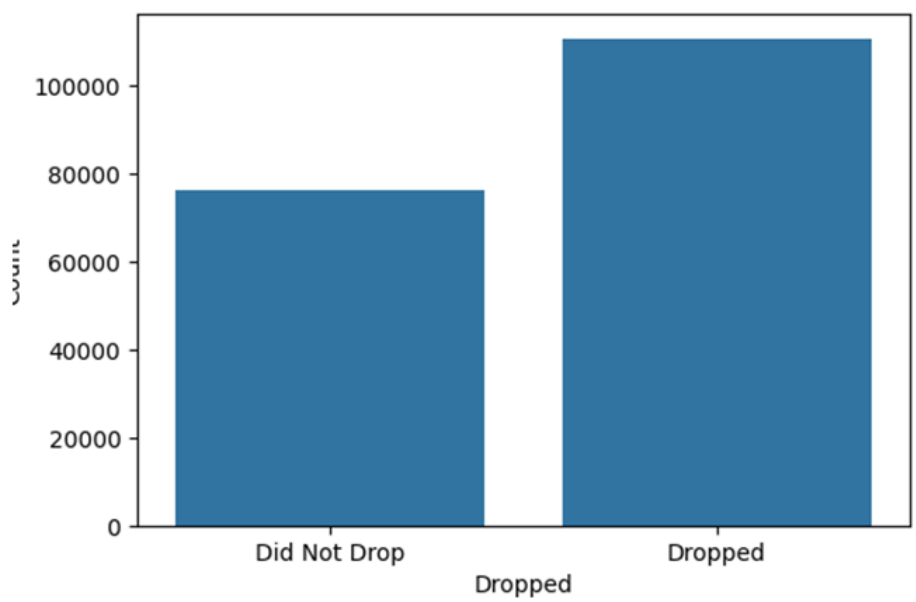

Figure 4 Player Drop Status

Figure 5 visualizes the relationship between wins and losses for each player. It reveals a clear trend where players with higher wins also tend to accumulate more losses, forming a diagonal pattern. This suggests that players who perform well in tournaments are exposed to more competitive matches, leading to an increase in the number of losses. It reinforces the competitive nature of Pokémon TCG tournaments, where success correlates with facing stronger opponents. The plot highlights that skill is a significant factor in determining success, with players who consistently perform well also encountering tougher competition.

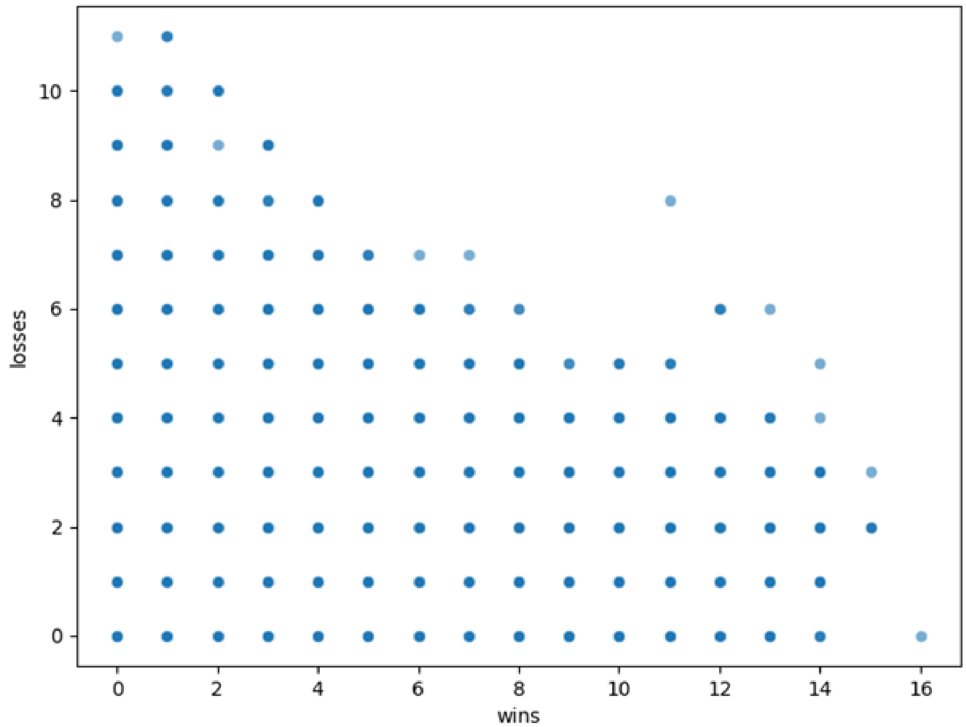

Figure 5 Wins vs Losses Plot

Data Preprocessing for Clustering

After the initial exploration of the dataset, the preprocessing steps were carried out to prepare the data for clustering. Since clustering requires clean and well-processed data, several steps were taken to ensure the dataset was ready. The selected features for clustering were wins, losses, and ties, as these represent the key indicators of player performance in the Pokémon TCG tournaments. During the preprocessing, missing values in these columns were handled using the SimpleImputer from sklearn. The imputation strategy employed was to replace missing values with the median value of the respective column, which is a robust method for handling missing data without introducing bias into the clustering model.

Once the missing values were handled, the data was scaled using the StandardScaler from sklearn. The scaling step was crucial for ensuring that all features contributed equally to the clustering algorithm. Without scaling, features with larger numerical ranges, such as wins, would disproportionately influence the clustering results. After standardizing the features, the data was ready for the clustering algorithm. The scaled data was saved into a CSV file for later use, ensuring that the dataset could be reused without needing to perform the preprocessing steps again.

K-means Clustering

With the data preprocessed and scaled, the K-means clustering algorithm was applied to group players based on their performance metrics. The number of clusters, K, was manually set to 4 (MANUALLY_CHOSEN_K), reflecting the hypothesis that there are four distinct performance groups among players. While methods like the Elbow Method or Silhouette Score could have been used to determine the optimal K, this study opted for a fixed K value to simplify the analysis and demonstrate how clustering can be applied with a predefined number of clusters.

To optimize the clustering process for larger datasets, MiniBatchKMeans was used instead of the standard K-means algorithm. MiniBatchKMeans processes data in smaller batches, which makes it faster and more memory-efficient compared to traditional K-means. This is particularly useful when dealing with large datasets, as it allows the algorithm to scale without significantly increasing computational costs. The final K-means model was trained with K=4, and the clustering process took 0.50 seconds to complete, which is a testament to the efficiency of the MiniBatchKMeans algorithm.

The resulting clusters were added to the original dataset, and the distribution of players across the four clusters was as follows: Cluster 0: 92,959 players; Cluster 1: 43,692 players; Cluster 2: 7,310 players and Cluster 3: 43,000 players. These results suggest that the majority of players fall into Cluster 0, indicating a large group of players with moderate performance. Cluster 2, with fewer players, represents a smaller group, likely consisting of top-performing players, as inferred from the clustering and subsequent analysis. The dataset with cluster labels was saved for further analysis, and both the trained K-means model and scaler were also saved using joblib to facilitate future use without needing to retrain the model.

Clustering Evaluation

To evaluate the performance of the K-means clustering model, the Silhouette Score was calculated. The Silhouette Score is a widely used metric that evaluates how similar each point is to its assigned cluster compared to other clusters. A higher silhouette score indicates that the clusters are well-separated, while a lower score suggests that the clustering may not be optimal. For this study, the silhouette score was computed using a sample size of 50,000 players due to the large size of the dataset. The resulting Silhouette Score for K=4 was 0.4582, which indicates that the clusters are moderately well-separated. Although the score is not extremely high, it suggests that the clustering algorithm was effective in grouping players with similar performance patterns, but there may still be some overlap between the clusters.

Visualization and Interpretation of Clusters

To facilitate the interpretation of the clustering results, several visualizations were generated. A scatter plot was created to visualize the relationship between wins and losses for each player, color-coded by their assigned cluster. Figure 6 offers a visual interpretation of the relationship between wins and losses for each player, with color coding for each cluster. This scatter plot reveals that players in Cluster 0 are predominantly located at the bottom left of the plot, with lower values for both wins and losses; players in Cluster 1 are scattered in the middle of the plot, with moderate wins and higher losses; cluster 2 players are more spread out, with some players having a high number of wins and losses, suggesting that this group includes more competitive players; and Cluster 3 players are primarily concentrated in the upper right, indicating that they have high wins but also face a fair number of losses. The red centroids on the scatter plot represent the average values of wins and losses for each cluster. These centroids serve as a reference point to understand the general performance level of each cluster. The distribution of players around these centroids indicates the variability in performance within each group.

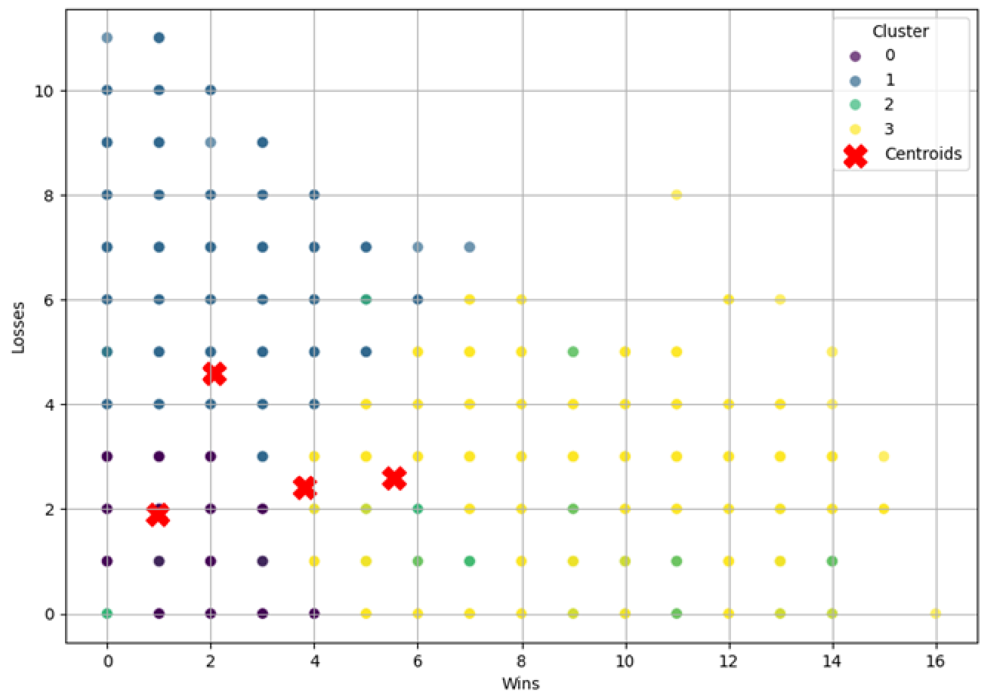

Figure 6 Player Clusters based on Wins vs Losses

Additionally, box plots were generated to compare the distribution of wins, losses, and ties across the clusters. Figure 7 offer a deeper look into the distribution of these metrics within each cluster. These plots help identify the spread and central tendency of each feature within the clusters, providing insights into player performance variability. Cluster 0 shows a low range of wins, with most players having fewer than 5 wins. Cluster 2 and Cluster 3, however, have a higher range of wins, with some players achieving up to 16 wins. Cluster 1 falls in between, with moderate wins. The presence of outliers in Clusters 1, 2, and 3 indicates that some players perform exceptionally well compared to others in their respective clusters. Cluster 0 has the lowest number of losses, with most players experiencing only 1 to 3 losses. Clusters

2 and 3 show a higher number of losses, with Cluster 2 containing some players with as many as 6 losses, suggesting they face tough competition. Interestingly, Cluster 1 has a similar range of losses, showing that even players with moderate wins also face many losses. As expected, the ties box plot shows that the majority of players in all clusters have 0 ties, with very few outliers indicating players who had more than 1 tie. These box plots effectively visualize the spread and central tendency of each feature, helping to compare the distribution of performance metrics across the clusters.

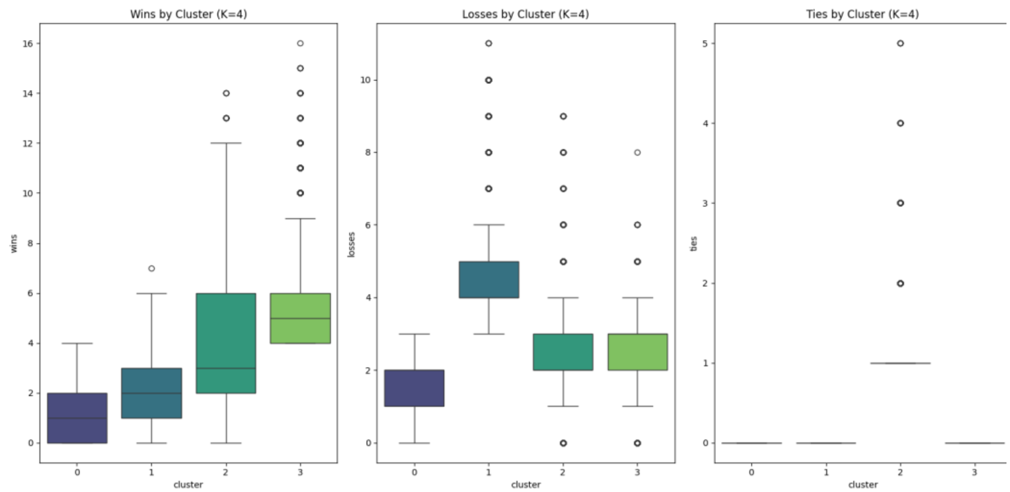

Figure 7 Boxplot of Wins, Losses and Ties by Cluster

The centroids of the clusters were also visualized through a heatmap, which provided a clear overview of the central values for wins, losses, and ties across each cluster. Figure 8 provides a visual representation of the central values for wins, losses, and ties across the four clusters. Each cell in the heatmap shows the average value of the respective feature for each cluster. Cluster 0 has an average of 0.97 wins, 1.89 losses, and close to 0 ties. This suggests that players in Cluster 0 are relatively low performers, with fewer wins and losses. Cluster 1 has an average of 2.06 wins, 4.58 losses, and close to 0 ties, indicating a moderate group of players who tend to win more but also face frequent losses. Cluster 2 shows higher performance with 3.81 wins and 2.41 losses, suggesting this cluster consists of more skilled players. Cluster 3 has the highest average 5.54 wins and 2.60 losses, reflecting the performance of highly competitive players. The tie values for all clusters are very low, emphasizing the rarity of ties in this dataset. This heatmap provides a quick overview of how player performance varies across clusters.

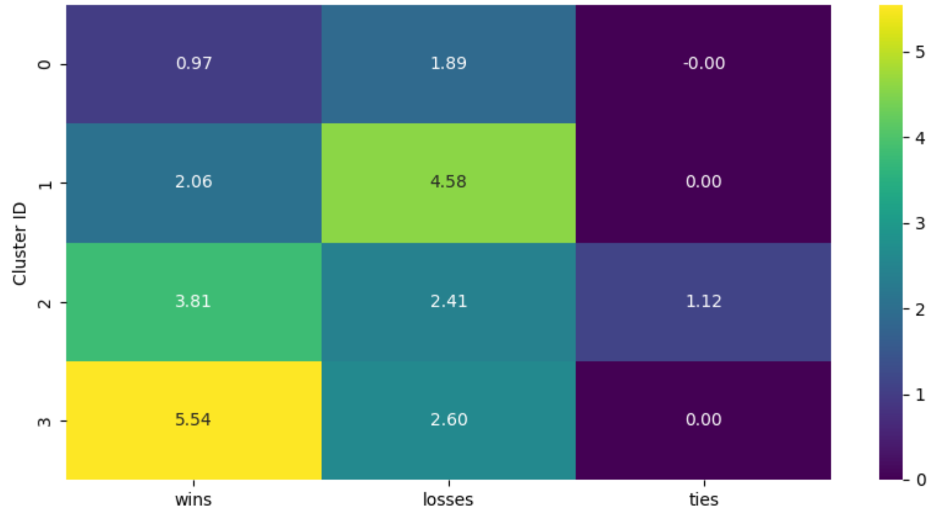

Figure 8 Cluster Centroids

Cluster Summary and Analysis

The final cluster summary revealed the mean values of wins, losses, and ties for each cluster, as well as the size of each cluster. The results showed that a) Cluster 0 had the lowest average wins (1.02) and losses (1.93), representing the group of players with the least success in tournaments; b) Cluster 1 had moderate wins (2.06) and losses (4.74), indicating a group of players who performed well but also faced frequent defeats; c) Cluster 2, the smallest group, had the highest average wins (3.85) and losses (2.38), suggesting it consisted of the most skilled players; d) Cluster 3 had the highest wins (5.54) but a similar number of losses (2.60) as Cluster 2, indicating that it represented another group of highly competitive players. The cluster summary was saved to a CSV file, which provides an easy reference for understanding the characteristics of each cluster. The centroids of each cluster were further analyzed to gain deeper insights into the groupings.

The clustering analysis successfully grouped players into four distinct performance clusters, each representing different levels of success in Pokémon TCG tournaments. The use of K-means clustering allowed for the identification of these groups, and the subsequent analysis provided valuable insights into player behavior and performance patterns. The Silhouette Score of 0.4582 indicated that the clustering was moderately effective, with players being grouped in a meaningful way. The visualizations and cluster summaries provided a comprehensive understanding of how players differ in terms of their competitive performance, offering opportunities for players to optimize their strategies and for tournament organizers to enhance the structure of competitive events. The results highlight the importance of clustering in understanding competitive dynamics and offer a foundation for future research and optimization of Pokémon TCG tournaments.

Discussion

The clustering analysis conducted in this study revealed four distinct performance groups among players in Pokémon TCG tournaments, based on their wins, losses, and ties. These groups, which were identified through the K-means clustering algorithm, represent players at different levels of success in competitive play. This approach aligns with similar research in other competitive gaming environments, where clustering is used to identify skill levels and strategic patterns among players.

In previous studies, clustering has been successfully applied to segment players in various competitive gaming settings, including esports and digital card games. For example, [4] applied K-means clustering to categorize players in digital card games, identifying performance-based clusters that helped differentiate between top performers and those with more moderate skills. Similarly, [2] utilized clustering techniques to group players in online competitive platforms like League of Legends, focusing on win rates and other performance metrics. This is similar to our study, where the performance metrics wins, losses, and ties were used to distinguish between player groups in Pokémon TCG. The consistent application of clustering across various games, including card games like Pokémon TCG, highlights the robustness of this technique in identifying meaningful player segments.

What sets this study apart is the use of MiniBatchKMeans, an optimization of the standard K-means algorithm. By processing data in smaller batches, MiniBatchKMeans allows the analysis to scale more efficiently with large datasets, making it particularly well-suited for tournaments with thousands of participants. This optimization makes the analysis not only faster but also more feasible when working with extensive datasets, a significant improvement over traditional K-means, as seen in [3], where more computationally intensive methods were used for tournament data analysis. This methodological innovation provides a more efficient way to segment large player populations, ensuring that clustering can be performed quickly without sacrificing accuracy.

The Silhouette Score of 0.4582, calculated for K=4, indicates that the clustering results were moderately effective. A Silhouette Score closer to 1 would suggest well-defined clusters with little overlap, while scores near 0 or negative would suggest poorly separated clusters. The moderate score observed in this study is consistent with findings from [4], who found similar scores when applying K-means clustering to digital card games. In their study, they noted that while clustering helped identify broad player segments, some overlap was inevitable due to the inherent variability in player strategies, gameplay decisions, and external factors like deck choice.

Our study confirms this trend, as the moderate silhouette score indicates that the clusters were reasonably well-separated, but some overlap likely exists, especially in the middle clusters where players' performance may fluctuate. This is a common challenge in clustering applications, particularly in environments like competitive card games, where the outcome of each match is influenced by a range of factors, including player decisions, deck composition, and opponent strategies. Future studies could explore the application of more advanced clustering algorithms, such as DBSCAN or Gaussian Mixture Models, which could handle clusters of varying shapes and densities, potentially improving the separation between performance groups.

The clusters generated in this study provide valuable insights into the competitive dynamics within Pokémon TCG tournaments. Cluster 0, which contains the largest number of players (92,959), represents the lowest-performing group, with an average of 1.02 wins and 1.93 losses. This group mirrors the "casual" or "beginner" players identified in other studies, such as [2], where a similar cluster was found to represent players who engage with the game but do not consistently perform well in competitive settings. In contrast, Cluster 2, with only 7,310 players, contains the top performers with 3.85 wins and 2.38 losses, making it the most successful group. This aligns with findings from [4], who found that high-performing players tend to form smaller clusters due to their distinct playstyles and higher win rates.

The insights gained from clustering can have practical applications for both tournament organizers and players. Tournament organizers can use the cluster analysis to design more balanced and engaging competition formats. For example, players in Cluster 0, with lower performance metrics, could be placed in beginner-level brackets to ensure a fairer competition for new or less experienced players. Meanwhile, players in Clusters 2 and 3, with higher performance levels, could be placed in advanced brackets, creating a more competitive and challenging environment for top players. This approach mirrors recommendations from [2], who proposed dynamic pairing algorithms to enhance fairness in tournament structures by matching players based on their skill levels.

For players, understanding their performance profile can help them optimize their strategies. Players in Cluster 0 may benefit from refining their deck construction and learning more advanced gameplay tactics, while players in Cluster 2 can analyze their performance patterns and focus on further improving their strengths. These insights can guide players in setting realistic goals for improvement, enabling them to target specific areas of weakness in their competitive play. This idea of using clustering to tailor strategic advice is supported by [5], who noted that understanding player behavior and performance clusters can significantly enhance strategy development and gameplay optimization.

Despite the valuable insights provided by the clustering analysis, several limitations should be acknowledged. One limitation is the manual selection of K=4, which may not be the optimal number of clusters for all datasets. Future research could explore the use of automated methods, such as the Elbow Method or Silhouette Score, to determine the optimal number of clusters based on the dataset's characteristics. Additionally, the K-means algorithm assumes that clusters are spherical and of equal size, which may not always be the case. Alternative clustering algorithms, such as DBSCAN or Gaussian Mixture Models, could provide better results by accommodating irregularly shaped clusters and varying cluster densities.

Another avenue for future research could involve incorporating more granular features into the clustering analysis, such as player behavior, deck types, or match decisions, which may provide a deeper understanding of player performance beyond simple win-loss metrics.

Conclusion

This study successfully applied K-means clustering to analyze player performance in Pokémon TCG tournaments, identifying four distinct clusters based on the performance metrics of wins, losses, and ties. The key clusters revealed significant insights into player behavior, with Cluster 0 representing the majority of lower-performing players, Cluster 2 containing top performers, and Clusters 1 and 3 indicating intermediate levels of success. These insights can help players understand their performance relative to others and refine their strategies for improvement. Tournament organizers can use these findings to better structure competitive events, ensuring that players are matched with others of similar skill levels to foster a more engaging and balanced competition. This research has important implications for both players and tournament organizers. For players, understanding their performance cluster allows for targeted strategy improvements and a clearer path for progression within the game. For organizers, these insights provide a framework for designing tournaments that are fairer and more competitive, enhancing the overall player experience. Moving forward, further research could explore more advanced clustering techniques, such as DBSCAN or Gaussian Mixture Models, to capture more complex player behaviors or incorporate additional data sources, such as deck composition or in-game decision-making. Ultimately, clustering plays a crucial role in understanding competitive dynamics within Pokémon TCG and esports, offering valuable tools for optimizing both player strategies and tournament formats.

Declarations

Author Contributions

Author Contributions: Conceptualization, G.S. and L.N.; Methodology, G.S. and L.N.; Software, G.S.; Validation, L.N.; Formal Analysis, G.S.; Investigation, G.S. and L.N.; Resources, L.N.; Data Curation, G.S.; Writing—Original Draft Preparation, G.S.; Writing—Review and Editing, L.N.; Visualization, G.S. All authors have read and agreed to the published version of the manuscript.

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Declaration of Competing Interest

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

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