Overwatch 2 META Analysis

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***Abstract*— Esports continuously influences gaming communities through METAs (Most Effective Tactics Available) that originate from professional players. This study examines how player choices correlate across skill levels in Overwatch 2, specifically analyzing hero pick rates to understand META adoption patterns. Using Principal Component Analysis, as well as K-Means cluster analysis on Blizzard's official statistics, Kaggle datasets, and professional league data, we assess META adaptation speed, convergence rates, and the relationship between skill level and hero selection. By comparing trends with patch notes and game updates, we determine how quickly METAs propagate through different skill tiers. This research provides valuable insights for game developers and esports organizations regarding player behavior and competitive dynamics.**

Keywords—casual players, eSports players, video game skill, game metrics, hero selection, meta

I. Introduction

"Nerf this!" The landscape of competitive gaming has evolved dramatically in response to the rise of eSports and the subsequent emphasis on game data analytics, but understanding how different players respond to game balance changes such as "buffing" (improving) and "nerfing" (worsening) a character's in-game abilities remains a challenge [3]. Today, multiplayer competitive games often undergo balance patches, which consist of buffs and nerfs to characters in an attempt to maintain competitive freshness, but lack understanding of how changes might affect players of differing skill levels in non-uniform ways [4]. For game developers, it would be highly beneficial to understand how quickly and thoroughly their decisions to "balance" the game trickle through the player base, and whether these METAs that emerge at higher ranks/skill levels bear any resemblance to how the majority of players truly experience the game [5, 6, 7]. In this study, we aim to quantify these ideas by examining Overwatch 2, a team-based first-person shooter (FPS) with over 35 million players and a range of player skill levels spanning from casual "bronze" players to professional "grandmaster" eSports competitors.

II. Methods

A. K-Means Cluster Analysis

K-means cluster analysis will group players into distinct clusters based on hero pick rate patterns, win rates, and seasonal trends. The algorithm will identify natural groupings in player behavior independent of assigned rank, revealing whether skill-based tiers align with observable play patterns. Cluster centroids will represent archetypal player profiles characterized by specific hero preferences and performance metrics. Cross-referencing clusters with patch notes will reveal how game updates shift the composition and characteristics of each cluster, illustrating whether balance changes create new player archetypes or consolidate existing ones.

B. Principal Component Analysis (PCA)

Dimensionality reduction will be performed on the dimensions of heroes, ranks, and seasons (official stretches of skill rating tracking) to isolate and identify the variations of hero choice across ranks over different time periods. PCA will show which features separate a player of one rank from another on the same hero. This process will be applied to 5 heroes that show high difference in win percentage and 5 heroes with close to no change in win percentage when comparing rank groups.

III. Results

A. K-Means Cluster Analysis

This study examined how player choices correlate across skill levels in Overwatch 2 by analyzing hero pick rates and win rates using Blizzard's official statistics [1] to understand META adoption patterns. K-Means cluster analysis was employed to identify natural groupings in player behavior independent of assigned rank, revealing whether skill-based tiers align with observable play patterns and how game balance changes affect different player segments.

1. Optimal Cluster Identification

The elbow method combined with silhouette score analysis was applied (see Figure 1) to determine the optimal number of clusters (k) for each rank tier. Silhouette scores measure cluster separation quality on a scale from -1 to 1, to which our silhouette scores indicated varying levels of meta homogeneity across ranks. Analysis of k values ranging from 2 to 10 revealed that most rank tiers achieved optimal clustering with k values between 2 and 4 which suggests that hero performance naturally separates into distinct meta archetypes. The optimal k values were identified for each rank tier (Bronze, Silver, Gold, Platinum, Diamond, Master, Grandmaster/Champion, and All Tiers) by selecting the number of clusters that maximized the silhouette coefficient. Based on the figures, the most optimal k for comparing all tiers lies at k=3 (see Appendix).

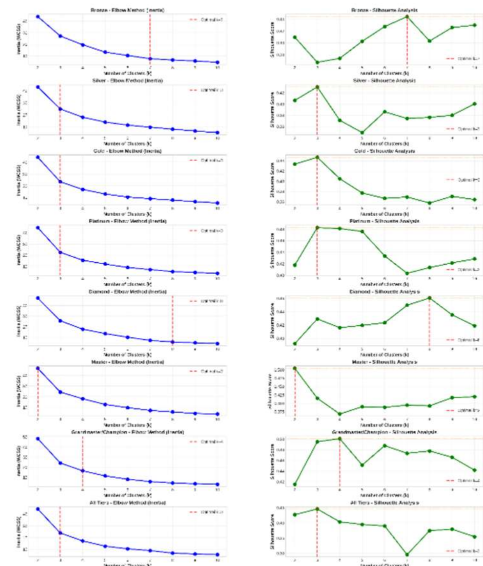

Figure 1: Elbow and Silhouette graphs for Current Season

2. Pick Rate versus Win Rate Correlations

Three primary meta-archetypes emerged consistently across rank tiers based on the positioning of cluster centroids in the pick rate-win rate feature space:

Meta Heroes (high pick, high win)**:** Heroes in this archetype represented the strongest current meta picks, demonstrating both popularity and effectiveness. These heroes were typically prominent in competitive play and indicated well-established strategies.

Average Heroes (balanced win/pick)**:** This cluster contained heroes who were selected around 10% of the time (the average pick rate) and had a near average win rate of around 50%.

Niche/Weak Heroes (low win or low pick)**:** This cluster comprised heroes struggling in either popularity and effectiveness, often representing characters negatively affected by recent balance patches or those poorly suited to the current game state.

Cluster analysis revealed important distinctions between hero popularity and effectiveness across all rank tiers. The correlation between pick rate and win rate strengthened at higher skill tiers, with Grandmaster/Champion showing the tightest alignment between popularity and effectiveness (see Figure 2). This suggested that experienced players made more data-driven hero selections, while lower rank players relied more heavily on personal preferences or community influence that did not always align with statistical performance.

Notably, several heroes maintained consistently high win rates across all rank tiers despite relatively low pick rates, representing potential underutilized strategies. These heroes appeared primarily in the Niche Pick archetype and suggested opportunities for players to gain competitive advantage by using statistically strong, but unpopular characters. For temporal analysis (current season against Seasons 1-4), see Appendix.

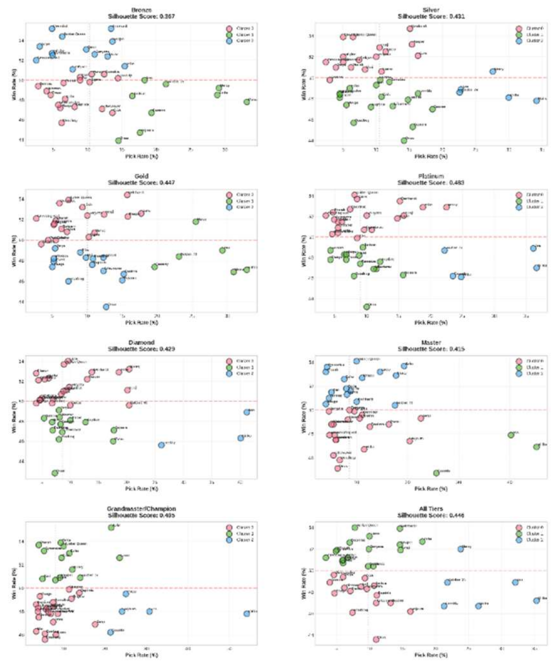

Figure 2: *K-Means Clustering for Current Season*

B. Principal Component Analysis (PCA)

PCA was conducted on data from competitive seasons 1-4 of Overwatch 2 using data collected from a public Kaggle dataset [2]. The goal of this analysis is to identify factors associated with differences in found success using the same hero across different skill tiers (ranks). The findings of this analysis allow players to better understand what changes in their gameplay could be associated with success and potentially model their gameplay in a similar way.

1. Identifying Affected Heroes

To narrow down our approach to a representative group of heroes, we first grouped heroes by rank and then cleaned each heroes data to remove features that are irrelevant to them. Once data was grouped and cleaned, we calculated and visualized the differences in win rate between high- and medium-ranked players (Figure 3). Our focus was to find 5 heroes that see much greater success in high ranks when compared to medium ranks and 5 heroes that see no significant change in win rate between ranks, providing insights into general effectiveness of features and differences in hero utility respectively. These same heroes were then used for the comparisons of medium and low tiers (see appendix).

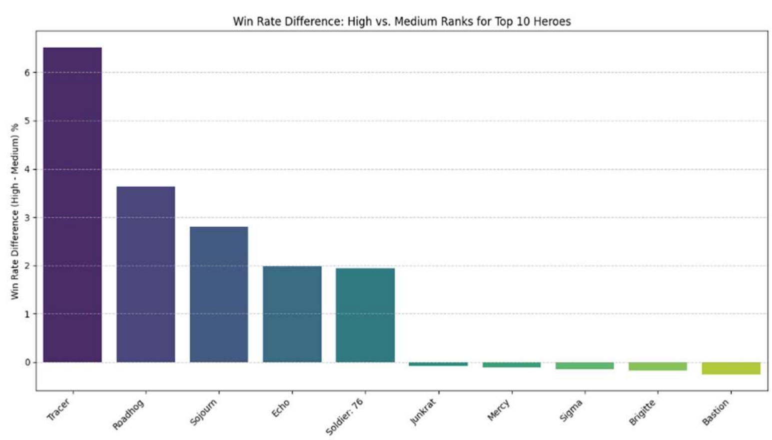

Figure 3: *Win Rate Differences for Selected Heroes*

2. Analyzing Variance of Features using PCA

From the identified 10 heroes, we conducted PCA to narrow down to components most representative of the variance between ranks of each. The dominant loading feature of each were noted with each principal component and then plotted against win rate (Figure 4). These visualizations allowed us identify visual trends in the data and note possible correlations. This was conducted for all heroes and for both high-medium and medium-low comparisons (see appendix). From these graphs we were able to identify both general gameplay improvements, such as damage, and hero-specific kit utilizations as leading contributing factors to variance, with results differing greatly between heroes and ranks.

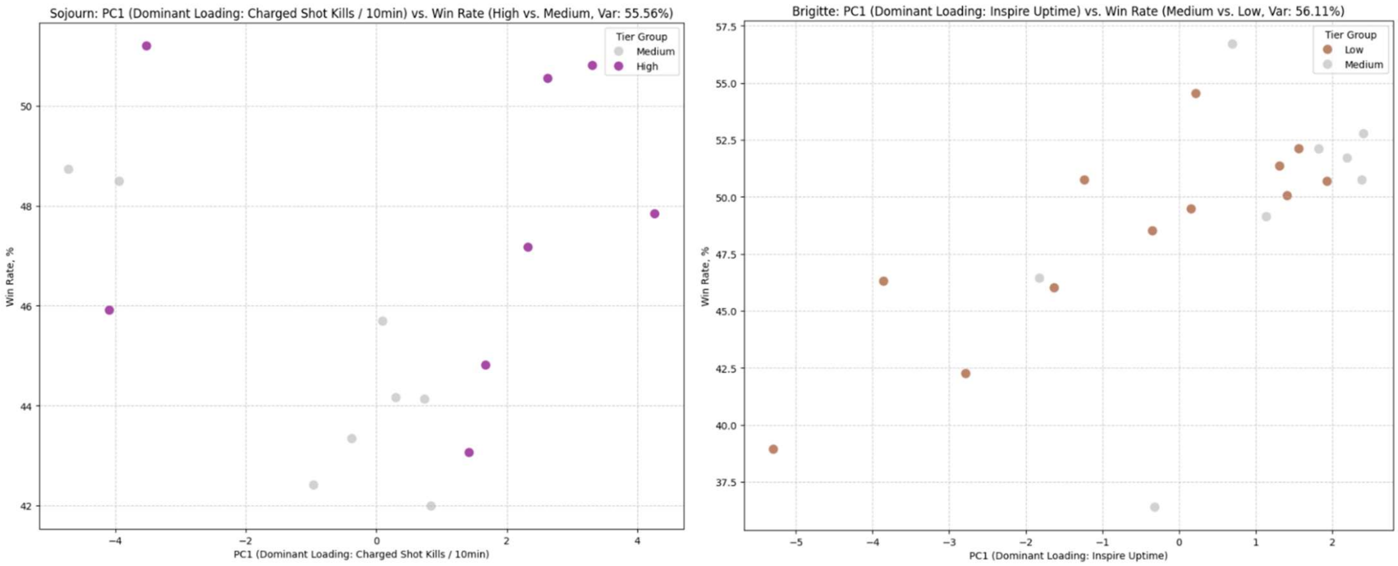

Figure 4: *PC1 vs. Win Rate for Sojourn (High vs. Medium) and Brigitte (Medium vs. Low)*

IV. Discussion

A. K-Means Cluster Analysis

The K-Means cluster analysis revealed significant distinctions in how players across skill all levels engage with Overwatch 2's competitive mode, and provided evidence for the hierarchical nature of METAs, and the varying responsiveness of different player segments to game balance changes.

1. Practical Applications

For game developers, these findings emphasize the importance of multi-tier balance testing and the potential need for categorized balance patches or rank-specific adjustments. The data suggests that a one-size-fits-all balance approach may not be optimal given the fundamental differences in how heroes perform across ranks. Developers should consider whether certain heroes are intended to be more mechanically intensive (thus requiring higher rank) and design accordingly, or whether all heroes should ideally maintain relatively stable performance across the skill spectrum.

For players that are seeking rank improvement, the cluster analysis reveals that understanding the META appropriate to one's skill tier is more important and valuable than blindly copying high-rank strategies. The persistence of strong Niche Pick heroes across multiple seasons suggests that META-defiant strategies can be successful if they align with a player's mechanical capabilities and gameplay knowledge. Players might benefit more from identifying underutilized strong heroes in their specific rank rather than attempting to play mechanically demanding Meta Heroes from professional play.

2. Limitations

Several limitations should be acknowledged about the K-Means cluster analysis technique. The cluster analysis approach treats pick rate and win rate as independent, but these metrics are inherently related (i.e., popular heroes may experience win rate suppression due to overuse or counter-picking). Additionally, the analysis aggregates data across time periods within seasons, potentially overshadowing the short-term META changes that occur occasionally between patches. Finally, the focus on hero selection excludes other important factors such as player positioning, ability usage, and team coordination that contribute significantly to performance outcomes.

Despite these limitations, the K-Means cluster analysis demonstrates that Overwatch 2 supports multiple simultaneous METAs at each different skill level, that META propagation from professional to casual play does not appear immediately or in a uniform fashion, and that game balance changes affect different player groups on different timescales and to different degrees.

B. *Principal Component Analysis*

PCA revealed defining differences between how heroes find success in different ranks. Findings from each hero vary greatly, showing a need to look at individual hero differences instead of generalizing terms for success.

1. Practical Applications

Developers can analyze the different use cases of heroes from rank to rank, allowing them to understand how a potential balance change might have varying effects across ranks. These analyses can contribute to changes being more positively received across the general player base instead of individual skill levels.

Players can benefit from this information by identifying how the hero they play is generally used differently by players who are more successful. From this, they can adapt their playstyle to adhere to standards to attempt to mimic the success of others.

2. Limitations

In all applications of the data, the findings are not representative of a causal relationship, but rather as an identification of existing differences. Confounding variables and combinations of gameplay alterations could be more representative of changes that lead to success, but are simply not identified as the dominant loading of a principal component. The identified features do not explain the circumstances in which the changes are achieved, so players attempting to increase/decrease a certain statistic in general might not find the same success as someone pursuing the same goal strategically. In general, players attempting to find success and developers aiming to balance heroes would have to use these findings in conjunction with other data in order to effectively see successful change.

V. References

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VI. Appendix

1. Visualization Collection

https://github.iu.edu/B365-Fall2025/Project-olibelch-spletz/tree/main/Visualizations