Overwatch Competitive Analysis

High Ranked Pick and Win Rate Statistics vs Pro League Ban Strategies

This project analyzes Overwatch 2 hero performance metrics from high ranked competitive play and compares them against hero ban data from professional play: the Overwatch Championship Series (OWCS). It primarily investigates how a hero's win rate correlates with ban frequency in OWCS, and it also investigates whether pick rate and win rate correlate. Overwatch 2 is a 5v5 team-based first-person shooter where players select from diverse characters, known as heroes, each with unique abilities and ultimates, classified into one of three roles (Tank, Damage, or Support), to compete in objective-based matches. The analysis reveals that win rate and OWCS ban rate are not very correlated, and neither are pick rate and win rate. This low correlation is what I expected; there is a lot of nuance in Overwatch that requires additional context not captured by simple pick rate, win rate, or ban rate metrics.

Introduction

In professional Overwatch play, including OWCS, matches between teams are a best-of-5 series, made up of five standard games of Overwatch. In each game, both teams can ban one hero, meaning that neither team is allowed to play that hero in that game. Per the OWCS ban rules, two heroes of the same role cannot be banned in the same game. For instance, if my team bans a support hero, the other team cannot also ban a support hero. Additionally, a team cannot ban the same hero twice in a best-of-five series. However, a hero can be banned by the other team. For instance, Team A bans Kiriko in the first game, then team B bans Kiriko in the second game.

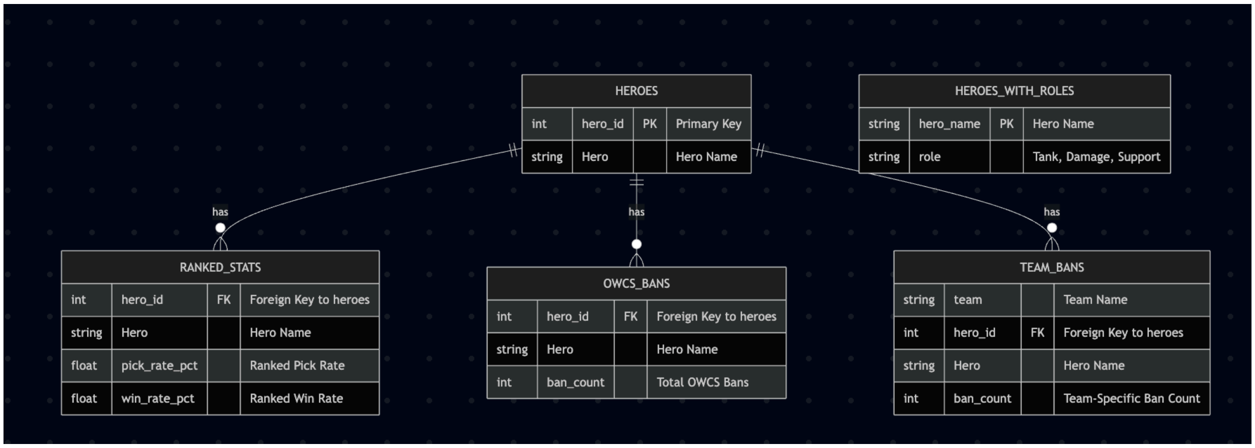
Data Sources and Integration

My project consisted of three data sources. First, the official hero statistics page from Blizzard, which includes pick rate and win rate numbers for each hero. Pick rate specifically is how many games is the hero played in, and win rate is how often does the hero win when it is not played by both teams, known as “unmirrored winrate”. I scraped this page and downloaded it as a plain text html file to preserve the data in case of an update which changed the power of any heroes. Second, I used a CSV file from Kaggle consisting of OWCS match history. Third, I created another CSV file which contains hero names and roles, the same roles as mentioned above.

Data Cleaning And Transformation

Integrating the Blizzard official data and the OWCS data was a bit challenging. First, the OWCS data had some typos and inconsistencies. Lúcio and Torbjörn were missing accent marks from their names, and three heroes had their names spelled incorrectly. Secondly, the OWCS data included five hero bans per standard game for each team, which was confusing since each team only gets one ban per game. This was because it showed a ban for each player in the 5v5 match. To solve this, I created a key built on the hero that was banned along with the match date and time, then dropped duplicates based on that key. Finally, the HTML scraping proved difficult due to the design of Blizzard’s website. I had to do two separate scrapes and concatenate them into one file, then create a complex parser, and remove duplicates.

Relational Database Schema



I created five main tables: Heroes, Heroes with Roles, Ranked Stats, OWCS Bans, and Team Bans. They are defined as follows:

Table Definitions

heroes (Core Dimension)

Primary Key: hero_id
Purpose: Master list of all 44 heroes
Records: 44

ranked_stats (Ranked Performance Facts)

Primary Key: hero_id

Foreign Key: hero_id → heroes.hero_id

Metrics: Pick Rate (%), Win Rate (%)

Records: 44

owcs_bans (Aggregated Professional Bans)

Primary Key: hero_id
Foreign Key: hero_id → heroes.hero_id
Metric: ban_count (sum of bans across all OWCS matches)
Records: 43 (1 hero never banned)

team_bans (Team-Specific Ban Strategies)

Composite Key: (team, hero_id)
Foreign Key: hero_id → heroes.hero_id
Tracks: Which teams ban which heroes and how often
Records: 488 team-hero combinations

heroes_with_roles (Role Classification)

Primary Key: hero_name
Attributes: Tank, Damage, Support
Records: 44

Key Queries

1. Top 10 Most Banned Heroes And Their Ranked Win Rates

Top 10 Most Banned Heroes in OWCS

```
SELECT
    h.Hero,
    ob.ban_count,
    rs.'Win Rate (%)' as win_rate
FROM heroes h
JOIN owcs_bans ob ON h.hero_id = ob.hero_id
JOIN ranked_stats rs ON h.hero_id = rs.hero_id
ORDER BY ob.ban_count DESC
LIMIT 10;
```

	Hero	ban_count	win_rate
0	Lúcio	96	53.2
1	D.Va	75	51.7
2	Kiriko	71	46.9
3	Hazard	64	47.9
4	Ana	63	48.0
5	Juno	58	50.4
6	Tracer	56	48.9
7	Ramattra	47	48.0
8	Wrecking Ball	44	47.7
9	Brigitte	43	50.1

Main takeaway: A common trend is that ban count and win rate are not very correlated.

2. Inverse Correlation Score Between Number of Bans and Win Rate

Inverse Correlation Score

```sql
WITH stats AS (
    SELECT
        h.Hero,
        ob.ban_count,
        rs."Win Rate (%)" AS win_rate,
        rs."Pick Rate (%)" AS pick_rate,
        AVG(rs."Win Rate (%)") OVER () AS avg_win,
        AVG(ob.ban_count) OVER () AS avg_ban
    FROM heroes h
    JOIN owcs_bans ob ON h.hero_id = ob.hero_id
    JOIN ranked_stats rs ON h.hero_id = rs.hero_id
)
SELECT
    Hero,
    ban_count,
    win_rate,
    pick_rate,
    ROUND(
        (win_rate - avg_win) * (avg_ban - ban_count),
        2
    ) AS inverse_correlation_score
FROM stats
ORDER BY inverse_correlation_score DESC;
```

	Hero	ban_count	win_rate	pick_rate	inverse_correlation_score
0	Kiriko	71	46.9	45.2	124.38
1	Junker Queen	8	54.0	10.0	85.33
2	Ashe	8	53.7	19.6	79.21
3	Mercy	5	52.8	17.7	69.77
4	Hazard	64	47.9	4.5	68.35
5	Echo	5	52.6	7.6	65.08
6	Ana	63	48.0	40.2	62.97
7	Venture	12	53.2	6.3	55.48
8	Reaper	9	52.6	11.1	53.97
9	Orisa	37	45.2	6.3	39.65
10	Ramattra	47	48.0	6.2	33.84
11	Wrecking Ball	44	47.7	5.7	33.05
12	Wuyang	20	53.5	19.1	30.97
13	Tracer	56	48.9	16.0	25.40
14	Junkrat	3	50.7	4.5	22.34
15	Reinhardt	2	50.6	10.0	20.58
16	Zarya	21	52.0	8.0	16.17
17	Illari	20	51.7	5.0	15.82
18	Sigma	19	51.3	8.1	13.93
19	Sojourn	33	47.5	20.7	10.63
20	Winston	42	49.1	10.4	9.79
21	Freja	36	48.8	6.2	7.74
22	Genji	41	49.3	22.3	6.55
23	Sombra	31	47.7	5.9	5.47
24	Pharah	27	53.6	4.0	5.36
25	Torbjörn	34	49.6	4.6	1.23
26	Zenyatta	18	49.8	8.5	−0.22
27	Mauga	31	50.2	4.0	−0.98
28	Brigitte	43	50.1	9.6	−4.07
29	Baptiste	25	48.6	12.5	−4.17
30	Doomfist	3	49.6	11.1	−5.62
31	Widowmaker	14	48.8	5.1	−14.72
32	Hanzo	1	49.2	8.3	−17.03
33	Juno	58	50.4	10.4	−17.13
34	Symmetra	35	53.4	4.4	−23.56
35	Bastion	5	48.8	5.5	−23.91
36	Cassidy	23	44.7	25.5	−27.75
37	Mei	9	48.1	4.8	−33.42
38	Moira	9	46.5	11.5	−64.49
39	Roadhog	12	45.8	6.7	−66.02
40	Lifeweaver	7	46.5	5.7	−71.13
41	D.Va	75	51.7	8.7	−87.53
42	Lúcio	96	53.2	14.4	−228.36

Main takeaway: most hero bans are not based on their win rate.

3. Ban Diversity of Teams (How Many Different Heroes Do They Ban)

Diversity of Banned Characters

```sql
SELECT
    team,
    COUNT(DISTINCT Hero) as unique_heroes_banned,
    SUM(ban_count) as total_bans,
    ROUND(COUNT(DISTINCT Hero) * 1.0 / SUM(ban_count), 3) as diversity_ratio
FROM team_bans
GROUP BY team
ORDER BY diversity_ratio DESC;
```

	team	unique_heroes_banned	total_bans	diversity_ratio
0	Team Z	7	9	0.778
1	Goud Guys	10	13	0.769
2	Avidity	16	27	0.593
3	Vision Esports	21	36	0.583
4	Shikigami	12	22	0.545
5	Supernova	13	24	0.542
6	Rad	14	26	0.538
7	Amplify	13	25	0.520
8	DhillDucks	16	31	0.516
9	Extinction	19	38	0.500
10	Frost Tails	11	23	0.478
11	Timeless	17	37	0.459
12	Quick Esports	18	43	0.419
13	GenG	31	75	0.413
14	Geekay Esports	21	52	0.404
15	Sakura	25	64	0.391
16	SpaceStation	32	85	0.376
17	Team Peps	26	70	0.371
18	Twisted Minds	30	88	0.341
19	Team Liquid	28	82	0.341
20	The Ultimates	25	74	0.338
21	Al qadsiah	29	89	0.326
22	NTMR	28	97	0.289
23	Virtuspro	26	92	0.283

The diversity ratio shrinks as teams play more matches: the highest diversity ratios all come from teams with low total_bans.

4. Each Team's Favorite Ban and their Role

Team Top Bans and Role

```sql
WITH team_top_bans AS (
    SELECT
        tb.team,
        tb.Hero,
        tb.ban_count,
        hr.role,
        ROW_NUMBER() OVER (
            PARTITION BY tb.team
            ORDER BY tb.ban_count DESC
        ) AS rn
    FROM team_bans tb
    JOIN heroes_with_roles hr ON tb.Hero = hr.hero_name
)
SELECT
    team,
    Hero AS favorite_ban,
    role AS favorite_ban_role,
    ban_count
FROM team_top_bans
WHERE rn = 1
ORDER BY ban_count DESC;
```

	team	favorite_ban	favorite_ban_role	ban_count
0	The Ultimates	Lúcio	Support	14
1	Virtuspro	Lúcio	Support	13
2	Al qadsiah	Ramattra	Tank	10
3	Geekay Esports	Kiriko	Support	10
4	Team Liquid	Lúcio	Support	10
5	SpaceStation	Hazard	Tank	9
6	GenG	Kiriko	Support	8
7	NTMR	Lúcio	Support	8
8	Team Peps	Juno	Support	8
9	Twisted Minds	Genji	Damage	8
10	Vision Esports	Lúcio	Support	7
11	Frost Tails	Freja	Damage	6
12	Quick Esports	Illari	Support	6
13	Sakura	Ana	Support	6
14	Extinction	Freja	Damage	5
15	Supernova	Hazard	Tank	5
16	Timeless	Lúcio	Support	5
17	Amplify	D.Va	Tank	4
18	DhillDucks	Juno	Support	4
19	Shikigami	Hazard	Tank	4
20	Avidity	Ana	Support	3
21	Goud Guys	D.Va	Tank	3
22	Rad	Ana	Support	3
23	Team Z	Lúcio	Support	2

Almost every team's favorite hero to ban is a hero in the support role.

5. Role Ban Percentage

Percentage of Ban Being From Each Role

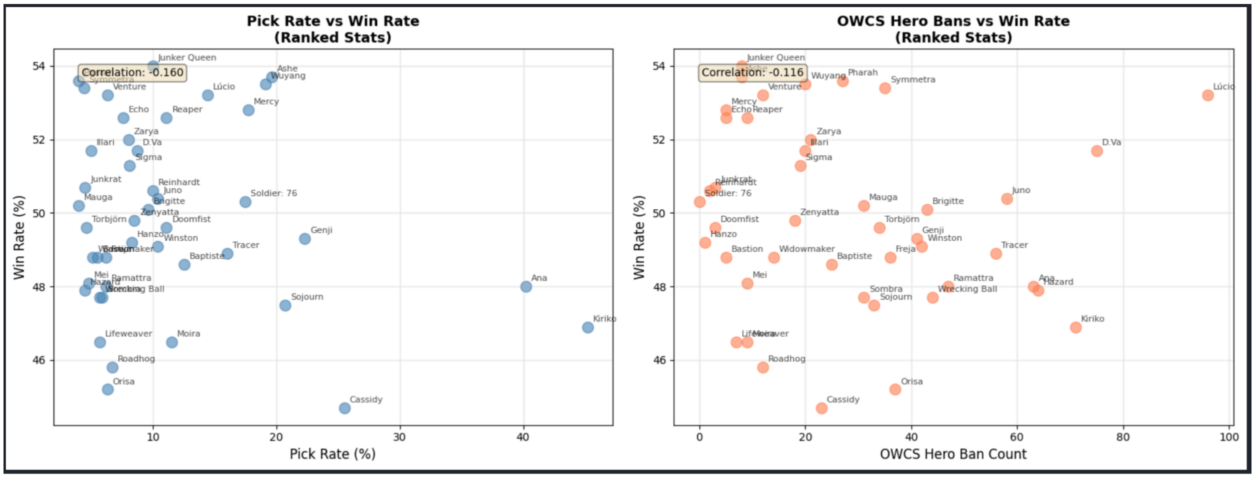
```sql
SELECT
    hr.role,
    COUNT(DISTINCT tb.Hero) as unique_heroes_banned,
    SUM(tb.ban_count) as total_bans,
    (SELECT SUM(ban_count) FROM team_bans) as overall_total_bans,
    ROUND(SUM(tb.ban_count) * 100.0 / (SELECT SUM(ban_count) FROM team_bans), 2) as
pct_of_total_bans
FROM team_bans tb
JOIN heroes_with_roles hr ON tb.Hero = hr.hero_name
GROUP BY hr.role
ORDER BY total_bans DESC;
```

```
      role  unique_heroes_banned  total_bans  overall_total_bans  \
0  Support                    12         435                1222
1     Tank                    13         405                1222
2   Damage                    18         382                1222

   pct_of_total_bans
0              35.60
1              33.14
2              31.26
```

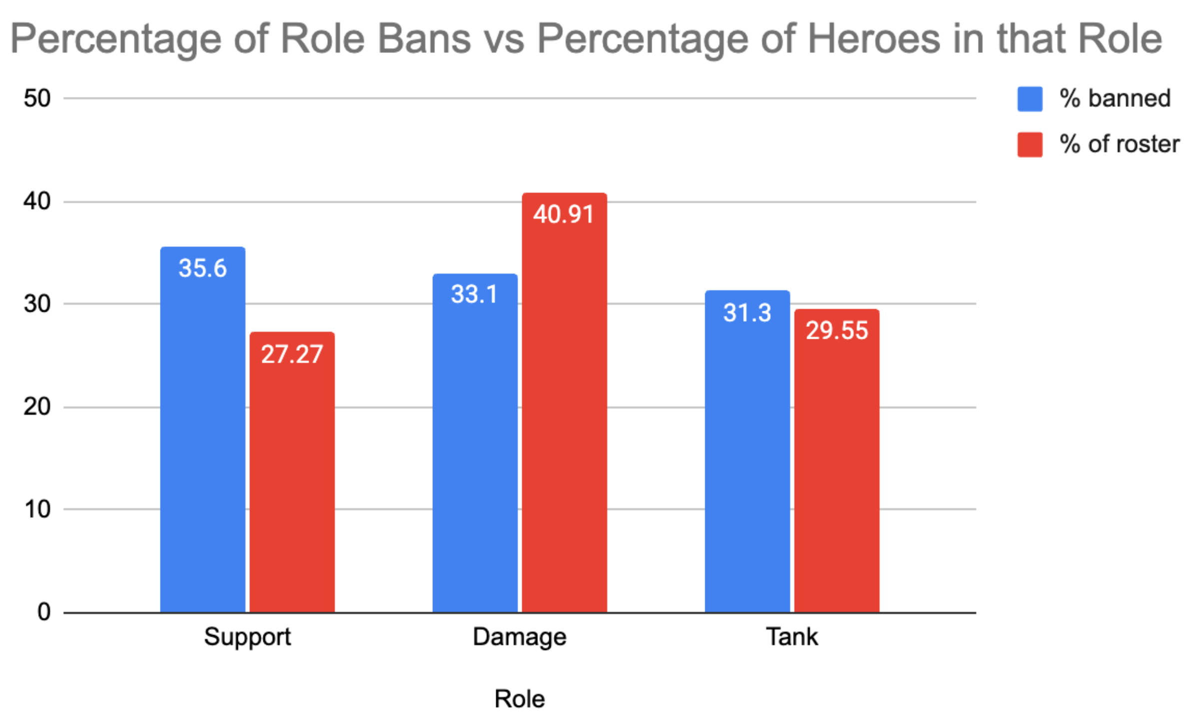
Support heroes are banned disproportionately more than tank or damage heroes.

Data Visualizations



I created the above scatterplots to show correlation (or lack thereof) between win rate and OWCS hero ban count as well as ranked pick rate. Both scatterplots have a low negative correlation which suggests the numbers are not very related. This aligns with my prediction that the numbers would have low correlation. Comparing pick rate and win rate alone is difficult as a lot of context is missing. First, heroes with low win rates are not necessarily bad heroes. If a hero has a high pick rate, but a low win rate, this can indicate that players play them because their perception is that the character is strong, even if it's not true. Additionally, this can mean that the hero is strong, but also hard to play so players pick that hero as a crutch, yet cannot make full use of the hero. Heroes with high win rate but low pick rate are generally niche, or only played by specialists. They have high win rates due to only being played where they excel, or only being played by people with immense dedication to the hero. However, we can draw conclusions when the numbers align: high pick rate and high win rate suggest the hero is overpowered relative to other heroes, and low pick rate and low win rate suggest the hero is underpowered relative to other heroes.

OWCS hero bans and win rates in high-ranked competitive play are not strongly correlated. Professional play differs significantly from ranked play, even at the highest levels. In ranked matches, two teams consist of random players who likely do not communicate and may not synergize well. In contrast, professional teams focus on specific hero compositions that emphasize strong synergy. In ranked play, players often choose their favorite heroes without considering their teammates' selections. For instance, Reinhardt is typically paired with Lúcio because Lúcio provides a speed boost, allowing Reinhardt to engage effectively. Without speed, Reinhardt struggles to close the gap on enemies. This level of synergy is rare in ranked play, even among top players.



Finally, the above bar chart shows that support heroes are disproportionately banned over heroes in other roles despite having the fewest heroes. This makes sense because support heroes frequently determine the composition that a team can play. Prior to the hero Juno’s addition to the game, speed boost was a utility only found in Lúcio's kit, and if he wasn't available, Reinhardt and other close range tanks were unplayable. Even today, Juno and Lúcio do not fulfill the same niche and cannot be interchanged, which is why Lúcio is the most banned hero in OWCS; he most frequently determines the composition played. Support heroes also have the strongest abilities in the game, and additionally have the strongest ultimates in the game, meaning they determine outcomes more than any other role.

Conclusion

This project answers a straightforward question: Do metrics from high ranked competitive play predict professional ban strategy? The answer is definitively no. The data reveals that win rate has minimal correlation with pick rate and professional bans (correlations of -0.160 and -0.116, respectively). Kiriko is banned 71 times in OWCS despite a 46.9% ranked win rate, while Pharah maintains a 53.6% win rate with only 27 bans. This discrepancy demonstrates that teams are banning heroes based on what composition they want to play, what composition they want the enemy to not play, and the setting of the game (the map), not statistics from ranked play. My most interesting findings are:

1. High pick-rate heroes suffer from casual player dilution, while low-pick-rate heroes maintain high win rates through specialist playor only being picked in situations where they excel.
2. Support heroes represent 35.6% of bans despite comprising only 27% of the hero roster, reflecting their meta-defining role.
3. Team ban strategies vary significantly, with some teams employing diverse approaches while others concentrate on a small set of heroes.

4. Professional play differs fundamentally from ranked play in synergy, communication, and strategic depth.

This analysis aligns with what I expected: Basic numbers without context can tell an incomplete story at best, and a misleading story at worst. This is similar to American football where looking solely at some basic numbers such as passing yards and passing touchdowns can tell a deeply misleading story about how good a player is. If I had access to more data, including a larger sample size and different types, as well as more time, I would be interested in comparing how hero pick rates and win rates vary based on the map played in each game, particularly which game mode Lúcio excels in. I would also analyze historical data over a specific time period, the outcome of an OWCS match given a specific ban, and explore machine learning models to suggest optimal bans.