Impact of Social Media Sentiment and Engagement on Esports Performance

David Bishop
Johns Hopkins University
Laurel, MD 20723
dtbishop7@jh.edu

***Abstract*—Social media and esports have experienced a significant rise in popularity over the past few years, with esports maintaining a particularly strong connection to the internet compared to traditional sports. This study examines the relationship between social media engagement, sentiment, and the performance of esports teams. A dataset of community-generated posts categorized by sentiment (positive, negative, and neutral) is analyzed to evaluate metrics such as post volume, sentiment ratios, and weighted sentiment scores for their potential to predict match outcomes. While the analysis did not indicate a strong direct correlation between social media posts and esports performance, the findings highlight nuanced relationships that provide valuable insights into the impact of community sentiment in competitive environments.**

***Index Terms*—esport, Data Collection, Social Media, Sentiment Analysis, Social Media Analytics, Social Influence**

I. Introduction

Over the past few years esports, or competitive video gaming, has emerged as a global phenomenon, with millions of players, fans, and organizations contributing to its rapid growth. Unlike traditional sports, where much of the community engagement revolves around in person attendance and television broadcasts, esports thrive in an ecosystem rooted in communities of digital platforms. While attending events in person remains a popular and recommended option, esports fans can also engage with others in ways that go beyond traditional sports. Platforms like Twitch streams enable real-time interaction with fellow viewers which is not a common thing for traditional sports.

While there are many research papers about esports and social media the true impact of social media posts have on esports is seemingly unexplored. Studies in traditional sports have demonstrated correlations between fan sentiment and team performance, the unique dynamics of esports and social media warrant a more focused investigation.

This paper examines the relationship between social media engagement, sentiment, and team performance in esports competitions. Using a dataset of community generated posts categorized into positive, negative, and neutral sentiment, metrics such as post volume, sentiment ratios, and weighted sentiment scores are analyzed for their predictive value. By uncovering patterns in online discussions, the study seeks to determine whether community sentiment influences or reflects team success. These findings contribute to a deeper understanding of the changing role of social media in esports and its potential implications for teams, players, and industry stakeholders.

II. Background

As esports have grown in popularity, numerous studies have been conducted on various aspects of the field. Research has explored the health impacts of esports players, highlighting the rise in social media usage and its effects on player well-being [5]. Other studies have focused on the expansive communities that have formed around esports, examining their role in fostering fan engagement and online interactions [1]. While these studies provide valuable insights, they largely overlook the direct impact that these communities and social media posts may have on player performance during matches.

In traditional sports, athletes often engage with social media peripherally, as their professional space remains separate from their online presence. Esports professionals, however, are deeply embedded in the digital space, where they are expected to actively participate by posting about their teams or teammates and interact with fans in both live streams and through apps in real time. This constant exposure to online sentiment, both positive and negative, may have significant psychological implications, potentially influencing their ability to perform in competitions.

Previous research has identified the prevalence of ”chronically online” behaviors among esports players and their communities, yet little attention has been paid to how these dynamics impact players’ mental readiness or performance outcomes. Additionally, while social media analytics have been employed in other domains to study public sentiment, their application to esports remains under explored. This study aims to address these gaps by investigating the relationship between social media engagement, sentiment, and esports team performance, leveraging advancements in data analysis to provide new insights into this unique digital ecosystem.

III. Methodology

This study followed a structured approach comprising three main stages: Data Collection, Data Classification, and Data Analysis and Visualization. Each stage was carefully designed to ensure the dataset’s quality, relevance, and suitability for answering the hypothesis.

A. Data Collection

Data for this study was sourced from social media platforms, specifically BlueSky and Reddit, which were identified as hubs for discussions about the Counter-Strike 2 Major tournament, Perfect World Shanghai Major 2024 European RMR A. To facilitate efficient data collection, custom scraping functions were developed or modified from previous code, enabling the retrieval of thousands of data points, including post bodies, timestamps, and other important metadata. These tools ensured that the data acquisition process was both systematic and scalable.

Initially, the study intended to utilize X (formerly Twitter) as a primary data source. However, due to restrictions on API access and the limitations imposed on scraping, the platform was deemed impractical for this research. As an alternative, BlueSky, an emerging platform experiencing rapid growth in user activity, was chosen. This substitution provided two key advantages offering a sufficient volume of relevant data and allowed for a unique exploration of BlueSky's data collection policies, adding an innovative dimension to the study.

Following the initial data collection, preprocessing steps were implemented to refine the dataset. Posts were automatically examined for the presence of keywords associated with teams, players, or the Major itself. This filtering process significantly reduced the dataset size by excluding irrelevant content, ensuring that only pertinent posts were retained. Additionally, posts were limited to those published a few days before gameplay, with the analysis window closing before the match under investigation. This temporal filtering ensured that the dataset captured pre-match sentiment while avoiding potential biases from post-match discussions.

B. Data Classification

Once the dataset was filtered, posts were classified into one of four sentiment categories: Positive, Negative, Neutral, and N/A. While Positive, Negative, and Neutral sentiments are straightforward, the N/A category had to be introduced to account for posts that, despite passing the initial filtering stage, did not pertain directly to Counter-Strike or the Major. This classification was conducted through self-annotation. Each data point was independently annotated by five individuals using the predefined categories. The final classification for each data point was determined based on the majority consensus among the annotations. A custom annotation function was developed to streamline the classification process, looping over each data point asking for a selection of 1-4 correlating to the categories.

After annotation, the data was aggregated and collated for each team, creating a comprehensive dataset that linked sentiment data to specific teams. This step allowed for team-level analyses, making it possible to explore correlations between social media sentiment and performance outcomes systematically.

C. Data Analysis

With a classified dataset in hand, the analysis phase focused on exploring potential relationships between social media engagement, sentiment, and team performance. Five key analyses were conducted, each addressing a specific research objective:

1) **Correlation Between Post Count and Performance:** Examining whether teams with higher community engagement performed better.
2) **Sentiment Breakdown by Performance:** Comparing sentiment proportions (positive, negative, and neutral) for winning and losing teams.
3) **Sentiment Ratios as Predictors:** Defined a sentiment ratio metric to assess the balance between positive and negative sentiment.
4) **Weighted Sentiment Analysis:** Developed a composite weighted sentiment score to emphasize positive and negative posts as neutral posts were overwhelming.
5) **Dynamically Adjusted Weighted Performance:** Introduced a dynamic performance modifier based on sentiment proportions and team age.

To enhance readability, various graphs and tables were generated, including scatter plots and boxplots. These visual tools provided a clearer understanding of the relationships between variables, highlighting trends and outliers within the dataset.

In addition to visual analysis, statistical tests were conducted to assess the significance of observed trends. T-tests were used to compare means between groups (e.g., winners vs. losers) and to determine whether differences in sentiment proportions, ratios, or weighted scores were statistically significant.

IV. Findings/results

This section presents the findings derived from analyzing the relationship between social media engagement, sentiment, and esports team performance during the Counter-Strike 2 Perfect World Shanghai Major 2024 European RMR A. The analyses performed provide a deeper understanding of how social media data might correlate with team performance, highlighting key trends and exceptions.

TABLE I
TEAM STATISTICS FOR SOCIAL MEDIA POSTS AND PERFORMANCE

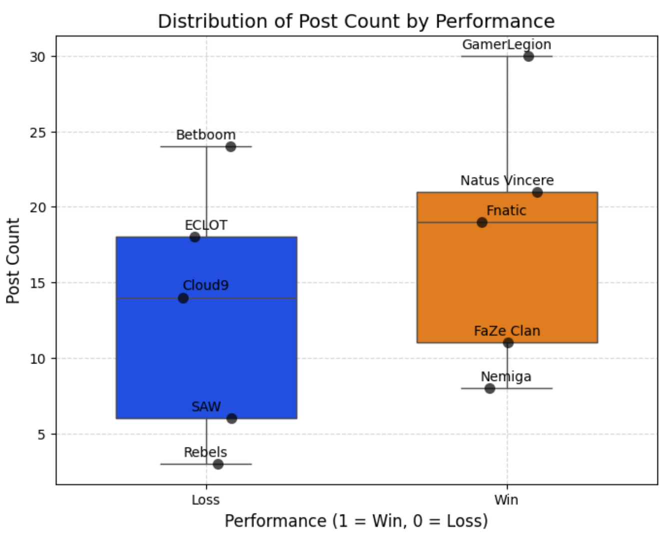
Team	Posts	Pos_Posts	Neg_Posts	Neu_Posts	W/L	Team_Age
Betboom	24	5	3	16	L	490
Cloud9	14	4	0	10	L	3776
ECLOT	18	4	2	12	L	3133
FaZe Clan	11	4	1	6	W	3239
Fnatic	19	5	5	9	W	7437
GamerLegion	30	7	5	17	W	2075
Natus Vincere	21	5	1	15	W	5464
Nemiga	8	1	3	4	W	2737
Rebels	3	0	0	3	L	325
SAW	6	1	0	5	L	1797

*Team Age is in Days since creation

A. *Team Statistics*

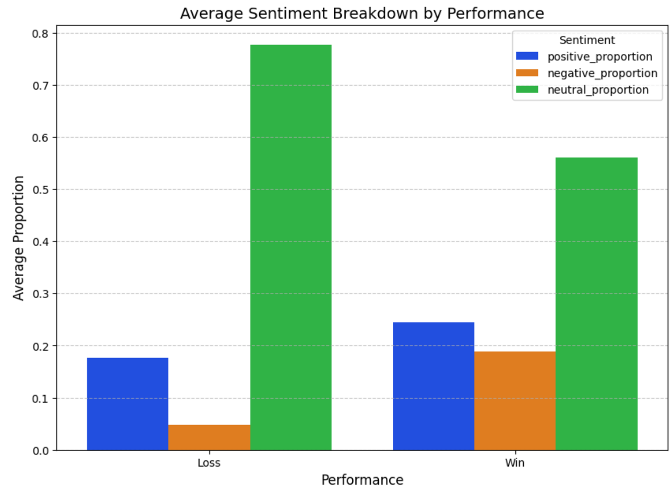
The dataset used for this analysis includes key statistics for each team, providing a comprehensive view of their social media presence and performance metrics. These include the team that the posts were collected for, the total number of posts generated by the community per team, columns for the count of positive, negative, and neutral posts, win/loss outcomes from the tournament, and the team's age measured in days since its formation. Each of these categories played an important role in creating the coming analysis. While most teams had some amount of positive and negative posts about them, Rebels ended up having only 3 neutral posts for them, SAW had no negative posts and only one positive post, and Cloud9 had no negative posts but plenty of positive and neutral posts.

B. *Correlation Betwen Post Count and Performance*



This analysis explored whether teams with a higher volume of community-generated posts were associated with better performance outcomes. As illustrated in the figure above, teams that achieved wins generally exhibited higher post counts compared to those that experienced losses. However, the correlation coefficient between post count and performance was relatively weak, at just 30%. This suggests that while high engagement levels may reflect an active and supportive fanbase, they do not necessarily translate into improved performance on the competitive stage. These findings highlight the distinction between fan enthusiasm and measurable success, underscoring the complexity of using social media activity as a predictive metric for esports outcomes.

C. *Sentiment Breakdown by Performance*



Sentiment breakdowns for winning and losing teams are visualized in the figure above. Winning teams tended to have higher proportions of positive and negative posts compared to losing teams, while neutral posts dominated across both groups. Statistical testing revealed slight significance for neutral sentiment (p-value: 0.026), suggesting that neutral sentiment might have a subtle influence on team performance. Despite this, the lack of strong statistical significance in positive and negative proportions indicates that sentiment alone cannot reliably predict outcomes.

D. *Sentiment Ratios as Predictors*

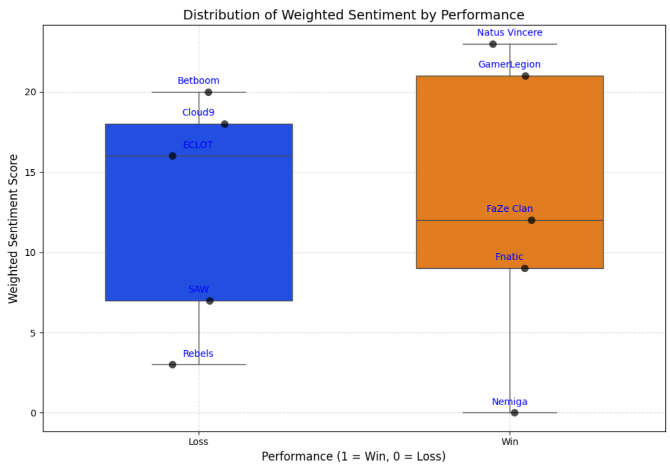
TABLE II
METRICS

Metric	Value
Positive Proportion Difference	0.068057
Negative Proportion Difference	-0.141448
Mean Sentiment Ratio (Win)	2.346343
Mean Sentiment Ratio (Loss)	9048.352318
Median Sentiment Ratio (Win)	1.399916
Median Sentiment Ratio (Loss)	1.999820
Positive Proportion T-Test p-value	0.301133
Negative Proportion T-Test p-value	0.077169
Neutral Proportion T-Test p-value	0.025554

The table above displays different metrics to determine if any of them seem to heavily correlate with win percentage. While a majority of these values display that there was no statistical significance there are a couple interesting values that can be pointed out. The mean sentiment ratio (loss) has a value of 9048.35, an insane value that doesn't really make sense. This was caused due to some teams either performing well and having 0 negative posts or performing poorly and having

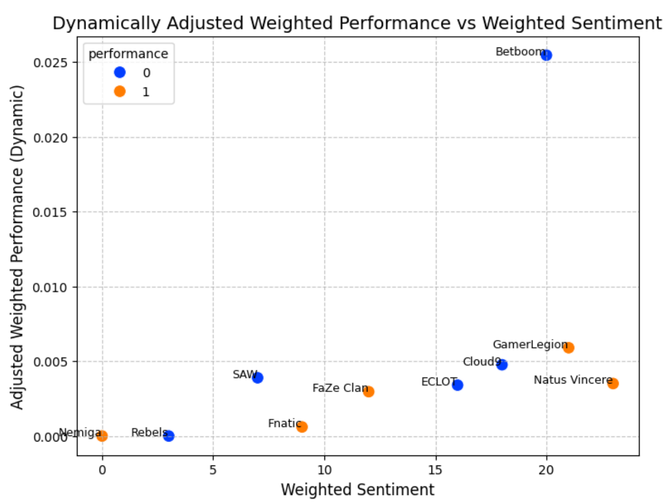
0 negative posts, to combat this, the median sentiment ratios were calculated which balanced this number down to around 2, still not significant. However, the positive proportion T-Test P-values indicate some form of significance with both negative and neutral appearing to play some form of role as a predictor.

E. Weighted Sentiment Analysis



To account for the dominance of neutral posts, a weighted sentiment score was computed for each team. The figure above illustrates the distribution of these scores by performance. Despite the adjustment, no significant correlation was observed between weighted sentiment and performance. Weighted sentiment analysis provided a nuanced perspective on team sentiment, but failed to demonstrate strong predictive power for match outcomes.

F. Dynamically Adjusted Weighted Performance



Incorporating team age and a dynamic performance modifier, dynamically adjusted weighted performance was calculated and compared against weighted sentiment. The results did not reveal a significant correlation (T-test p-value: 0.348), but interesting outliers emerged. For example, Nemiga managed to secure a win despite having a nearly zero adjusted weighted performance and weighted sentiment, whereas Betboom, with high values for both metrics, experienced a loss. These exceptions highlight the complexity of predicting the outcomes of esports and suggest that external factors may play a significant role.

V. CONCLUSIONS & RECOMMENDATIONS

This section will discuss the insights derived from the data analysis conducted in the preceding sections. Although the key findings have been briefly addressed, this section aims to explore these results in greater depth, highlighting their implications, and providing a more nuanced interpretation of their significance. In addition, recommendations for future research and potential applications of these findings will be outlined.

A. Conclusions

The analysis conducted in this study suggests that the hypothesis, "Post count and sentiment is a predictor of team performance," is largely unsupported by the data. Instead of serving as reliable predictors of success, metrics such as post count and sentiment proportions appear to reflect team popularity and community engagement levels. However, there does seem to be some statistically significant data patterns that could be explored further in future research.

One of the more compelling findings involves the role of sentiment influence. While post count alone does not predict team performance, the distribution of sentiments in posts offers some insights. Winning teams tended to have a higher proportion of non-neutral posts (both positive and negative), whereas losing teams had a higher prevalence of neutral sentiments. This suggests that increased emotional investment or polarization within a team's fan base might correlate with their competitive outcomes, though the causal relationship remains unclear.

Another interesting observation is related to Sentiment Ratios, though this metric also highlighted some of the challenges in analyzing this type of data. As discussed earlier, the Mean Sentiment Ratio (Loss) displayed an unusually high value of over 9000, caused by the lack of negative posts for some teams. This issue illustrates the limitations and potential biases inherent in analyzing small datasets or cases where sentiment distribution is highly skewed. It underscores the need for more robust data preprocessing and alternative metrics that can better account for such anomalies.

The sentiment data, categorized into positive, negative, and neutral posts, has potential utility beyond performance prediction. For instance, team managers could leverage this data to monitor and maximize positive sentiment in their community. By understanding the sentiment trends and what prompts these emotional responses, teams could adopt strategies to foster a more supportive and engaged fan base. Additionally, while post count alone does not predict performance, the relative proportions of sentiments (e.g., positive vs. negative) might offer indirect signals about the emotional dynamics of a team's fan community.

While these findings do not directly validate the hypothesis that "Post count and sentiment is a predictor of team performance," they reveal important avenues for refining future analysis. Although the collected data does not serve as a reliable predictor of success, it provides valuable insights into team popularity and community engagement.

B. Recommendations

This study uncovered several challenges and opportunities in handling data collection, classification, and modeling. The most significant limitation of this study was the small sample size—only 154 posts across 10 teams. This limited dataset likely introduced biases and restricted the ability to draw clear conclusions. While BlueSky was a useful platform for data collection, it lacked the scale and established esports conversations found on platforms like X (formerly Twitter). Revisiting X or integrating additional platforms such as YouTube comments or TikTok could yield more comprehensive datasets. Expanding the time frame for data collection to include posts from weeks or even months before matches, as well as after matches, could also provide a better overview. Such an approach would allow for analysis incorporating trends in sentiment and performance over time rather than focusing solely on isolated matches.

While this study focused on teams, a player-specific approach may yield more actionable insights. Individual players often receive direct attention from fans, which could make sentiment data more predictive of performance. It would also allow different avenues of data collection. Looking at what players post on their own pages and the comments they are receiving towards those posts may affect their ability to perform as a player over their teams performance. If looking at specific players pages is not the approach taken here are some issues that this project ran into. Searching for generic names like "Rain" or "iM" often returned irrelevant results, whereas unique player names like "Boombl4" were easier to track. A more sophisticated filtering or scraping tool is needed to address this issue. Also posts about players were often tied to team announcements or lineups rather than individual performance. Future efforts should refine the data filtering process to capture player-specific sentiment and performance correlations instead of generic mass messages.

To continue this study focusing on teams as a whole still should include more information per team than what was gathered for this project. As mentioned the data was quite limited, this is not only about datapoints but also data categorization, only having 7 variables, 3 of which were one hot encoded categories of post sentiments. Here are a few recommendations on variables to add. The type of match that the teams are playing, is it a group stage match, qualifier, final. Player or team ranking differences, which may give incredible insight if a team ranked lower is being given more positive sentiment possibly suggesting an upset. Previous match performance and sentiment surrounding that, allowing for exploration into teams that may have lost their past matches.

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