Statistical Analysis of Personal Dota 2 Match Performance

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***Abstract*—This study performs a quantitative analysis of a single player's *Dota 2* match history ($N = 199$) to identify the statistical drivers of victory. Using match telemetry retrieved via the OpenDota API, the research evaluates metric correlations with winning, performance consistency, optimal hero selection, map side asymmetry, and efficiency relative to match duration. Pearson correlation analysis reveals that team-oriented metrics, specifically Assists ($r = 0.44$) and Tower Damage ($r = 0.42$), are significantly stronger predictors of winning than individual Kills ($r = 0.33$). A Chi-Square test confirms a statistically significant performance bias, with the player achieving a 56.99% win rate on the Radiant side compared to 39.62% on Dire. Furthermore, temporal analysis using LOWESS regression identifies a distinct "efficiency window," where player impact peaks between 35 and 45 minutes before declining in ultra-late game scenarios. These findings demonstrate how personal data analytics can be applied to diagnose playstyle patterns and optimize strategic decision-making in competitive esports.**

***Index Terms*—Data Analytics, Dota 2, LOWESS Regression, Performance Analysis, Statistical Correlation.**

I. Introduction

Dota 2 is a globally popular Multiplayer Online Battle Arena (MOBA) game characterized by its high strategic depth and mechanical complexity. Matches, which typically range from 15 to 60 minutes, demand that players balance resource management, team coordination, and real-time decision-making to secure victory [1]. While professional esports analytics is a well-established field, the application of data science to personal gameplay data offers a unique opportunity for individual players to diagnose weaknesses and optimize performance systematically [2].

Dota 2 generates a vast volume of structured data, including discrete variables (e.g., kills, deaths, assists) and continuous metrics (e.g., Gold Per Minute, Experience Per Minute). By subjecting this data to rigorous statistical analysis, players can move beyond intuition and rely on quantitative evidence to inform their gameplay strategies [2].

This study conducts a quantitative analysis of a single player's Dota 2 match history from May 2025 to February 2026, isolating individual performance variables from the noise of team-based outcomes. The research addresses the following key questions:

1) Which specific performance metrics have the strongest statistical correlation with winning?
2) Does the player demonstrate consistent performance stability across different matches?
3) Which hero selections yield the optimal balance of win rate and statistical output for the player?
4) Does map side assignment (Radiant vs. Dire) significantly influence win rates and performance metrics?
5) How does player performance efficiency evolve as match duration increases?

To address these research questions, this study implements a structured statistical workflow. The analysis begins with a comprehensive visualization of the personal dataset using descriptive statistics to establish a baseline of player performance. Subsequently, Key Performance Indicators (KPIs) associated with victory are identified through Pearson correlation matrices and independent t-tests. Second, gameplay stability is quantified by analyzing the Average Deviation and Coefficient of Variation (CV) of these optimal metrics. Third, the study determines the most effective heroes by filtering out rarely played characters via standard error thresholding, ranking the top selections based on a weighted evaluation of win rate, performance metrics, and consistency. Fourth, the impact of map geography (Radiant vs. Dire) on match outcomes is evaluated using a Chi-Square Test of Independence, followed by t-tests to detect significant disparities in key performance metrics between sides. Finally, performance trends over time are analyzed using Locally Weighted Scatterplot Smoothing (LOWESS) regression, normalizing metrics via Z-scores to create a composite "efficiency score" that tracks player impact across varying match lengths.

By focusing on these specific objectives, this research provides a statistically grounded approach to understanding personalized success factors in a competitive MOBA environment.

II. Review of Related Literature

A. Predictive Analytics and Performance Indicators

The identification of victory-determinant metrics is a foundational challenge in Multiplayer Online Battle Arena (MOBA) research. In Dota 2, the complexity arises from the high-dimensional nature of gameplay, where over 120 unique heroes interact across roughly 1.16×10^{14} possible starting combinations [2]. Previous studies have established that economic indicators, specifically Gold Per Minute (GPM) and Experience Per Minute (XPM), serve as the most reliable predictors of match outcomes. Research by Katona et al. [3] demonstrates that these rolling averages of "box-score" metrics are highly predictive of victory, as they represent a team's ability to out-scale opponents in power.

However, the use of aggregate performance metrics is often criticized for introducing "noise." As noted by Drachen et al. [4], simple metrics like Kill-Death-Assist (KDA) ratios can be misleading if not contextualized within a player's specific role. For instance, a support hero may exhibit a low GPM but contribute significantly through objective-based play. This study addresses this limitation by employing Pearson correlation analysis to filter only those metrics with statistically significant ($p < 0.05$) associations with victory, thereby isolating high-impact performance indicators specific to the subject's dataset.

B. Environmental Asymmetry and Side-Based Performance

Map asymmetry is a defining characteristic of the Dota 2 environment. Unlike symmetrical esports maps found in tactical shooters, the Dota 2 map features distinct topographical differences between the Radiant and Dire sides, affecting jungle camp proximity, warding locations, and accessibility to the Roshan pit.

Existing literature suggests a persistent "Radiant Advantage" in public matchmaking. Statistical analysis by Dotametrics [5] observed that Radiant win rates often exceed 50%, particularly in matches of shorter duration, due to superior laning phase ergonomics and camera orientation. Conversely, historical data suggests the Dire side may possess advantages in the "ultra-late" game due to strategic positioning near high-value objectives. This study utilizes the Chi-Square Test of Independence and Welch's t-test to determine if these global asymmetries translate to the individual level, providing a personalized assessment of performance asymmetry.

C. Quantifying Stability via Statistical Dispersion

While much research focuses on peak performance (the "best" game), there is a significant gap in measuring the stability of player performance across successive matches. In traditional sports science, the **Coefficient of Variation (CV)** is a standard for assessing the reliability of quantitative measurements [6].

The application of CV to esports allows for a "dimensionless" comparison of volatility across disparate metrics. For example, while GPM typically exhibits low volatility due to the constant nature of resource accumulation, combat metrics like Tower Damage are often subject to high variance or "feast or famine" scenarios. This study builds upon the framework proposed by Yang et al. [7], using CV as a "Volatility Index" to categorize which aspects of a player's performance are foundational versus those that are highly dependent on external match conditions.

III. Methodology

A. Participants and Data Source

The dataset analyzed in this study consists exclusively of match-level gameplay data from a single player (the author). The matches were collected from the author's personal gameplay history in Dota 2 over the period from May 2025 to February 2026.

The participant is an active competitive player with experience in standard ranked matchmaking modes. No other players' personal or identifiable information was collected; the dataset contains only performance-related statistics automatically recorded by the game system.

As the study utilizes publicly available in-game performance metrics and does not involve human subject experimentation, surveys, or intervention procedures, there are no associated ethical risks or privacy concerns.

B. Operational Definitions

The variables analyzed in this study are defined as follows:

- **Won**: The dependent variable of the study, coded as a binary value (1 = Win, 0 = Loss).
- **Date**: The date when the match was played, recorded as a datetime value.
- **Hero Name**: The nominal identifier of the hero played (e.g., *Puck, Tusk*).
- **Team**: The nominal variable identifying the player's side (*Radiant* or *Dire*).
- **Kills**: The number of enemy heroes personally eliminated by the player.
- **Deaths**: The number of times the player was eliminated during the match.
- **Assists**: The number of enemy hero eliminations in which the player participated but did not secure the final blow.
- **Last Hits**: The number of enemy units for which the player secured the final blow, granting gold.
- **Denies**: The number of allied units intentionally killed by the player to prevent the opponent from gaining gold and experience.
- **Gold per Minute (GPM)**: The average rate of gold income earned per minute of gameplay.
- **XP per Minute (XPM)**: The average rate of experience gained per minute of gameplay.
- **Hero Damage**: The total damage dealt to enemy heroes.
- **Tower Damage**: The total damage dealt to enemy structures.
- **Hero Healing**: The total health restored to allied heroes.
- **Duration Minutes**: The total match length measured in minutes.

C. Data Cleaning and Preprocessing

Although the raw dataset was obtained from the OpenDota API in a structured format, specific transformation protocols were required to convert the hierarchical JSON data into a tabular format suitable for inferential analysis.

1) Data Parsing and Flattening: The raw match telemetry was retrieved in nested JavaScript Object Notation (JSON) format. A custom parsing algorithm was employed to flatten the hierarchical structure (Match $\rightarrow$ Players $\rightarrow$ Subject) into a tabular Comma-Separated Values (CSV) format. This process isolated the subject's specific performance vector from the aggregate match data.

2) Handling Missing and Non-Essential Data: To ensure dataset integrity, a filtering protocol was applied during the extraction phase. Matches where the subject's specific player data could not be resolved (e.g., due to API privacy restrictions or corrupted logs) were programmatically skipped to prevent null-value propagation. Furthermore, high-granularity but non-essential telemetry such as frame-by-frame `teamfight_participation` and `lane_efficiency` values that returned null or zero in older match IDs—were excluded from the final CSV output. The dataset was restricted to completed public Ranked matchmaking games to avoid skewing performance statistics with incomplete or practice lobby data.

3) Feature Engineering: To enhance analytical interpretability, several variables were transformed or derived from the raw logs:

- **Temporal Standardization:** Match duration was converted from raw seconds to minutes (T_{min}). This transformation standardizes the time unit used for efficiency metrics (e.g., *Gold Per Minute*).
- **Outcome Derivation:** Since the API provides the match winner in terms of team side (*Radiant* vs. *Dire*), the subject's personal outcome (*Won*) was derived based on team alignment. A win (1) was recorded if the player was on the winning side, and a loss (0) otherwise:

$$\text{Won} = \begin{cases} 1 & \text{if Player Team} = \text{Winning Team} \\ 0 & \text{if Player Team} \neq \text{Winning Team} \end{cases} \tag{1}$$

D. Statistical Analysis

The statistical analysis of personal Dota 2 match data was conducted using descriptive and inferential analysis methods, the statistical methods are defined.

1) Descriptive Analysis: Descriptive statistics were computed to provide a general overview of personal match performance numerical data using the following measures:

- **Mean:** Average value of a variable, computed as

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$

  where x_i represents each observation and n is the total number of matches.
- **Win Rate (%):** A derived metric representing the percentage of matches won, calculated as the arithmetic mean of the binary outcome variable ($1 = \text{Win}, 0 = \text{Loss}$):

$$\text{Win Rate} = \left(\frac{\sum \text{Won}}{n}\right) \times 100 \tag{3}$$

- **Median:** The middle value in the ordered data set, representing a measure of central tendency less affected by outliers.
- **Standard Deviation:** Measure of dispersion calculated as

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{4}$$

- **Range:** Difference between the maximum and minimum values.

2) Pearson Correlation Analysis: To identify which in-game behaviors most strongly influence victory, a **Pearson correlation analysis** was conducted. This method measures the linear relationship between performance metrics (e.g., Gold Per Minute, Kills) and the match outcome (1 = Win, 0 = Loss).

The analysis produces two key statistics for each metric:

1) **Correlation Coefficient (r):** A value ranging from -1 to 1 that describes the strength of the relationship.
   - $r > 0$: The metric is positively associated with winning (e.g., higher Tower Damage).
   - $r < 0$: The metric is associated with losing (e.g., higher Deaths).
   - $r \approx 0$: The metric has no impact on the match outcome.
2) **Statistical Significance (p-value):** This probability indicates if the correlation is real or due to random chance. We rejected the null hypothesis (that there is no relationship) for any metric with a p-value below 0.05.

$$\text{Significance Levels:} \begin{cases} *** & p < 0.001 \\ ** & p < 0.01 \\ * & p < 0.05 \\ \text{ns} & p \geq 0.05 \end{cases}$$

Only metrics showing a statistically significant positive correlation ($p < 0.05$) were selected as Key Performance Indicators (KPIs) for subsequent analysis.

3) Performance Stability Metric (Coefficient of Variation): To consistently quantify the stability of player performance across all analysis dimensions (Hero, Side, and Match Duration), the Coefficient of Variation (CV) was adopted as the primary measure of dispersion. This statistical metric normalizes variability, enabling direct comparisons between disparate data types—such as high-magnitude variables (e.g., Gold Per Minute) and low-magnitude variables (e.g., Kills). The CV is defined as the ratio of the standard deviation (σ) to the mean (μ):

$$CV = \frac{\sigma}{\mu} \tag{5}$$

In this study, the CV serves as a standardized "Volatility Index," interpreted as follows:

- Low CV (¡ 0.2): Indicates a "Foundation Metric"—a reliable aspect of the player's performance that remains consistent regardless of external factors (e.g., hero choice or map side).

- High CV (¿ 0.5): Indicates a ”Volatile Metric”—an aspect of performance highly sensitive to specific game conditions (e.g., a ”snowball” effect or hero-specific dependency).

By utilizing a dimensionless ratio, this method eliminates scale bias, ensuring that stability assessments are mathematically comparable across all research questions.

4) Standard Error of the Proportion: To mitigate small sample size bias, the reliability of each hero's win rate was assessed using the Standard Error of the Proportion. To complement the dropping of Heroes with less than 5 in the analysis of optimal hero choices, heroes with high variance due to insufficient match history were excluded. The SE was calculated as:

$$SE_p = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}} \tag{6}$$

where $\hat{p}$ is the observed win rate and n is the number of matches played. A threshold of $SE \leq 0.2$ was applied to ensure that selected heroes possessed a statistically significant performance record.

5) Chi-Square Test of Independence: The *Chi-Square Test of Independence* is a non-parametric statistical method used to determine whether a significant association exists between two categorical variables. It evaluates whether observed frequency distributions differ from theoretical expectations under the assumption of independence.

In this study, the test was employed to investigate the relationship between *Side* (Radiant vs. Dire) and *Match Outcome* (Win vs. Loss) within the subject's personal match dataset. The objective was to ascertain whether the player's win rate is statistically dependent on the starting side, or if observed disparities are attributable to random variance.

The hypotheses are formulated as follows:

- **Null Hypothesis** (H_0): There is no association between the side played and the match outcome. The player's probability of winning is independent of starting on the Radiant or Dire side.
- **Alternative Hypothesis** (H_a): There is a statistically significant association between the side played and the match outcome, indicating a performance asymmetry based on the map side.

The test statistic is calculated using the Pearson Chi-Square formula:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{7}$$

where O_i is the observed frequency and E_i is the expected frequency for each cell in the contingency table. A *p-value* less than the significance level ($\alpha = 0.05$) leads to the rejection of the null hypothesis, suggesting that the player possesses a statistically significant performance advantage on one specific side of the map.

6) Comparative Normalization: To facilitate the comparison of disparate metrics (e.g., comparing *Kills* vs. *Tower Damage*) within the top hero pool, a **Ratio-to-Maximum** normalization technique was applied. For each hero i and metric j, the normalized score S_{ij} was calculated as:

$$S_{ij} = \frac{x_{ij}}{\max(x_j)} \tag{8}$$

where x_{ij} is the hero's average value for that metric and $\max(x_j)$ is the highest average observed among the top five heroes. This scales all performance indicators to a range of $[0, 1]$, where 1.0 represents the group's peak performance.

7) Mann-Whitney U Test: To determine whether specific performance metrics (e.g., *Gold Per Minute*, *Hero Damage*) differed significantly between the Radiant and Dire sides, the **Mann-Whitney U Test** was employed. This non-parametric test was selected because the descriptive analysis revealed that several key metrics (specifically *Tower Damage* and *Hero Healing*) violated the assumption of normality required for parametric t-tests.

The null hypothesis (H_0) states that the distributions of the metrics are identical across both team sides. The test statistic (U) evaluates whether a randomly selected value from the Radiant population is equally likely to be less than or greater than a randomly selected value from the Dire population. Significance was established at $\alpha = 0.05$.

8) Temporal Binning: To analyze the impact of match duration on win probability, continuous time data was discretized into five strategic phases:

- **Very Early:** < 25 minutes
- **Early:** $25 - 35$ minutes
- **Mid:** $35 - 45$ minutes
- **Late:** $45 - 60$ minutes
- **Ultra Late:** > 60 minutes

Win rates were computed as the mean of the binary outcome variable for each bin, utilizing the sample size (N) to filter out statistically insignificant durations.

9) LOWESS Regression: To evaluate how player performance scales with match duration, a Locally Weighted Scatterplot Smoothing (LOWESS) regression was applied. Unlike standard linear regression, which forces a rigid linear trend, LOWESS fits a flexible curve to the data, allowing for the detection of non-linear performance phases (e.g., mid-game farming peaks vs. late-game fatigue).

Prior to analysis, all volume-based metrics (e.g., *Total Kills*, *Total Tower Damage*) were normalized by match duration (T) to derive **Efficiency Rates**:

$$R_{metric} = \frac{\text{Total Value}}{T_{minutes}} \tag{9}$$

This normalization ensures that the analysis measures *intensity of play* rather than simple accumulation over time. The LOWESS curve visualizes the player's ”Efficiency Trajectory,” identifying whether performance accelerates (scaling) or decays (fatigue) as the match extends into the late game.

10) Software Implementation: All analyses were performed using the Python programming language with libraries including `pandas`, `numpy`, `scipy`, and `statsmodels`. Visualizations were created using `matplotlib` and `seaborn`. The results from these analyses provide the basis for interpretation in subsequent chapters.

IV. Results

A. Overview of the Dataset

The dataset analyzed in this study consists of 199 publicly available ranked matches played by the author in Dota 2. Each match contains comprehensive, automatically recorded performance statistics, including combat metrics, economic indicators, objective contributions, and contextual game variables.

The data captures a range of match durations, player actions, and hero selections, providing a detailed view of individual performance across diverse in-game scenarios. Key variables include wins, hero identity, team side, kills, deaths, assists, last hits, denies, gold per minute, experience per minute, hero damage, tower damage, hero healing, and match duration.

Data preprocessing ensured that only complete, valid matches were included. Matches with missing player-specific data or non-essential telemetry were excluded, and all metrics were standardized for comparability. This dataset enables the analysis of personal performance patterns, hero-specific effectiveness, team-side advantages, and temporal trends in match efficiency. The dataset was from the 2025 05 to 2026-02 as seen in Figure 1.

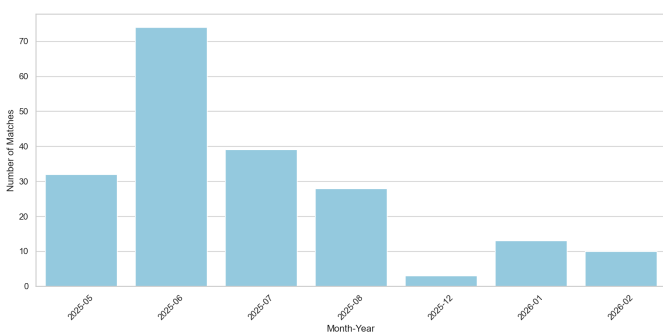

Fig. 1. Distribution of Matches by Date

B. Descriptive Results

Table I presents the descriptive statistics for the eleven performance metrics analyzed in this study. The data indicates that for combat-related metrics, the average number of **Kills** per match was 8.97 ($SD = 5.51$) with a median of 9.00, while **Deaths** averaged 8.56 ($SD = 3.58$) and **Assists** averaged 18.29 ($SD = 8.61$). The distributions for these variables showed low positive skewness (0.78, 0.33, and 0.44, respectively).

Regarding resource accumulation, **Gold Per Minute (GPM)** had a mean of 476.31 ($SD = 132.69$) and a median of 462.00, while **Experience Per Minute (XPM)** averaged 692.68 ($SD = 228.15$) with a median of 668.00. Both economic metrics exhibited low skewness (0.26 and 0.27) and negative kurtosis (-0.06 and -0.18). **Last Hits** averaged 198.10 with a standard deviation of 122.98 and a range of 787.00, showing higher skewness (1.43) and kurtosis (3.81) compared to the rate-based metrics.

Objective-based metrics displayed greater variability. **Tower Damage** resulted in a mean of $2,674.89$ ($SD = 3,570.45$) with a significantly lower median of $1,190.00$ and a positive skewness of 2.06. **Hero Healing** showed the most extreme distribution characteristics, with a mean of 607.12 and a median of 0.00, accompanied by the highest skewness (6.46) and kurtosis (57.99) values in the dataset. The average match **Duration** was 44.98 minutes ($SD = 10.13$), with a range of 63.80 minutes.

TABLE I
Descriptive Statistics of Personal Match Performance Metrics

Metric	Mean	Median	SD	Range	Skew	Kurt
Kills	8.97	9.00	5.51	25.00	0.78	0.44
Deaths	8.56	8.00	3.58	20.00	0.33	-0.08
Assists	18.29	18.00	8.61	51.00	0.44	0.39
Last hits	198.10	190.00	122.98	787.00	1.43	3.81
Denies	9.21	8.00	6.68	33.00	1.12	1.33
Duration (min)	44.98	43.50	10.13	63.80	0.78	1.10
GPM	476.31	462.00	132.69	753.00	0.26	-0.06
XPM	692.68	668.00	228.15	1192.00	0.27	-0.18
Hero Damage	33,039	30,022	16,420	83,189	0.66	0.15
Tower Damage	2,674	1,190	3,570	19,962	2.06	4.52
Hero Healing	607.12	0.00	1,868	19,849	6.46	57.99

C. Winning Factors

Figure 2 presents the correlation coefficients for eleven specific in-game statistics, revealing a hierarchy of association strengths. Assists demonstrated the highest positive correlation in the dataset with a coefficient of 0.44. This was followed closely by Tower Damage, which recorded a value of 0.42.

The economic and progression metrics also showed strong positive alignment, as XP Per Minute (0.39) and Gold Per Minute (0.38) ranked third and fourth, respectively. Kills completed the upper tier of positive variables with a correlation of 0.33. In contrast, Hero Damage (0.14) and Hero Healing (0.09) displayed comparatively weaker positive correlations, while Duration Minutes showed a negligible association of 0.02.

Regarding negative correlations, Deaths presented the most significant inverse relationship with a coefficient of -0.25. The remaining metrics, Denies and Last Hits, exhibited minimal negative correlations of -0.06 and -0.01, respectively.

A Pearson correlation analysis was conducted to evaluate the relationship between various in-game performance metrics and the likelihood of winning. The analysis identified five variables with statistically significant positive correlations ($p < 0.001$) with the match outcome. Among these, *Assists* demonstrated the strongest association ($r = 0.443$), followed closely by *Tower Damage* ($r = 0.425$). Economic indicators also proved to be strong predictors, with *XP Per Minute*

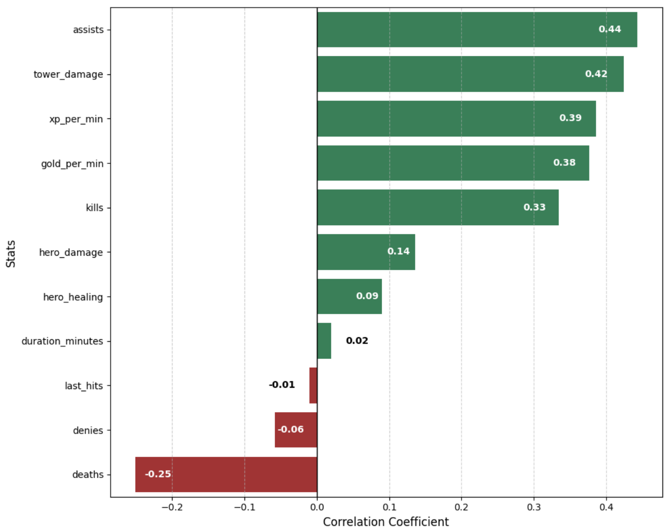

Fig. 2. Pearson Correlation Matrix of Performance Metrics vs. Match Outcome

($r = 0.386$) and *Gold Per Minute* ($r = 0.377$) showing significant positive relationships. Additionally, *Kills* exhibited a moderate positive correlation ($r = 0.334, p < 0.001$).

In terms of negative predictors, *Deaths* was the only variable to demonstrate a statistically significant negative correlation with the match outcome ($r = -0.251, p < 0.001$). This indicates that higher death counts are reliably associated with a lower probability of winning.

Notably, several metrics did not reach statistical significance at the $\alpha = 0.05$ level. *Hero Damage* ($p = 0.055$), *Hero Healing* ($p = 0.207$), *Duration* ($p = 0.778$), *Last Hits* ($p = 0.893$), and *Denies* ($p = 0.414$) showed no significant linear relationship with the match result in this dataset. These findings suggest that, unlike objective-based or team-fight metrics, raw damage output and passive farming statistics were not reliable predictors of victory in this sample.

TABLE II
CORRELATION OF PERFORMANCE METRICS WITH MATCH OUTCOME (WIN)

Variable	r	p-value
assists	0.443	<0.001
tower_damage	0.425	<0.001
xp_per_min	0.386	<0.001
gold_per_min	0.377	<0.001
kills	0.334	<0.001
hero_damage	0.136	0.055
hero_healing	0.090	0.207
duration_minutes	0.020	0.778
last_hits	-0.010	0.893
denies	-0.058	0.414
deaths	-0.251	<0.001

D. Performance Consistency

The distribution analysis of performance metrics (Figure 3) highlights distinct statistical patterns across the dataset. Economic indicators, specifically XP Per Minute and Gold Per Minute, exhibit symmetric distributions with narrow interquartile ranges, centering on medians of approximately 680 and 460, respectively. In contrast, Tower Damage displays a pronounced positive skew, combining a near-zero median with outliers extending to 20,000. Among combat metrics, Assists show an interquartile range of 12–24, while Kills are clustered around a median of 9 with a tighter distribution range.

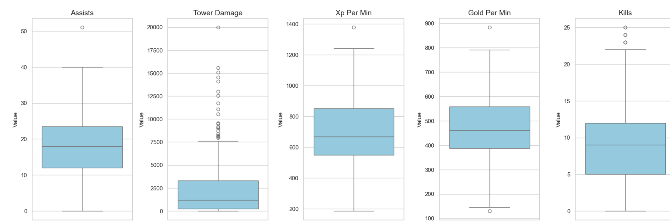

Fig. 3. Distribution of Key Performance Indicators

Figure 4 presents the Coefficient of Variation (CV) for the five key performance metrics. *Tower Damage* exhibits the highest relative variability, with a CV of 1.33. This is followed by *Kills* ($CV = 0.61$) and *Assists* ($CV = 0.47$). The economic metrics demonstrate the highest stability, with *XP Per Minute* recording a CV of 0.33 and *Gold Per Minute* showing the lowest variation at 0.28.

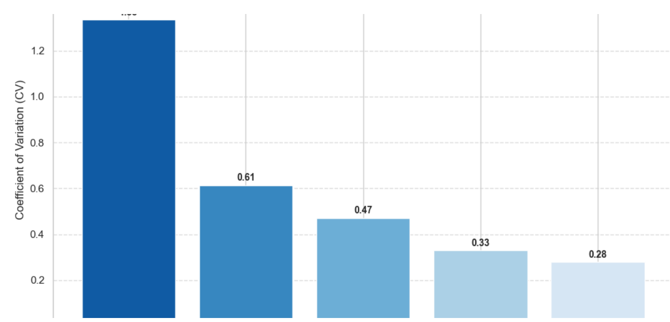

Fig. 4. Coefficient of Variation (CV) Across Metrics

E. Optimal Hero choice

Figure 5 presents the top heroes based on Win Rate, filtered for statistical reliability (minimum 5 matches, Standard Error ≤ 0.2). In the visualization, *Axe* dominated the player's performance profile with a win rate of approximately 0.81 (81%). This outlier performance suggests a specific proficiency with the hero relative to the rest of the pool.

Spirit Breaker secured the second-highest rank with a win rate of 0.71, followed by *Nature's Prophet* at 0.66. The remaining top performers, *Slark* (0.57) and *Earthshaker* (0.53), also maintained positive win rates above the 50% threshold, indicating consistent contributions to match outcomes.

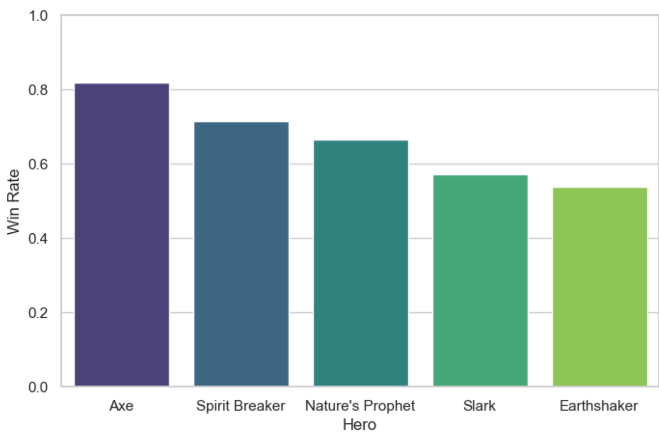

Fig. 5. Top 5 Heroes by Win Rate

comparative analysis of top-performing heroes using normalized metrics is presented in Figure 6. Each metric was scaled relative to the maximum value within the cohort to facilitate a cross-category comparison, with a score of 1.0 signifying the peak performance level for a given statistic. The profiles reveal distinct specialization patterns: *Axe* achieved the highest relative score in **Kills (1.0)**, whereas *Spirit Breaker* led in **Assists (1.0)**. Conversely, *Nature's Prophet* dominated the macro-game metrics, recording perfect relative scores in both **Tower Damage** and **Gold Per Minute (1.0)**. *Slark* demonstrated the highest leveling efficiency with a score of **1.0 in XP Per Minute**, while maintaining significantly higher objective damage than the primary combat-oriented heroes.

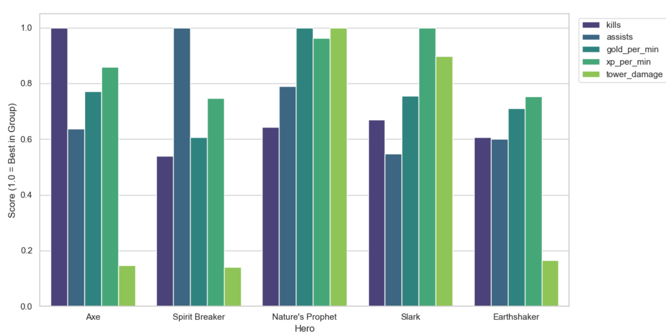

Fig. 6. Normalized Performance Metrics by Hero

The Coefficient of Variation (CV) was utilized to assess the stability of performance metrics for the top five heroes (Figure 7). Standardizing the variance relative to the mean allows for a direct comparison of consistency across heroes with different playstyles.

Economic indicators (*Gold Per Minute* and *XP Per Minute*) remained the most consistent across all heroes, with CV values consistently below 0.40. This suggests that the player maintains stable resource accumulation patterns irrespective of the hero's primary role.

Conversely, *Tower Damage* exhibited the highest degree of volatility, particularly for *Earthshaker* ($CV > 1.2$). Among combat metrics, *Kills* showed the greatest fluctuation for *Slark* ($CV \approx 0.82$), while *Axe* demonstrated the most stable offensive output ($CV \approx 0.45$). These variations highlight that while economic baseline performance is stable, combat and objective contributions are highly dependent on individual match dynamics.

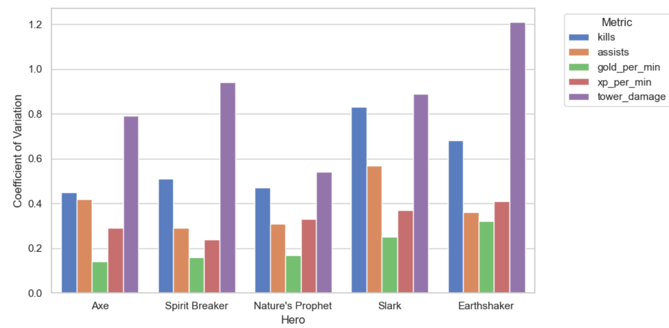

Fig. 7. Coefficient of Variation (CV) by Hero

F. Team Side performance

An analysis of match outcomes based on team side was conducted to identify potential environmental advantages. As shown in Table III, the *Radiant* side achieved a win rate of 56.99% across 93 matches, while the *Dire* side recorded a lower win rate of 39.62% over 106 matches.

To determine the statistical significance of this observation, a Chi-Square (χ^2) test of independence was performed. The resulting p-value of 0.0212 ($p < 0.05$) indicates that the relationship between team side and match victory is statistically significant. These findings suggest a significant performance bias favoring the Radiant side within this specific dataset.

TABLE III
WIN RATE ANALYSIS AND CHI-SQUARE TEST OF INDEPENDENCE BY TEAM SIDE

Team Side	Matches (n)	Win Rate (%)
Dire	106	39.62%
Radiant	93	56.99%
Statistical Test:		
Chi-Square (χ^2) p-value: 0.0212*		

A comparative analysis of in-game metrics by team side (Figure 8) reveals a performance bias favoring the Radiant side. Consistent with the significant win rate disparity previously noted, the Radiant side exhibits higher median values across all five performance indicators.

The economic metrics show a clear shift; *Gold Per Minute* and *XP Per Minute* medians are approximately 15–20% higher on the Radiant side. Similarly, objective participation, represented by *Tower Damage*, shows a higher median and a more extensive upper distribution for Radiant. Combat metrics follow this trend, with *Kills* and *Assists* maintaining higher central tendencies on the Radiant side compared to Dire.

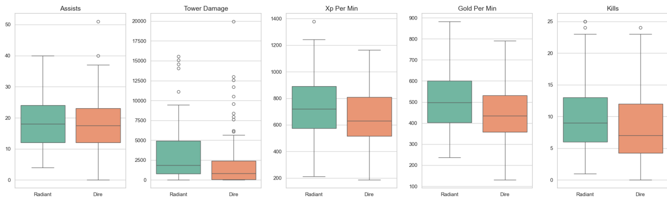

Fig. 8. Performance Metric Comparison: Radiant vs. Dire

Table IV shows comparison of performance metrics by team side revealed several statistically significant differences. Tower Damage was significantly higher on the Radiant side (mean = 3386.16) than Dire (mean = 2050.85, p ¡ 0.001), indicating a strong side-based advantage in objective damage. Economic metrics also showed significant differences, with Gold per Minute (505.02 vs. 451.11, p = 0.004) and XP per Minute (738.46 vs. 652.52, p = 0.016) higher for Radiant. Additionally, Kills were significantly greater on Radiant (9.89 vs. 8.17, p = 0.0208). No significant difference was observed for Assists (18.72 vs. 17.91, p = 0.6171).

TABLE IV
STATISTICAL SIGNIFICANCE OF PERFORMANCE METRICS BY TEAM SIDE

Metric	Radiant Mean	Dire Mean	p-value
Tower Damage	3386.16	2050.85	<0.001***
Gold per minute	505.02	451.11	0.004**
XP per minute	738.46	652.52	0.016*
Kills	9.89	8.17	0.0208*
Assists	18.72	17.91	0.6171

G. *Efficiency on Varying Duration*

The relationship between temporal match progression and win probability is visualized in Figure 9. The analysis utilizes binned duration categories to identify specific performance windows and account for sample size variations (N).

The data indicates a progressive increase in win rate during the early phases, rising to 40% in the *Early* (25–35m) category. Peak performance is achieved during the *Mid* (35–45m) phase, where the win rate reaches its maximum of approximately 55%, crossing the 50% baseline.

A subsequent decline is observed as matches extend into the *Late* (45–60m) and *Ultra* (60m+) categories, where the win rate stabilizes at approximately 44–45%. While the *Very Early* (¡25m) category shows a 0% win rate, it is considered statistically insignificant for this analysis due to the minimal sample size ($N = 1$). These findings suggest that the player's strategic efficacy is highest in matches concluding between 35 and 45 minutes.

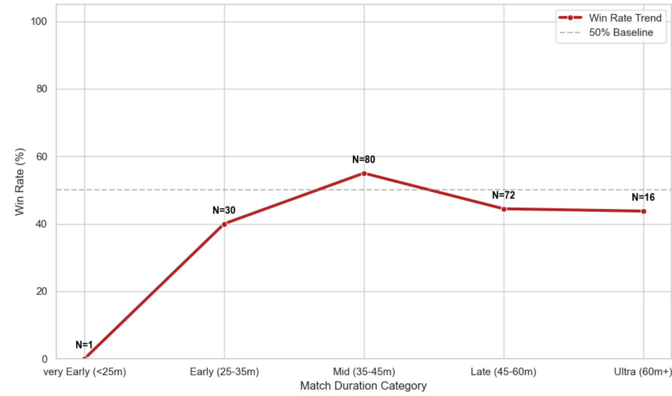

Fig. 9. Win Rate Trend across Match Duration Categories

The relationship between temporal match progression and per-minute performance metrics is visualized in Figure 10. Lowess trend lines are employed to represent the rate of change for each indicator as match duration increases.

Gold per Minute and *XP per Minute*, show a positive correlation with duration through the mid-game, with Gold peaking at approximately 500 units ($T = 50$) and XP plateauing at approximately 900 units in late-game scenarios. Combat efficiency, specifically *Kills per Minute*, exhibits a parabolic trend peaking at 0.2 before declining after 50 minutes. Conversely, *Assists per Minute* and *Tower Damage per Minute* demonstrate high stability, maintaining consistent rates of 0.4 and < 50 units, respectively, across the mid and late-game phases.

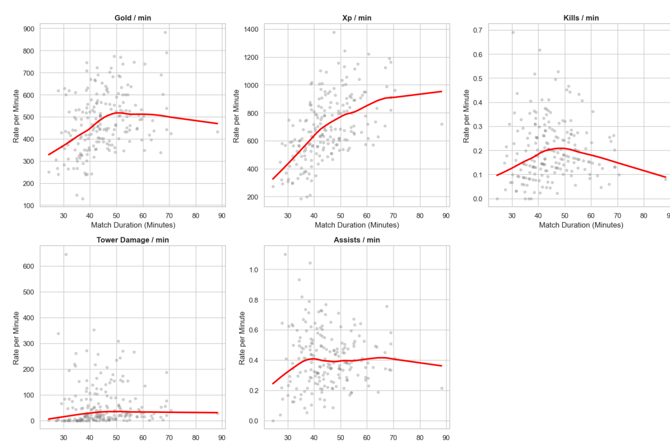

Fig. 10. Performance Metrics per Minute vs. Duration

To provide a unified view of performance intensity, a *Composite Efficiency Index* was developed by aggregating standardized Z-scores for resource accumulation, combat, and objective metrics. Figure 11 presents this index relative to match duration, utilizing a LOWESS regression to identify the overall efficiency trajectory.

The analysis reveals that total output intensity is lowest during the early game, starting at -1.0 standard deviations for matches under 30 minutes. The player reaches the personal average efficiency baseline at approximately 40 minutes, with peak output occurring during the 50–65 minute interval (+0.2 Std Dev). In ultra-late scenarios (> 70m), efficiency exhibits a gradual decline, returning toward the mean baseline.

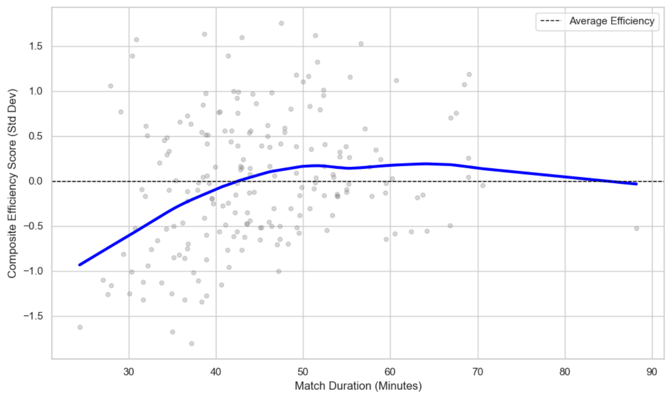

Fig. 11. Composite Efficiency Index Trajectory

V. Discussion

A. Interpretation of Results

The analysis reveals that the player's likelihood of winning is most strongly associated with team-oriented metrics rather than individual combat alone. Among the variables examined, *Assists* ($r = 0.44$) and *Tower Damage* ($r = 0.42$) demonstrated the highest positive correlations with match victory (Figure 2, Table II), followed by economic indicators (*XP per Minute* $r = 0.39$, *Gold per Minute* $r = 0.38$) and *Kills* ($r = 0.33$). Conversely, *Deaths* was negatively associated with winning ($r = -0.25$). These findings indicate that contributing to team fights and objectives is a stronger determinant of success than individual kill counts, highlighting the strategic importance of coordinated play and objective control.

Performance consistency was assessed using the Coefficient of Variation (Figure 4). Economic metrics, including *Gold* and *XP per Minute*, were highly stable ($CV = 0.28$ and 0.33), reflecting reliable resource accumulation across matches. Combat and objective metrics exhibited greater variability: *Assists* ($CV = 0.47$) and *Kills* ($CV = 0.61$) fluctuated with match context, while *Tower Damage* ($CV = 1.33$) was the most inconsistent, occurring primarily in advantageous situations. Overall, the player demonstrates consistent progression and farming efficiency, but the ability to convert impact into kills or objectives depends on in-game dynamics.

Hero-specific analysis revealed strong specialization effects. Performance was concentrated in a small set of preferred heroes, with one hero achieving an exceptional win rate of 0.81 (Figure 5), and the remaining top performers ranging from 0.53 to 0.71. Normalized metrics (Figure 6) highlight role-specific strengths: some heroes excelled in kills, others in assists, macro objectives, or experience efficiency. Economic performance remained stable across heroes ($CV < 0.40$, Figure 7), while combat and objective contributions were more variable, reinforcing the importance of aligning playstyle with the hero's functional role.

Environmental factors also influenced outcomes. Matches played on the *Radiant* side had a significantly higher win rate (56.99% vs. 39.62%; χ^2 $p = 0.0212$, Table III), accompanied by stronger economic and combat metrics, including *Gold per Minute*, *XP per Minute*, *Tower Damage*, and *Kills* (Figure 8, Table IV). These results suggest that spatial familiarity or map positioning can provide tangible advantages that translate into more effective performance.

Temporal analysis showed that match duration affects performance and win probability (Figure 9). The player's win rate increased through the early phase, peaked during mid-length matches (35–45 minutes, 55%), and declined slightly in longer games (44–45%). Resource accumulation and scaling metrics improved steadily into the mid-game, while kills per minute peaked around 50 minutes before tapering (Figure 10). Assists and tower damage per minute remained stable throughout, indicating sustained team contribution. The Composite Efficiency Index (Figure 11) corroborates this pattern, showing lowest output in early matches, baseline efficiency around 40 minutes, and peak performance between 50 and 65 minutes, followed by gradual decline in ultra-late scenarios.

In summary, the player's success is driven by a combination of: 1. Team-focused contributions (assists and objective control) rather than solely individual kills. 2. Reliable economic progression ensuring scaling potential. 3. Hero specialization that aligns with functional roles. 4. Environmental advantages such as team side. 5. Optimal mid-game timing, when scaling and team impact are maximized.

These findings collectively emphasize that victory is determined by strategic, coordinated play and efficiency in resource and objective management, rather than purely individual combat performance.

B. Comparison to Similar Works

Several studies have investigated match outcome prediction and performance evaluation in MOBA titles like Dota 2, but most focus on predictive modeling rather than interpretive performance analysis. For example, Yangibaev *et al.* proposed a decision tree ensemble framework using Extra Trees, Random Forest, and Gradient Boosting to predict Dota2 match results under early, mid, and late phases of play, extracting features such as assists, gold per minute, and experience per minute from OpenDota data [9]. Similarly, Akhmedov and Phan employed machine and deep learning models (e.g., neural networks and LSTMs) to predict real-time match outcomes, achieving significant accuracy improvements over simple classifiers [10].

Other research has applied traditional multi-criteria methods, such as Analytical Hierarchy Process, to estimate match outcomes by prioritizing metrics like GPM and XPM [11], or compared classification algorithms like Random Forest and XGBoost specifically for Dota2 win/loss prediction [12]. There are also IEEE-indexed efforts (e.g., "Predictive Analytics of First Blood and Match Outcome in Dota 2") that explore early match signals such as first blood events to enhance real-time prediction accuracy [13]. Finally, MOBA-Slice established a time slice–based evaluation framework for relative team advantage over the course of a match, providing foundation work for temporal modeling in MOBA games [14].

In contrast, the present study does not focus on building or benchmarking outcome prediction models. Instead, it performs a statistical performance analysis of personal match data, identifying which in-game actions (e.g., assists, tower damage, economic outputs) are most strongly associated with winning, and assessing performance consistency across heroes, sides, and match durations. This interpretive approach complements predictive analytics work by providing actionable insights into the drivers of personal success rather than estimating match outcomes per se.

C. Limitations

The study has several limitations that should be considered:

- The analysis is based on a single player's data, limiting generalizability to other players or skill levels.
- External factors such as teammate skill, opponent behavior, and patch updates were not fully controlled and may influence results.
- Some performance-related variables, like item choices, ability usage, and communication, were not included.
- The dataset only includes the most recent 199 matches recorded by the Dota API, so earlier games were not analyzed, which may limit the comprehensiveness of the findings.
- Findings may not fully apply to broader competitive or team-based contexts without further validation.

D. Recommendations for Future Work

Based on the findings and limitations of this study, future research could consider the following:

- **Expand the dataset:** Include multiple players across different skill levels to improve generalizability and identify broader patterns of success.
- **Incorporate additional variables:** Analyze performance-related factors such as item builds, ability usage, warding, communication, and team coordination to gain a more comprehensive understanding of player impact.
- **Control for external factors:** Consider teammate skill, opponent behavior, patch changes, and hero meta shifts to isolate individual contributions more effectively.
- **Explore alternative methods:** Use machine learning models (e.g., logistic regression, random forests, or neural networks) to predict match outcomes and identify key performance indicators.
- **Longitudinal analysis:** Track player performance over longer periods to assess improvement, adaptation, and consistency across different patches and competitive environments.
- **Side and map-specific analysis:** Investigate how spatial dynamics, side advantages, and lane assignments affect performance more deeply.

VI. Conclusion

This study conducted a comprehensive statistical analysis of personal Dota 2 match performance, examining factors associated with winning, performance consistency, optimal hero choices, side-based advantages, and efficiency across match durations.

The analysis revealed that the player's success is driven primarily by team-oriented contributions rather than individual combat alone. Assisting teammates, contributing to objectives such as tower damage, and avoiding deaths were key determinants of victory. Consistent economic performance, including gold and experience accumulation, was essential for scaling effectively throughout matches. Hero selection also played a crucial role, with a small set of preferred heroes consistently contributing to higher win rates and highlighting the importance of aligning playstyle with a hero's functional role. Environmental factors, such as playing on the Radiant side, provided measurable advantages, demonstrating the impact of map asymmetry. Additionally, player efficiency and impact were highest during mid-length matches, emphasizing the significance of match timing.

These findings indicate that personal success in Dota 2 depends on coordinated team contributions, efficient resource management, strategic hero selection, and situational awareness, rather than raw individual combat skills alone. Players can leverage these insights to optimize gameplay by focusing on team-oriented actions, choosing heroes that suit their strengths, taking advantage of side-based benefits, and prioritizing performance during mid-game scenarios. Coaches and analysts can also apply similar approaches to evaluate player consistency and identify areas for improvement.

Overall, victory in competitive MOBA games is determined more by strategy, coordination, and efficiency than by individual combat prowess. Evidence-based performance analysis can guide players in making smarter in-game decisions, maximizing team impact, and achieving consistent success.

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