Performance Consistency and Playstyle Analysis of a Dota 2 Player Using OpenDota Match Data

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***Abstract*—This study analyzes the performance consistency of a Dota 2 player using OpenDota match data collected between November 16, 2025, and February 6, 2026. The overall win rate was 51.52%. Winning matches exhibited higher mean values for KDA (4.58 vs. 2.05), gold per minute (539.67 vs. 455.98), and experience per minute (769.94 vs. 654.56). Independent-samples *t*-tests confirmed statistically significant differences in KDA ($t = 6.892$, $p < 0.001$), gold per minute ($t = 2.869$, $p = 0.005$), and experience per minute ($t = 2.672$, $p = 0.009$). Correlation analysis indicated a moderate relationship between win outcome and KDA ($r = 0.564$) and weaker correlations with gold ($r = 0.280$) and experience ($r = 0.262$), suggesting that combat effectiveness is the strongest contributor to match success.**

***Index Terms*—Dota 2, OpenDota, data science, exploratory data analysis, player performance analysis, gaming analytics, descriptive statistics, data visualization**

I. Introduction

Dota 2 is a multiplayer online battle arena (MOBA) game developed and published by Valve Corporation and released in 2013. It is one of the most played esports titles and provides detailed in-game statistics that enable systematic performance analysis. Evaluating player performance and playstyle is relevant for skill assessment, competitive analysis, and esports research. Public data platforms such as OpenDota collect match statistics from the official Dota 2 application programming interfaces (APIs) and make them available for structured analysis. OpenDota provides match histories and key performance metrics, including kills, deaths, assists, gold per minute (GPM), experience per minute (XPM), and win–loss outcomes. Documentation and structured data access are available through the OpenDota website [1] and API documentation [2].

The objective of this study is to explore and quantify how a single player's performance varies over a selected observation period and how different playstyle factors relate to match outcomes. This research applies descriptive statistics, exploratory data analysis (EDA), inferential statistical testing, and data visualization techniques to provide insights into performance consistency and gameplay patterns associated with wins and losses.

Specifically, the study seeks to answer the following research questions:

1) Does combat efficiency, measured by calculated KDA, significantly differ between wins and losses?
2) Do economic performance metrics, including gold per minute and experience per minute, significantly differ between wins and losses?
3) Which performance metric shows the strongest statistical association with match outcome?
4) How consistent are combat and economic performance metrics over time?

To address these research questions, the following hypotheses were formulated:

Research Question 1: H_0: There is no significant difference in calculated KDA between winning and losing matches. H_1: There is a significant difference in calculated KDA between winning and losing matches.

Research Question 2: H_0: There is no significant difference in gold per minute and experience per minute between winning and losing matches. H_1: There is a significant difference in gold per minute and/or experience per minute between winning and losing matches.

Research Question 3: H_0: No performance metric (KDA, gold per minute, experience per minute) is significantly associated with match outcome. H_1: At least one performance metric is significantly associated with match outcome.

Research Question 4: H_0: There is no difference in variability between combat-related and economic-related performance metrics over time. H_1: There is a difference in variability between combat-related and economic-related performance metrics over time.

By leveraging publicly available match data from OpenDota, this study provides statistical evidence on how combat effectiveness and economic efficiency relate to match success. Through structured hypothesis testing and longitudinal performance analysis, the research demonstrates how individual gameplay data can be transformed into measurable insights regarding consistency, efficiency, and performance-driven outcomes.

II. Review of Related Works

Esports analytics has grown rapidly due to the availability of gameplay data and the strategic complexity of games like Dota 2. Many studies use data-driven methods to analyze player performance and predict match outcomes, showing that in-game metrics such as kills, gold, and experience can forecast results with high accuracy [3].

Professional esports teams, such as Team Liquid, also use analytics to review replays, track key performance indicators, and guide coaching, highlighting the value of descriptive analytics in competitive strategy [4]. Bibliometric analyses further show that esports research spans multiple fields, including computer science, sports management, and psychology, with growing interest in approaches beyond predictive models [5].

Despite this, few studies focus on descriptive, exploratory analyses of individual player performance over time using public platforms like OpenDota. This study addresses this gap by applying descriptive statistics and visual analysis to a week of match data, providing insights into playstyle and performance trends that complement predictive research.

III. Methodology

This section describes the complete data preparation, preprocessing, and analytical procedures implemented to address the research questions and test the stated hypotheses in Chapter 1. The methodology follows a structured data science pipeline to ensure reproducibility, transparency, and alignment between research objectives and statistical procedures. All preprocessing and analysis were conducted using Python 3.12.12 within Visual Studio Code 1.109.2.

A. Participants

The participant in this study is an individual who provided informed consent for their gameplay data to be used for research purposes. The analysis was conducted using the participant's publicly available Dota 2 match records obtained from the OpenDota platform through its publicly accessible application programming interface (API).

No private or sensitive personal information was collected. The dataset was strictly limited to publicly available gameplay statistics, and the participant's identity was anonymized to ensure confidentiality. The study adopts a single-subject longitudinal design to evaluate performance consistency and metric–outcome relationships over time.

B. Data Collection Methods

Match data were collected from the OpenDota platform, which provides structured Dota 2 match statistics through its official API. The dataset included match identifiers, hero selections, combat performance metrics, economic statistics, match duration, and win/loss outcomes. Data extraction was performed programmatically using Python to ensure consistency, minimize manual errors, and preserve reproducibility.

1) Variables Collected: The variables collected for this study are summarized in Table I on the next page. These variables were selected to support the operationalization of combat efficiency, economic performance, temporal trends, and match outcomes in accordance with the research questions.

2) Frequency of Data Logging: Match data were collected on a weekly basis from November 16, 2025, to February 6, 2026. Weekly match records were downloaded in comma-separated values (CSV) format and merged into a consolidated dataset. The chronological structure of the dataset enabled time-series and variability analysis in alignment with Research Question 4.

3) Tools and Platforms Used: The following tools and platforms were utilized in this study:

1) VS Code 1.109.2 (computational environment)
2) Python 3.12.12 (programming language)
3) Pandas 2.3.3 (data manipulation)
4) NumPy 2.3.5 (numerical computing)
5) Matplotlib 3.10.0 (data visualization)
6) Seaborn 0.13.2 (statistical visualization)
7) SciPy 1.16.3 (scientific computing)
8) Requests 2.32.5 (HTTP requests)
9) Built-in Python modules: os, glob, re

C. Operational Definitions

To ensure clarity and replicability, the following operational definitions were applied in accordance with the research questions:

1) Kills = Number of enemy heroes killed by the player in a match.
2) Deaths = Number of times the player died in a match.
3) Assists = Number of enemy kills in which the player contributed.
4) Gold per Minute (GPM) = Average gold earned per minute
5) Experience per Minute (XPM) = Average experience gained per minute
6) Kills per Minute (KPM) = Average kills achieved per minute.
7) Match Duration = Total length of the match in seconds.
8) Win Outcome = Binary indicator (1 = Win, 0 = Loss).

A derived metric was computed to operationalize combat efficiency:

$$KDA = \frac{\text{kills} + \text{assists}}{\text{deaths}}$$

Fig. 1. KDA Formula

KDA served as the primary indicator of combat efficiency for testing Research Question 1 and its corresponding hypothesis. When deaths equaled zero, the denominator was set to one to avoid division by zero.

Performance consistency over time was measured using standard deviation and coefficient of variation (CV).

D. Data Cleaning and Preprocessing

Data preprocessing was conducted prior to analysis to ensure accuracy and reliability.

TABLE I
COLLECTED DOTA 2 MATCH VARIABLES

Player Info	Hero Info	Items / Purchases	Performance Metrics
account_id	hero_id	item_0	actions_per_min
player_slot	hero_variant	item_1	life_state_dead
party_id		item_2	cosmetics
permanent_buffs		item_3	
party_size		purchase_time	
team_number		first_purchase_time	
team_slot		item_win	
		item_usage	
		purchase_ward_observer	
		purchase_ward_sentry	
		purchase_tpscroll	

1) Handling Missing Values: Missing values were handled using a structured approach:

- A complete audit of missing counts and percentages was performed for all columns.
- Rows with missing values in critical analytical variables, such as `kills_per_min` (4 rows removed in total), were removed to preserve inferential validity.
- Non-essential or redundant columns were removed manually, including `name`, `last_login`, `party_id`, `party_size`, `permanent_buffs`, `region`, `account_id`, `personaname`, `hero_variant`, `start_time_iso`, and others.

This ensured that statistical comparisons between wins and losses were not influenced by incomplete or irrelevant data.

2) Datetime Conversion: The `start_time` column was converted to `datetime` format to enable chronological and weekly trend analysis.

3) Feature Engineering: The KDA ratio was computed as a derived feature to directly test differences in combat efficiency between match outcomes.

The cleaned and consolidated dataset was stored as `combined_player_data.csv`.

E. Statistical Analysis

Statistical analyses were explicitly selected to address each research question and evaluate the corresponding null and alternative hypotheses.

1) Descriptive Statistics: Descriptive statistics were computed to summarize central tendency and dispersion. These statistics were computed for the following variables:

- kills
- deaths
- assists
- gold_per_min
- xp_per_min
- kills_per_min
- KDA

Measures included mean, median, standard deviation, and minimum–maximum values.

2) Time-Series Analysis: To address performance consistency over time, matches were ordered chronologically and grouped by week. The following weekly metrics were analyzed:

- Average KDA
- Win rate
- Gold per minute

Line plots were generated to visualize short-term fluctuations and long-term stability.

3) Comparative Analysis: Non-parametric Mann–Whitney U tests were conducted comparing wins and losses for:

- KDA
- Gold per minute
- Experience per minute

Rank-biserial correlation coefficients were computed to quantify the magnitude of differences. These tests directly evaluated the null hypotheses stating that no significant differences exist between match outcomes.

4) Correlation Analysis: Spearman rank correlation coefficients were computed to measure associations between:

- KDA
- gold_per_min
- xp_per_min
- kills_per_min
- win outcome

A correlation matrix was generated to identify which performance metric showed the strongest monotonic association with match outcome, thereby evaluating the corresponding null hypothesis.

5) Variability Measurement: The coefficient of variation (CV) was calculated for key combat and economic metrics to assess relative variability. This allowed comparison of the consistency of KDA and farming-related statistics between winning and losing matches, providing insight into which metrics were more stable in contributing to match outcomes.

IV. RESULTS

This section presents the statistical findings derived from the cleaned dataset `combined_player_data.csv`. The results are organized according to the research questions stated. Statistical interpretation and implications are reserved for the Discussion section.

A. Dataset Overview

The final dataset consists of consolidated weekly match records collected between November 16, 2025, and February 6, 2026. Each row represents a single match played by the participant. It also consisted of 99 matches, of which 51 were wins and 48 were losses.

The dataset includes the following primary variables:

- Match identifiers and timing: `match_id`, `start_time`, `duration` in seconds
- Player and hero information: `player_slot`, `hero_id`, `hero_name`
- Performance metrics: `kills`, `deaths`, `assists`, `gold_per_min`, `xp_per_min`, `kills_per_min`
- Derived metric: `KDA`
- Match outcome: `win` (derived from `radiant_win`)

This structure supports analysis of combat efficiency, economic performance, metric–outcome relationships, and temporal consistency.

1) Overall Descriptive Statistics: Table I presents overall descriptive statistics for the primary performance variables.

TABLE II
DESCRIPTIVE STATISTICS OF PERFORMANCE METRICS

Metric	Mean	Median	Std. Dev.	Min	Max
kills	10.41	9.0	6.22	1.0	34.0
deaths	9.84	10.0	4.46	3.0	24.0
assists	16.26	16.0	7.34	2.0	39.0
calculated_kda_ratio	3.35	2.67	2.25	0.75	12.67
gold_per_min	499.09	480.0	150.40	234.0	896.0
xp_per_min	714.00	673.0	221.51	312.0	1263.0
kills_per_min	0.24	0.20	0.13	0.02	0.76
duration	2556.28	2388.0	698.94	1503.0	4560.0

These statistics provide baseline context for subsequent hypothesis testing and variability analysis.

B. Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted to understand the shape, central tendency, and spread of key performance distributions prior to formal hypothesis testing.

1) Dataset Analysis: The cleaned dataset `combined_player_data.csv` contains 99 player-level observations described by 39 variables, where each row corresponds to a single match played by the participant. The dataset spans matches collected between November 16, 2025, and February 6, 2026.

The feature set includes match and player identifiers (*match_id*, *hero_id*, *player_slot*), team and outcome indicators (*isRadiant*, *win*), and numerical performance metrics. Performance variables consist of discrete combat statistics such as *kills*, *deaths*, and *assists*, as well as continuous rate-based metrics including *gold_per_min*, *xp_per_min*, and *kills_per_min*. Binary variables (*isRadiant* and *win*) are encoded using values of 0 and 1.

All variables contain complete data, with no missing values across the 99 observations. Repeated *hero_id* values occur across different matches, reflecting hero reuse over time. The numerical structure and completeness of the dataset support exploratory distributional analysis and non-parametric statistical testing conducted in subsequent subsections.

2) Distribution of Key Combat and Economic Metrics: The histograms below (Figures 2–4) illustrate the empirical distributions of selected performance variables:

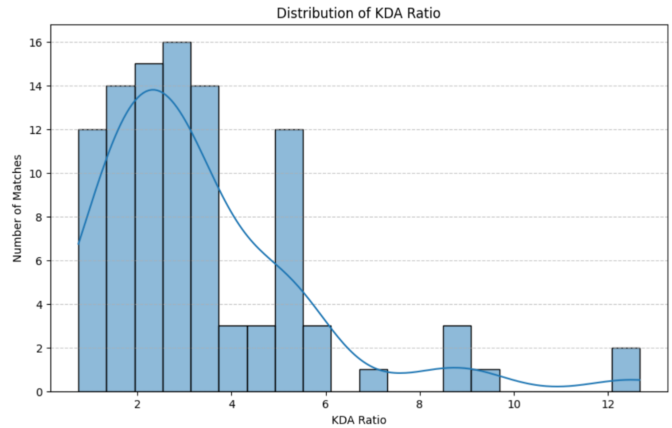

Fig. 2. Histogram of KDA Ratio

Figure 2 shows that most KDA ratios are concentrated between approximately 1 and 4, with the highest frequency occurring around the 2–3 range. The distribution is right-skewed, with a long tail extending toward higher KDA values above 8 and reaching roughly 12.5.

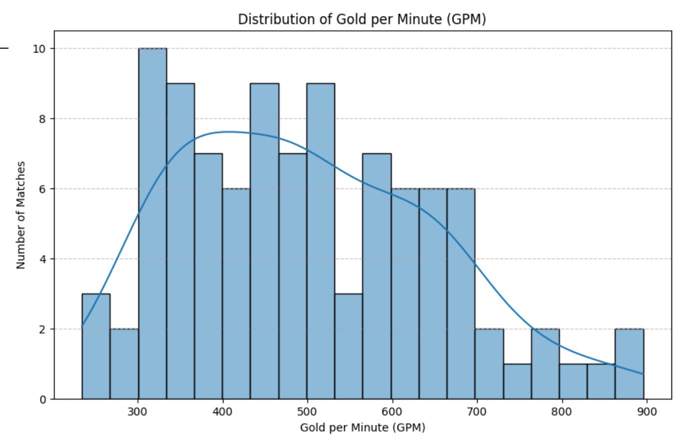

Fig. 3. Histogram of Gold per Minute (GPM)

As shown in Figure 3, most Gold per Minute (GPM) values are concentrated between approximately 350 and 600, with the highest frequencies around the 400–500 range. The distribution is positively skewed, with fewer observations extending toward higher GPM values above 700 and reaching close to 900.

Figure 4 shows that most experience per minute (XPM) values are concentrated between approximately 450 and 850, with the highest frequencies occurring in the 550–700 range. The distribution exhibits a positive skew, with a right tail

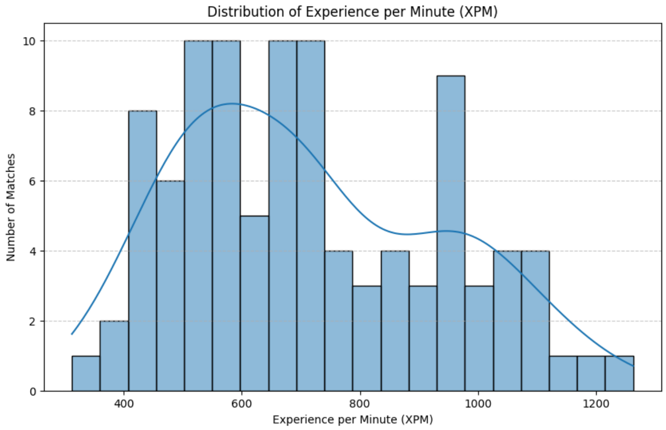

Fig. 4. Histogram of Experience per Minute (XPM)

extending toward higher XPM values above 1000 and reaching approximately 1250. Lower XPM values below 400 occur less frequently across the observed matches.

3) Summary Observations from EDA: The exploratory visualizations show that KDA values are distributed across a wide range, with a central concentration at lower to moderate levels and a pronounced right-skewed tail. Gold per minute and experience per minute similarly exhibit variability across matches, with most observations clustered within intermediate ranges and fewer values extending toward higher extremes.

Overall, the presence of dispersion and non-symmetric distributions across key performance metrics indicates heterogeneity in match-level performance. These distributional characteristics provide context for the use of non-parametric statistical tests and support subsequent comparisons between match outcomes.

C. Research Question 1: Difference in Combat Efficiency Between Wins and Losses

RQ1: Does combat efficiency (KDA) significantly differ between wins and losses?

Performance metrics were grouped according to match outcome to provide descriptive context prior to inferential testing. Table III summarizes the mean values of key combat and economic metrics for winning and losing matches.

TABLE III
MEAN PERFORMANCE METRICS BY MATCH OUTCOME

Metric	Win (Mean)	Loss (Mean)
KDA	4.58	2.05
gold_per_min	539.67	455.98
xp_per_min	769.94	654.56
kills_per_min	0.29	0.20

Differences in combat efficiency between winning and losing matches were formally evaluated using the Mann–Whitney U test. Effect sizes were quantified using the rank-biserial correlation coefficient.

For combat efficiency, the Mann–Whitney U test indicates a statistically significant difference in KDA between winning

TABLE IV
MANN–WHITNEY U TEST RESULTS FOR COMBAT AND ECONOMIC METRICS

Metric	U Statistic	*p*-value	Rank-Biserial r
KDA	2153.50	< 0.001	0.759
gold_per_min	1627.00	0.005	0.329
xp_per_min	1597.00	0.009	0.305

and losing matches ($p < 0.001$). The rank-biserial correlation coefficient ($r = 0.759$) indicates a large magnitude difference in KDA distributions across match outcomes.

D. Research Question 2: Differences in Economic Performance Between Wins and Losses

RQ2: Do gold per minute and experience per minute significantly differ between wins and losses?

Differences in economic performance metrics between winning and losing matches were evaluated using the Mann–Whitney U test.

The results indicate statistically significant differences for both gold per minute and experience per minute between match outcomes. Gold per minute differed significantly between wins and losses ($U = 1627.00$, $p = 0.005$), with a rank-biserial correlation of $r = 0.329$, indicating a moderate magnitude difference. Similarly, experience per minute showed a statistically significant difference between outcomes ($U = 1597.00$, $p = 0.009$), with a rank-biserial correlation of $r = 0.305$, also indicating a moderate effect size.

E. Research Question 3: Strength of Association Between Performance Metrics and Match Outcome

RQ3: Which performance metric shows the strongest statistical association with match outcome?

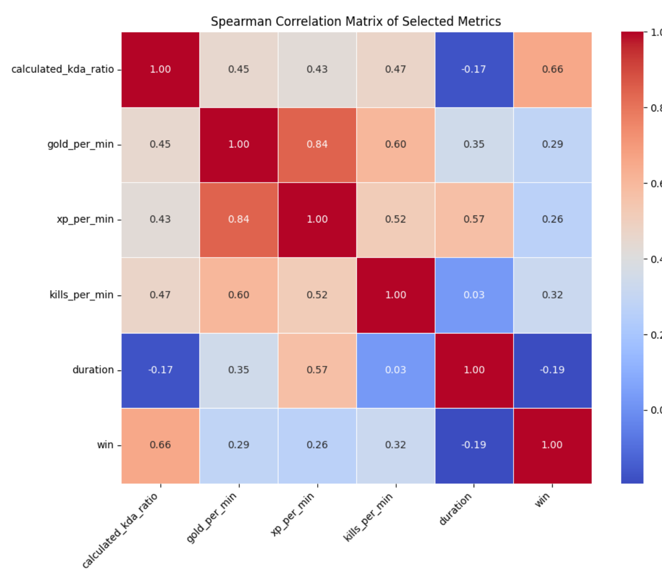

Fig. 5. Spearman Correlation Matrix of Performance Metrics

Spearman rank correlation coefficients were computed to evaluate the strength of association between performance metrics and match outcome.

The Spearman correlation coefficients between match outcome and selected performance metrics are KDA: $\rho = 0.66$, *gold_per_min*: $\rho = 0.29$, and *xp_per_min*: $\rho = 0.26$

Among the evaluated metrics, KDA exhibits the strongest positive monotonic association with match outcome.

F. Research Question 4: Performance Consistency Over Time

RQ4: How consistent are combat and economic performance metrics over time?

Performance metrics were aggregated on a weekly basis and examined using time-series visualizations.

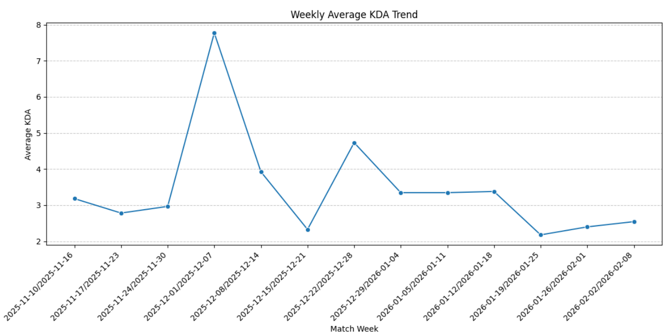

Fig. 6. Weekly Average KDA

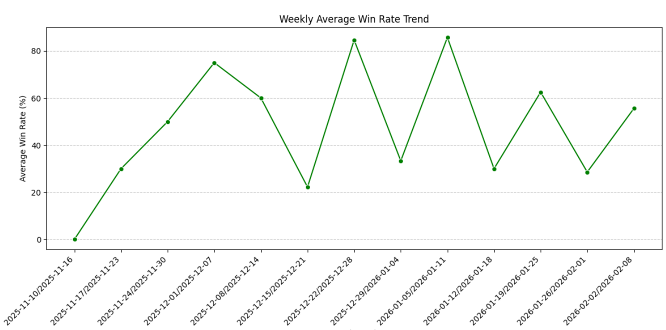

Fig. 7. Weekly Win Rate Trend

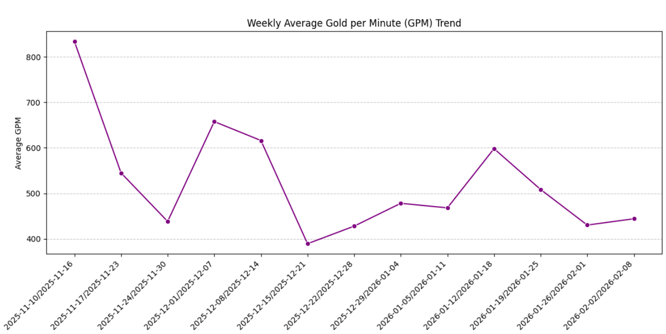

Fig. 8. Weekly Gold per Minute Trend

The weekly trend plots show observable fluctuations in average KDA and win rate across the observation period. In contrast, weekly average gold per minute exhibits comparatively smoother variation over time.

To quantify relative variability across metrics, standard deviation and coefficient of variation (CV) were calculated using weekly averages.

TABLE V
STANDARD DEVIATION AND COEFFICIENT OF VARIATION FOR CORE METRICS

Metric	SD	CV (%)
KDA	1.48	42.73
gold_per_min	123.80	23.55
xp_per_min	147.33	19.75

Among the evaluated metrics, KDA displays the highest relative variability over time, while economic performance metrics show lower coefficients of variation.

G. Summary of Hypothesis Testing Outcomes

Based on the statistical analyses conducted, the following outcomes were observed:

- **RQ1:** The null hypothesis was rejected, indicating a statistically significant difference in combat efficiency (KDA) between winning and losing matches.
- **RQ2:** The null hypothesis was rejected, indicating statistically significant differences in gold per minute (GPM) and experience per minute (XPM) between match outcomes.
- **RQ3:** The null hypothesis was rejected, indicating that performance metrics are significantly associated with match outcome, with KDA exhibiting the strongest monotonic association.
- **RQ4:** The null hypothesis was rejected, indicating that combat-related performance metrics exhibit greater relative variability over time compared to economic performance metrics.

Collectively, these findings provide statistical support for all proposed research questions.

V. DISCUSSION

This section interprets the statistical findings presented in Section IV and discusses their implications for gameplay behavior, performance consistency, and performance-driven match outcomes.

A. Interpretation of Results

The results indicate that both combat efficiency and economic performance are significantly associated with match outcomes. The overall win rate of 51.52% suggests relatively balanced performance across the observation period. However, winning matches demonstrated substantially higher averages in calculated KDA (4.58 vs. 2.05), gold per minute (539.67 vs. 455.98), and experience per minute (769.94 vs. 654.56). Among these metrics, KDA showed the strongest statistical separation between wins and losses, as indicated by the

Mann–Whitney U test ($p < 0.001$) and a large rank-biserial correlation ($r = 0.759$).

Correlation analysis further supports this finding. Spearman rank correlations showed that match outcome was most strongly associated with KDA ($\rho = 0.564$), while gold per minute ($\rho = 0.280$) and experience per minute ($\rho = 0.262$) exhibited weaker but positive monotonic associations with winning.

Time-series analysis revealed noticeable weekly fluctuations in KDA and win rate, indicating variability in short-term combat performance. In contrast, economic metrics displayed comparatively smoother trends over time. This pattern suggests that while farming efficiency remains relatively stable, combat execution varies more substantially across matches.

The coefficient of variation (CV) results reinforce this observation. KDA exhibited the highest relative variability (CV = 42.73%), compared to gold per minute (23.55%) and experience per minute (19.75%). This indicates that combat-related performance is less consistent over time than economic accumulation. Overall, the findings suggest that although stable farming contributes to match success, combat effectiveness serves as the primary differentiating factor between wins and losses.

B. Comparison to Related Work

Prior gaming analytics studies have emphasized the importance of economic efficiency in multiplayer online battle arena (MOBA) games, demonstrating that gold and experience accumulation are associated with increased win probability. The present findings partially align with this perspective, as both gold per minute and experience per minute were significantly higher in winning matches ($p < 0.05$). However, their associations with match outcome were weaker compared to combat efficiency metrics.

In contrast, KDA demonstrated a stronger relationship with winning, both in terms of statistical significance and magnitude of association. Unlike large-scale population studies, this research adopts a single-player longitudinal approach. Rather than aiming for generalization, it emphasizes individualized performance consistency and playstyle profiling, offering a focused, micro-level application of statistical gaming analytics.

C. Limitations

Several limitations should be acknowledged:

- **Single-subject design** (n = 1)**:** The dataset represents only one player; therefore, findings cannot be generalized to the broader Dota 2 population.
- **Short observation period:** The data cover approximately three months. A longer timeframe may yield more stable trend estimates.
- **Limited contextual variables:** Factors such as team composition, opponent skill level, role assignment, and patch updates were not included.
- **Public data constraints:** The dataset relies exclusively on publicly available OpenDota metrics, limiting deeper behavioral tracking.
- **Unmeasured external influences:** External factors such as academic workload, stress, and physical fatigue were not measured but may affect gameplay performance.

D. Recommendations and Future Work

Future studies may extend the observation period to assess long-term performance consistency. Incorporating additional variables such as role classification, matchmaking rating, and patch changes could provide deeper contextual insights. Expanding the analysis to include multiple players would allow comparative evaluation of playstyle consistency.

More advanced statistical approaches, including regression-based modeling or time-series methods, may also be applied to further examine performance trends. Consistent and structured data collection remains essential for improving analytical reliability in similar student-led projects.

E. Overall Interpretation

The findings indicate that both combat effectiveness and economic efficiency contribute to match success, with KDA emerging as the strongest differentiating metric between wins and losses. While gold per minute and experience per minute were significantly higher in winning matches, their associations with match outcome were weaker than that of KDA. Economic metrics also exhibited lower variability over time, suggesting greater consistency in farming-related performance.

Overall, the study demonstrates how descriptive statistics, non-parametric testing, and correlation analysis can transform individual gameplay data into quantifiable insights on performance consistency, efficiency, and match outcomes.

VI. Conclusion

This study examined the performance consistency and playstyle characteristics of a Dota 2 player using publicly available match data obtained from OpenDota. Through statistical analysis of weekly matches collected between November 16, 2025, and February 6, 2026, the research evaluated how combat efficiency, economic performance, and temporal trends relate to match outcomes.

The findings indicate that while gold per minute and experience per minute were significantly higher in winning matches, combat efficiency, measured by the calculated KDA ratio, exhibited the strongest association with match success. Winning matches were characterized by substantially higher KDA values, supported by a large effect size and a moderate positive correlation with match outcome. Economic performance metrics also differed significantly between wins and losses; however, their associations with match outcome were comparatively weaker. Variability analysis further showed that farming-related metrics were more stable over time than combat-related performance.

Time-series analysis revealed weekly fluctuations in performance metrics, suggesting that short-term consistency varies across the observation period. These results indicate that combat performance exhibits greater variability over time, whereas economic performance remains relatively consistent.

Although limited to a single participant and a relatively short observation period, this study demonstrates how structured data science techniques can be applied to personal gameplay data to produce quantifiable insights into performance consistency, efficiency, and match outcomes.

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