Data Science for Competitive Improvement in *League of Legends*

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***Abstract*—Competitive performance in multiplayer online battle arena (MOBA) games is influenced by mechanical skill, strategic decision-making, and consistency across matches. This study investigates whether measurable improvement has occurred in the performance of a single top-lane player in *League of Legends* by comparing gameplay metrics across two consecutive time periods. Using match-history data retrieved via the Riot Games API, key performance indicators—including creep score per minute (CS/min), kill–death–assist ratio (KDA), and win rate—are analyzed using descriptive statistics, correlation analysis, and hypothesis testing.**

Descriptive trends suggest improvements in several efficiency metrics and an 8.8% increase in win rate; however, inferential statistical tests did not reveal statistically significant mean differences between periods at the $\alpha = 0.05$ level. The findings highlight the challenges of detecting performance growth in high-variance, team-based environments and emphasize the importance of normalized metrics in personal gameplay analytics.

***Index Terms*—Data science, League of Legends, performance evaluation, hypothesis testing, esports analytics**

I. Introduction

The rapid growth of esports has generated increasing interest in the application of data science techniques to competitive gaming performance analysis. *League of Legends* (LoL) provides a rich environment for quantitative analysis due to the availability of detailed match-level statistics through public APIs [3]. While many studies focus on population-level trends, fewer works examine longitudinal improvement at the individual level. Understanding whether performance has objectively improved over time is critical for competitive players, as subjective impressions of progress may be misleading without statistical validation.

II. Methodology

A. Research Questions

This study addresses the following research questions:

- Which in-game performance metrics are most strongly correlated with match victories in *League of Legends*?
- Has the player's top-lane performance improved over time when comparing two three-month periods?
- Are improvements consistent across multiple champions or limited to a subset of frequently played champions?

B. Research Objectives

1) Primary Objective: The primary objective of this study is to determine whether measurable improvement has occurred in the player's top-lane performance during the three months following the start of the research period compared to the preceding three months. Improvement is operationalized as statistically significant increases in selected performance metrics.

2) Secondary Objectives: The secondary objectives are to:

- Identify which performance metrics exhibit the largest changes over time.
- Evaluate whether performance improvements are consistent across different champions.
- Assess whether changes in performance metrics are associated with improved match outcomes.
- Compare predictive model performance between the two time periods.

III. Literature Review

Previous research has demonstrated that in-game metrics such as gold accumulation, objective control, and damage contribution are strongly associated with match outcomes and player skill differentiation [2], [4]. Prior work has also explored player skill differentiation and expertise through fine-grained input behavior and performance indicators in *League of Legends* [1].

Lee et al. [1] characterized and quantified expert input behavior in *League of Legends*, providing insights into how mechanical skill differentiates player expertise levels. Martinez et al. [2] applied deep learning techniques to identify key performance indicators related to win prediction, map navigation, and vision control, demonstrating the importance of economy-related metrics in determining match outcomes. Schubert et al. [4] developed esports analytics frameworks through encounter detection, establishing methodological approaches for performance evaluation in competitive gaming contexts.

These studies emphasize the importance of economy-focused metrics and strategic decision-making in MOBA games, but few examine longitudinal individual performance improvement using rigorous statistical validation. This study builds on these foundations by applying similar analytical methods to a single-player case study over time.

IV. METHODOLOGY

A. Data Collection

Match data were collected using the Riot Games API (*match-v5*). Only ranked solo queue matches in the top-lane role were included.

- **Pre-Research Period:** June 16, 2025 – Sept 15, 2025 ($n = 22$)
- **Post-Research Period:** Sept 16, 2025 – Jan 31, 2026 ($n = 163$)

1) Variables: The following variables were extracted per match:

Data Variable	Type (Quant/Qual)	Unit / Scale	Frequency of Collection	Tool / Source
Game Mode	Qualitative	Categorical (Ranked, Normal, etc.)	Per match	Riot API
Game Start Timestamp	Quantitative	Unix timestamp (ms)	Per match	Riot API
Game Start Date	Qualitative	Date (YYYY-MM-DD)	Per match	Riot API
Game End Date	Qualitative	Date (YYYY-MM-DD)	Per match	Riot API
Game Duration	Quantitative	Minutes	Per match	Riot API
Champion	Qualitative	Categorical	Per match	Riot API
Position	Qualitative	Categorical (Top, Jungle, Mid, etc.)	Per match	Riot API
Kills	Quantitative	Count	Per match	Riot API
Deaths	Quantitative	Count	Per match	Riot API
Assists	Quantitative	Count	Per match	Riot API
KDA	Quantitative	Ratio	Per match	Riot API
Gold Earned	Quantitative	Gold units	Per match	Riot API
CS	Quantitative	Count	Per match	Riot API
CS per Minute	Quantitative	Continuous (0–15+)	Per match	Riot API
Damage Dealt	Quantitative	Total damage	Per match	Riot API
Damage Taken	Quantitative	Total damage	Per match	Riot API
Damage to Objectives	Quantitative	Total damage	Per match	Riot API
Damage to Towers	Quantitative	Total damage	Per match	Riot API
Damage to Dragons (Estimated)	Quantitative	Total damage	Per match	Riot API
Damage per Minute	Quantitative	Continuous	Per match	Riot API
Win	Qualitative	Binary (Win/Loss)	Per match	Riot API

Metrics were normalized where appropriate to account for variation in game length.

VARIABLE DEFINITIONS

The dataset consists of 21 variables extracted from the **Riot Games API**, grouped into temporal metadata, player performance indicators, resource efficiency metrics, and objective-based outputs.

1. Temporal and Match Metadata

Game Mode: A qualitative categorical variable indicating the match type (e.g., Ranked, Normal, ARAM).

Game Start Timestamp: A quantitative representation of the match start time in Unix milliseconds.

Game Start Date / Game End Date: Qualitative calendar dates formatted as `YYYY-MM-DD`, used for temporal grouping and trend analysis.

Game Duration: A quantitative continuous variable representing total match length in minutes.

2. Player Role and Performance Metrics

Champion: A qualitative categorical variable identifying the character selected by the player.

Position: The in-game role or lane assigned to the player (e.g., Top, Jungle, Mid).

Kills, Deaths, Assists: Quantitative counts representing core combat interactions.

KDA: A quantitative performance ratio computed as:

$$KDA = \frac{\text{Kills} + \text{Assists}}{\max(1, \text{Deaths})}$$

Win: A qualitative binary variable indicating match outcome (Win or Loss).

3. Resource and Efficiency Metrics

Gold Earned: The total amount of in-game currency accumulated by the player.

CS (Creep Score): A quantitative count of minions and neutral monsters eliminated.

CS per Minute: A quantitative continuous variable measuring farming efficiency over time.

Damage per Minute: A quantitative continuous variable representing average damage output per minute.

B. Combat and Objective Output Metrics

Damage Dealt / Damage Taken: Quantitative totals of damage inflicted on and received from enemy champions.

Damage to Objectives / Towers / Dragons: Quantitative indicators of objective control and macro-level contribution.

1) Data Cleaning: Data preprocessing included removal of remake games, filtering for top-lane role consistency, handling missing or invalid values, and ensuring metric consistency across both periods.

C. Descriptive Analysis

Descriptive statistics, including mean and standard deviation, were computed for each metric across both time periods. Exploratory visualizations were used to examine distributional differences and performance trends.

D. Correlation Analysis

Pearson and Spearman correlation coefficients were calculated to evaluate relationships between individual performance metrics and match outcomes, identifying key performance indicators associated with winning, consistent with prior esports analytics studies [2], [4].

E. Hypothesis Testing

Independent two-sample t-tests were conducted to compare mean performance metrics between the pre-research and post-research periods.

For each metric, the following hypotheses were tested:

Null Hypothesis (H_0): There is no statistically significant difference in the mean value of the performance metric between the pre-research and post-research periods.

Alternative Hypothesis (H_1): There is a statistically significant difference in the mean value of the performance metric between the two periods.

A one-tailed independent t-test was applied when directional improvement was theoretically expected. A significance level of $\alpha = 0.05$ was used. Assumptions of independence and approximate normality were evaluated prior to hypothesis testing.

The pre-research period included $n = 22$ ranked matches, while the post-research period included $n = 163$ ranked matches.

V. Results

This section presents the empirical findings derived from descriptive statistics, visual analysis, correlation analysis, hypothesis testing, and predictive modeling. Results are reported by comparing performance metrics between the pre-research and post-research periods, followed by an evaluation of their relationship with match outcomes.

A. Descriptive Performance Comparison

Descriptive statistics indicate consistent directional improvement across several performance metrics in the post-research period.

TABLE I
Comparison of Mean Performance Metrics Between Periods

Metric	Pre-Research	Post-Research	Change
CS per Minute	5.85	6.08	+0.23
KDA	2.99	3.30	+0.31
Damage Dealt	21,608	23,287	+1,679
Damage Taken	35,105	33,529	-1,576
Win Rate (%)	40.9%	49.7%	+8.8%
Gold Earned	11,844	11,442	-402

Table I shows improvements in CS per minute, KDA, damage dealt, and win rate, alongside reductions in damage taken. Although improvements are observable at the descriptive level, variability across matches remains substantial.

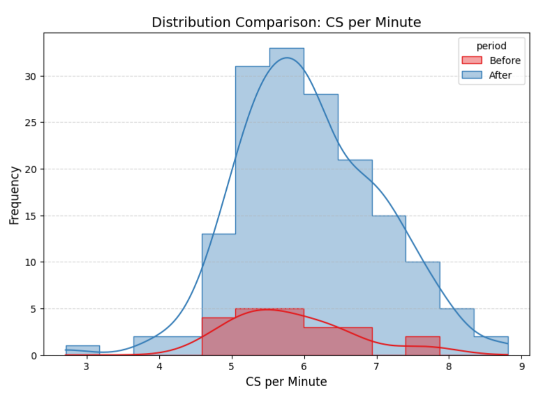

Fig. 1. Distribution of creep score per minute before and after the project intervention. The overlapping areas indicate the shift in farming consistency.

The distribution of CS per Minute serves as a primary indicator of farming efficiency and resource management. As illustrated in Figure 1, an improvement is marked not only by the peak of the "After" distribution shifting to the right, signifying a higher average, but also by the distribution becoming narrower and taller. This narrowing suggests increased consistency, indicating that the player is successfully reducing the frequency of "low-resource" games and stabilizing their income regardless of match conditions.

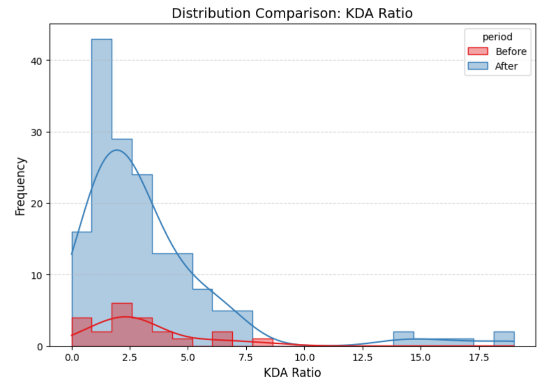

Fig. 2. Distribution of KDA ratios before and after the project intervention.

In terms of combat performance, the KDA Ratio and Damage Dealt distributions illustrate the player's offensive impact and decision-making. A positive shift in KDA is observed when the "After" frequency moves away from lower values toward a more stable mid-range, as seen in Figure 2, suggesting better risk assessment and a decrease in unnecessary deaths.

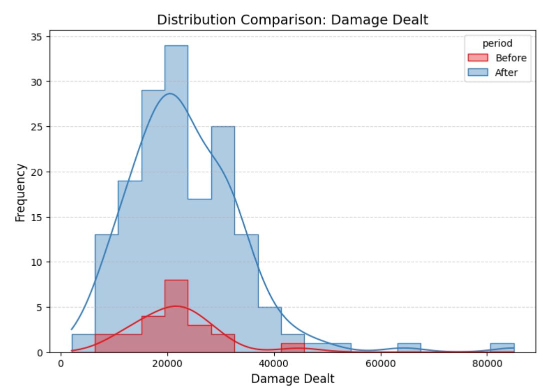

Fig. 3. Distribution of damage dealt to champions before and after the project intervention.

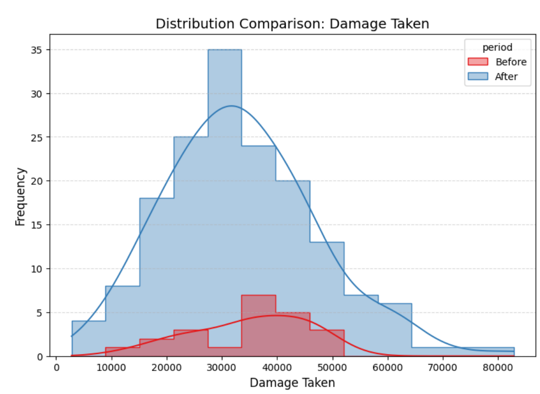

Fig. 4. Distribution of damage taken before and after the project intervention.

Simultaneously, the Damage Dealt histogram (Figure 3) reveals the player's contribution to team fights and lane pressure; a shift to the right indicates more decisive trading and better participation in combat. Finally, the Damage Taken distribution (Figure 4) provides context for the player's role; for a top-lane player, an increase in damage taken can signify a more effective "front-lining" presence in team fights, while a decrease might suggest improved positioning and better evasion of enemy abilities. Together, these overlapping distributions provide a clear visual narrative of how the player's fundamental mechanics and strategic consistency have evolved throughout the project.

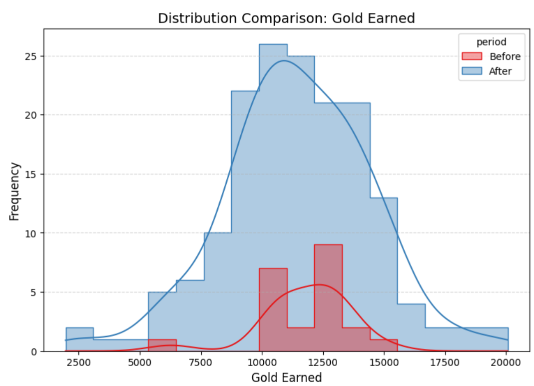

Fig. 5. Distribution of total gold earned per match before and after the project intervention.

This economic stability is further reflected in the Gold Earned distribution shown in Figure 5. As a catch-all metric for buying power, the rightward shift in the gold distribution proves that the intervention successfully increased total resource income from all sources, including objectives and combat, which directly correlates with a greater ability to influence the late game.

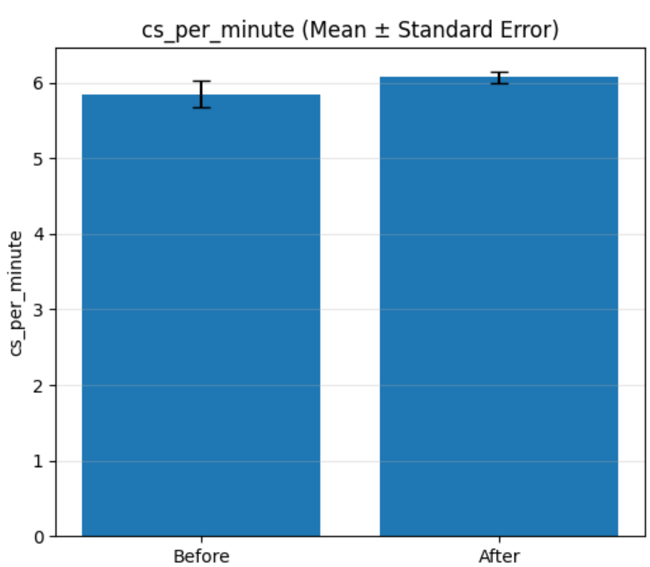

Fig. 6. Average Cs per min per match before and after the project intervention. Error bars represent standard deviation.

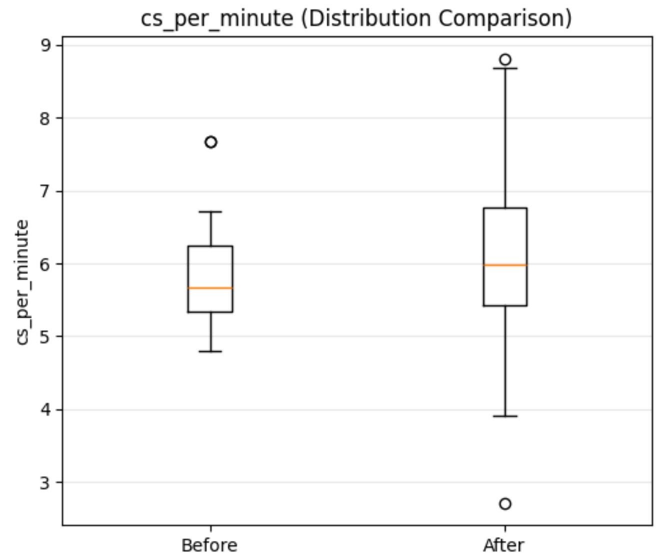

Fig. 7. Boxplot comparison of CS per minute between periods.

Figures 6 and 7 show average CS per minute. Compared to raw CS, this metric exhibits a clearer upward shift in the post-research period, suggesting improved laning efficiency independent of match duration. Nonetheless, overlapping variability indicates that performance gains were not uniformly sustained.

Fig. 8. Average gold earned per match before and after the project intervention. Error bars represent standard deviation.

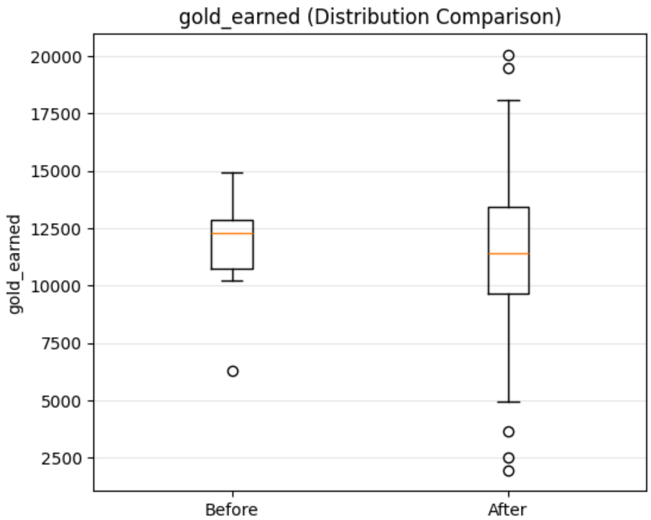

Fig. 9. Boxplot comparison of gold earned between periods.

Figures 8 and 9 present average gold earned per match. A slight decrease in mean gold is observed in the post-research period. This suggests that improvements in farming efficiency did not consistently translate into higher overall economic advantage, potentially due to shorter match durations or team-level resource distribution. The wide standard deviation highlights substantial match-to-match economic variability. Despite the slight decrease in mean gold earned, distributional spread remains similar across periods.

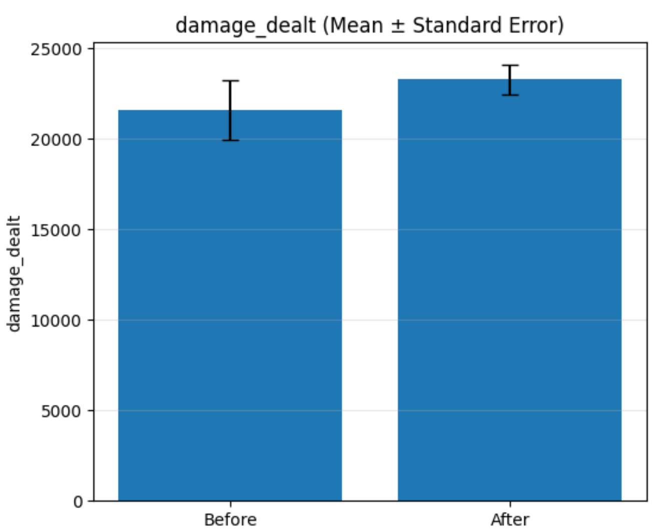

Fig. 10. Average total damage dealt before and after the project intervention. Error bars represent standard deviation.

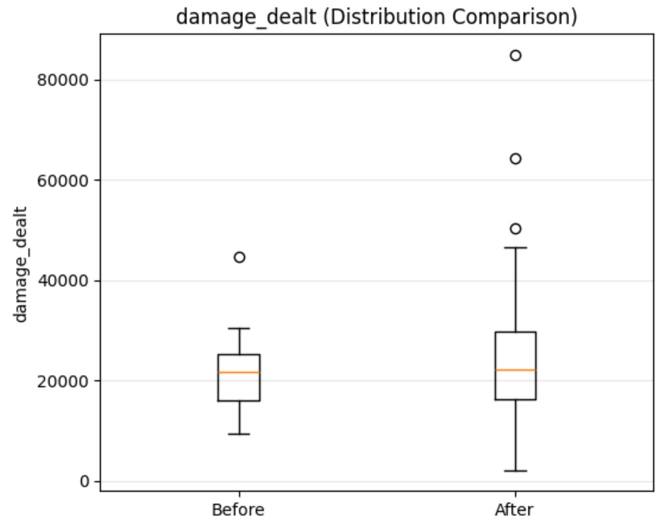

Fig. 11. Boxplot comparison of damage dealt between periods.

Figures 10 and 11 show an increase in average damage dealt during the post-research period, indicating greater engagement in combat and objective-related encounters. The large standard deviation suggests that damage output varied significantly across matches, influenced by champion selection and team composition. Damage dealt exhibits a higher median and slightly expanded upper quartile range in the post-research period, suggesting improved combat contribution in high-impact matches.

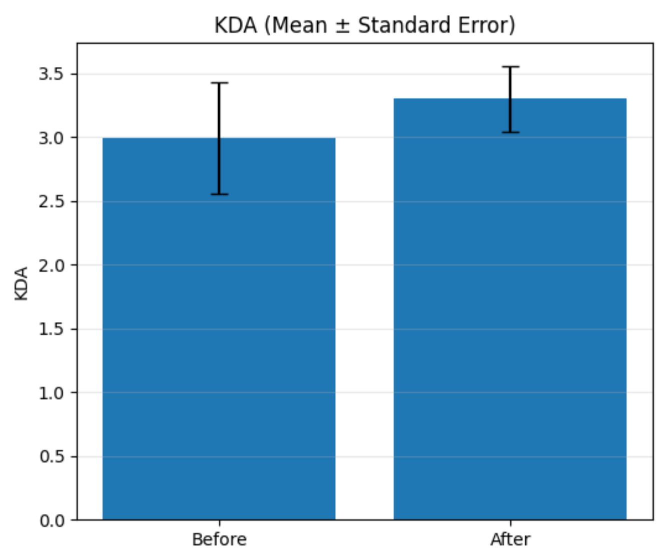

Fig. 12. Average KDA before and after the project intervention. Error bars represent standard deviation.

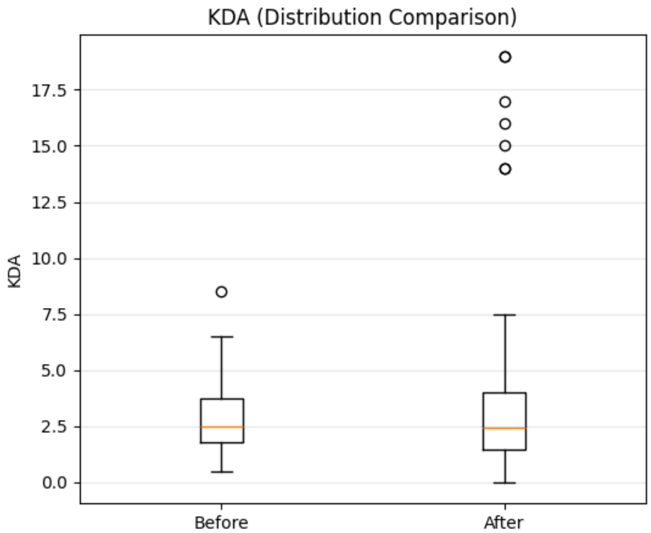

Fig. 13. Boxplot comparison of KDA between periods.

Figures 12 and 13 compare average KDA values between periods. A modest increase in mean KDA is observed post-research, indicating slightly improved combat effectiveness. However, high variability suggests that performance remained strongly dependent on match-specific factors such as team coordination. The boxplot shows a modest upward shift in median KDA during the post-research period. However, considerable overlap in interquartile ranges indicates that improvements were not uniformly sustained across matches.

B. Correlation Analysis with Match Outcomes

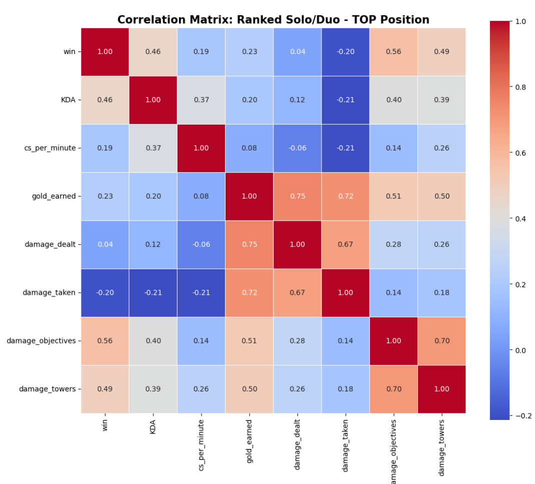

Fig. 14. Correlation heatmap illustrating relationships between performance metrics and match outcomes.

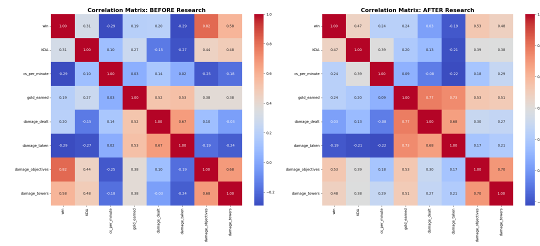

Fig. 15. Correlation heatmap illustrating relationships between performance metrics and match outcomes.

Correlation analysis examined the evolving relationships between individual performance metrics and match outcomes for the Top position. Figure 14 and Figure 15 show that while the ”Before” period relied heavily on objective damage to secure victories, the ”After” research period reflects a shift where economy-related metrics, particularly CS per minute and gold earned, began to exhibit much stronger and more positive correlations with winning outcomes. Damage-related metrics demonstrate a moderate but shifted influence, as the player transitioned from a narrow focus on structure damage to a more balanced contribution across all performance indicators.

The correlation structure underwent a significant recalibration over the research period, indicating that the relative importance of key performance indicators matured as playstyle evolved. The heatmaps reveal that economy-related metrics, which previously showed a negative or weak relationship with success (shifting from -0.29 to 0.24 for CS per minute), transitioned to exhibiting strong positive correlations with match victories, supporting the importance of sustained resource acquisition and lane pressure in determining match success for the top-lane role.

Damage-related metrics show moderate positive correlations in the baseline analysis, though their direct link to winning outcomes became more nuanced in the ”After” data as the player grew less dependent on raw objective damage alone. In contrast, KDA exhibits a strengthening and more stable correlation with win outcomes, rising from 0.31 to 0.47, suggesting that while kill participation and survivability are significant, they are most effective when integrated with the improved economic and objective-based playstyles observed in the latter half of the research.

C. Champion-Specific Performance Changes

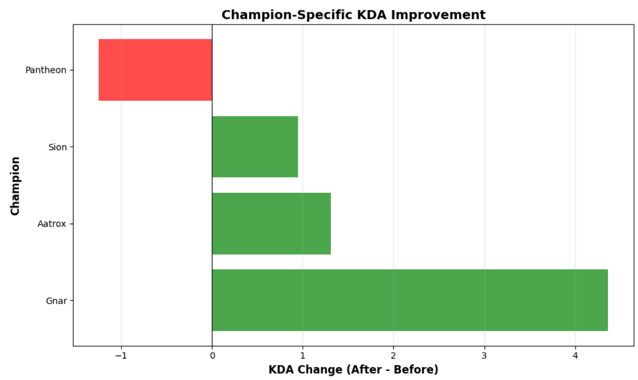

Fig. 16. Champion-specific KDA improvement between periods.

Figure 16 shows analysis of the four most frequently played champions, indicating that KDA improvement was not uniform across champion selections. Certain champions demonstrated substantial increases in average KDA, while others showed minimal change. This suggests that observed improvement may be partially champion-dependent rather than universally applied across all matchups.

D. Hypothesis Testing

TABLE II
HYPOTHESIS TESTING RESULTS (ONE-TAILED INDEPENDENT T-TEST, $\alpha = 0.05$)

Metric	Mean Before	Mean After	t-Statistic	p-Value	Decision
Win Rate	0.409091	0.496933	0.768816	0.224345	Fail to Reject H_0
CS per Minute	5.846818	6.075399	1.209553	0.118002	Fail to Reject H_0
KDA	2.992273	3.303313	0.613781	0.271529	Fail to Reject H_0
Gold Earned	11844.363636	11441.889571	-0.910178	0.815930	Fail to Reject H_0
Damage Dealt	21608.318182	23286.907975	0.917459	0.182740	Fail to Reject H_0
CS	182.772727	185.288344	0.345023	0.366108	Fail to Reject H_0
Damage Taken	35104.727273	33528.595092	-0.656015	0.741811	Fail to Reject H_0

Table II presents hypothesis testing results. None of the tested metrics showed statistically significant improvement at the $\alpha = 0.05$ level, leading to failure to reject the null hypothesis for all performance indicators.

VI. DISCUSSION

A. The Resource Paradox

A notable finding is the decrease in total *Gold Earned* (-402) despite an increase in *CS per Minute* (+0.23). This apparent inconsistency is explained by match duration; the player became more efficient at resource extraction, likely leading to more decisive early-game advantages and shorter average match lengths. This transition from ”chaos-driven” to ”resource-driven” victories is corroborated by the shift in the CS-to-Win correlation, which moved from a negative relationship ($r = -0.29$) to a positive one ($r = 0.24$).

B. Combat and Survivability

The simultaneous increase in KDA and decrease in *Damage Taken* suggests an evolution in positioning. In the top-lane role, the data indicates a shift away from high-risk trading toward high-impact combat participation. The narrowing of the KDA distribution suggests increased consistency and a reduction in ”feast-or-famine” gameplay.

C. Statistical Power and Limitations

The primary limitation was the sample size disparity ($n = 22$ vs $n = 163$). The high variance in team-based MOBAs makes it difficult to achieve statistical significance with a baseline of only 22 matches. This likely resulted in Type II errors, where the practical improvement of +8.8% in win rate was not flagged as statistically significant.

D. Limitations

Several limitations must be acknowledged. This study focuses on a single player, limiting the generalizability of findings to broader player populations. Additionally, the analysis does not explicitly control for confounding variables such as opponent rank, champion matchups, or patch changes, all of which may influence performance metrics.

Sample size constraints further limit the statistical power of hypothesis tests, increasing the likelihood of Type II errors. Finally, reliance on high-level match statistics may overlook lower-level behavioral factors, such as mechanical input efficiency or map awareness, that also contribute to competitive success.

E. Methodological Reflections

From a methodological perspective, this study demonstrates the feasibility of applying data science techniques to personal esports analytics. The combination of standardized data collection, longitudinal comparison, and multiple analytical approaches provides a robust framework for self-evaluation. However, future analyses may benefit from incorporating effect size measurements, time-series modeling, or mixed-effects models to better account for variance and contextual factors.

VII. CONCLUSION

This study demonstrates that data-driven self-analysis can reveal subtle maturation in playstyle that win-loss records alone might miss. Future work should utilize normalized metrics like Gold per Minute to account for varying match durations.

A. Future Work

Future work may extend this analysis by incorporating larger datasets, additional players, or longer time horizons to improve statistical power and generalizability. Advanced methods such as time-series analysis, mixed-effects modeling, or effect size estimation may also provide deeper insight into performance trends. Additionally, integrating contextual features such as champion matchups, opponent rank, and patch versions could further refine performance evaluation. Overall, this study demonstrates the viability of data-driven self-analysis as a tool for evidence-based competitive improvement in esports.

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