

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), a widely played multiplayer online battle arena (MOBA) game developed by Riot Games, provides a rich environment for quantitative analysis due to the availability of detailed match-level statistics through public application programming interfaces (APIs) [3].

While many studies focus on population-level trends or predictive modeling across thousands of players, fewer works examine longitudinal performance improvement at the individual level. For competitive players seeking self-improvement, understanding whether performance has objectively improved over time—and which metrics drive that improvement—is critical. Subjective impressions of progress may be misleading without statistical validation.

This study conducts a longitudinal analysis of a single player's top-lane performance across two consecutive time periods. By applying statistical hypothesis testing, correlation analysis, and regression-based modeling to consistently collected ranked match data, the study evaluates whether performance improvements are statistically significant and identifies the metrics most closely associated with winning matches.

II. OBJECTIVES

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.

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 – September 15, 2025 ($n = 22$; ≈ 3 months)
- Post-Research Period:** September 16, 2025 – January 31, 2026 ($n = 163$; ≈ 3 months)

Note that the two periods differ in duration (≈ 3 months vs. ≈ 4.5 months). This imbalance is the primary driver of the large sample size disparity ($n = 22$ vs. $n = 163$) and must be considered when interpreting comparative results.

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.

2) *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.

a) *Temporal and Match Metadata:* *Game Mode* is a qualitative categorical variable indicating the match type. *Game Start Timestamp* is a quantitative representation of match start time in Unix milliseconds. *Game Start / End Date* are qualitative calendar dates used for temporal grouping. *Game Duration* is a continuous variable representing match length in minutes.

b) *Player Role and Performance Metrics:* *Champion* identifies the character selected. *Position* denotes the in-game lane. *Kills*, *Deaths*, and *Assists* are core combat counts. *KDA* is computed as:

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

Win is a binary variable indicating match outcome.

c) *Resource and Efficiency Metrics:* *Gold Earned* is total in-game currency accumulated. *CS* counts minions and neutral monsters eliminated. *CS per Minute* measures farming efficiency normalized to game length. *Damage per Minute* captures average damage output.

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.

C. Data Cleaning

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

D. 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.

E. 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].

F. 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:

Null Hypothesis (H_0): There is no statistically significant difference in the mean value of the metric between the two periods.

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

A one-tailed test was applied when directional improvement was theoretically expected, at significance level $\alpha = 0.05$.

V. RESULTS

This section presents findings from descriptive statistics, correlation analysis, and hypothesis testing, comparing performance metrics between the pre-research and post-research periods.

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 a reduction in damage taken. Although improvements are observable at the descriptive level, variability across matches remains substantial.

The distribution of CS per Minute shifted rightward and became narrower in the post-research period, indicating both higher average farming efficiency and greater consistency across matches.

The KDA distribution moved away from lower values toward a more stable mid-range, suggesting better risk assessment and fewer unnecessary deaths. The Damage Dealt histogram similarly shifted right, reflecting more decisive trading and greater combat participation.

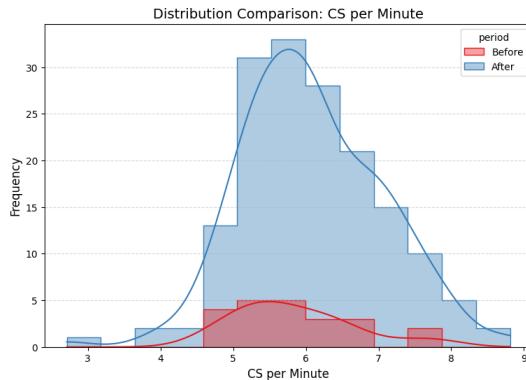


Fig. 1. Distribution of creep score per minute before and after the project intervention. The overlapping areas indicate the shift in farming consistency.

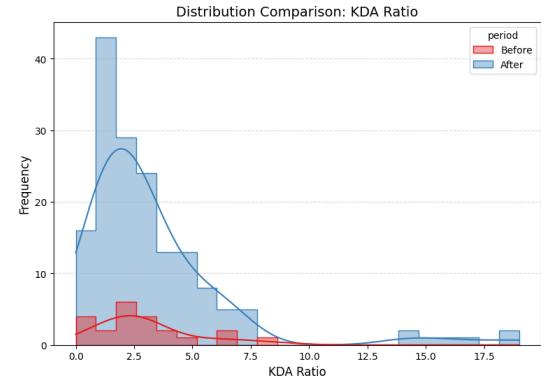


Fig. 2. Distribution of KDA ratios before and after the project intervention.

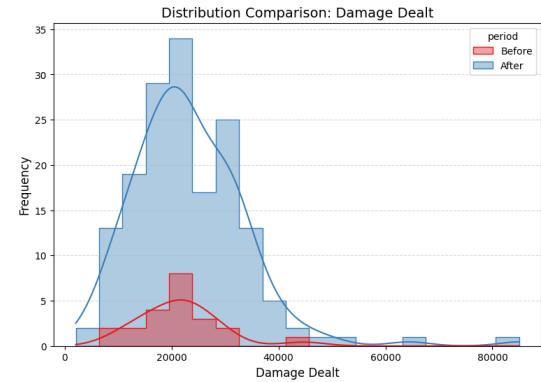


Fig. 3. Distribution of damage dealt to champions before and after the project intervention.

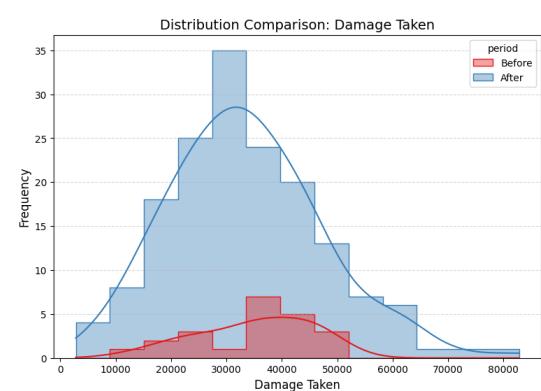


Fig. 4. Distribution of damage taken before and after the project intervention.

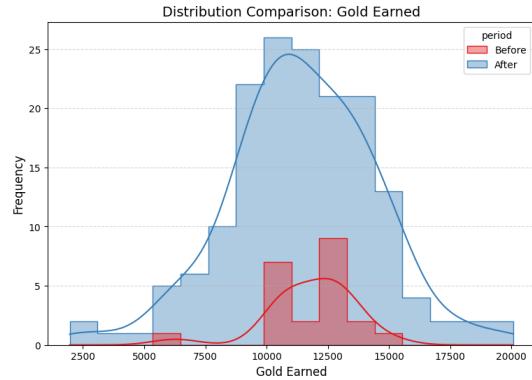


Fig. 5. Distribution of total gold earned per match before and after the project intervention.

Gold Earned decreased slightly in the post-research period (-402 gold on average), consistent with the data in Table ???. Despite higher CS per Minute, total gold was lower on average—most likely because more decisive early-game advantages led to shorter match durations, reducing the total time available to accumulate gold from all sources. This is consistent with a shift from longer attrition-based games to shorter, resource-driven victories.

CS per Minute 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 across all matches.

A modest increase in mean KDA is observed post-research, indicating slightly improved combat effectiveness. However, high variability suggests performance remained strongly dependent on match-specific factors such as team coordination.

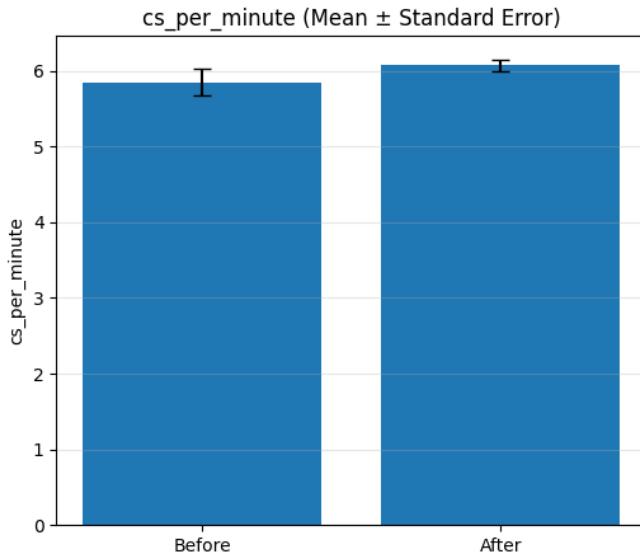


Fig. 6. Average Cs per min per match before and after the project intervention. Error bars represent standard deviation.

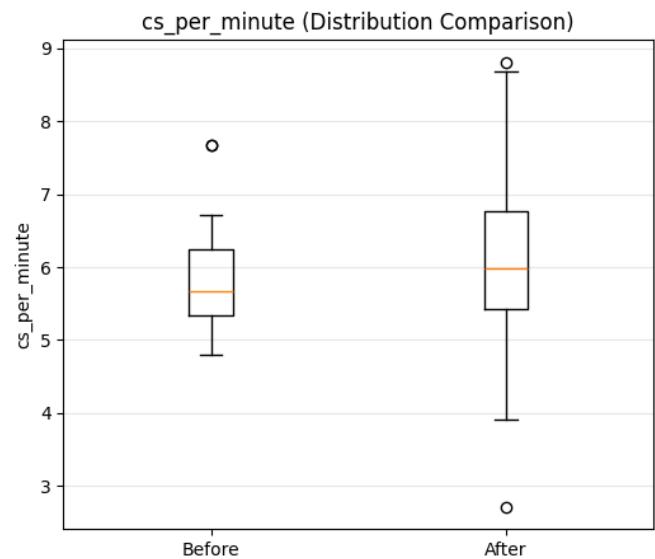


Fig. 7. Boxplot comparison of CS per minute between periods.

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.

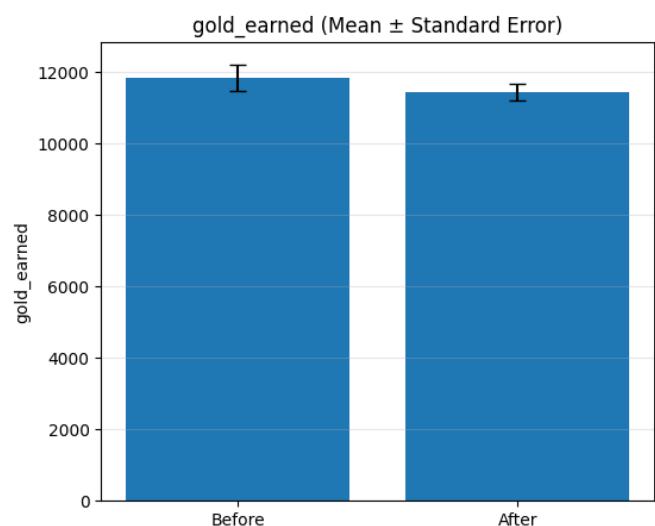


Fig. 8. Average gold earned per match before and after the project intervention. Error bars represent standard deviation.

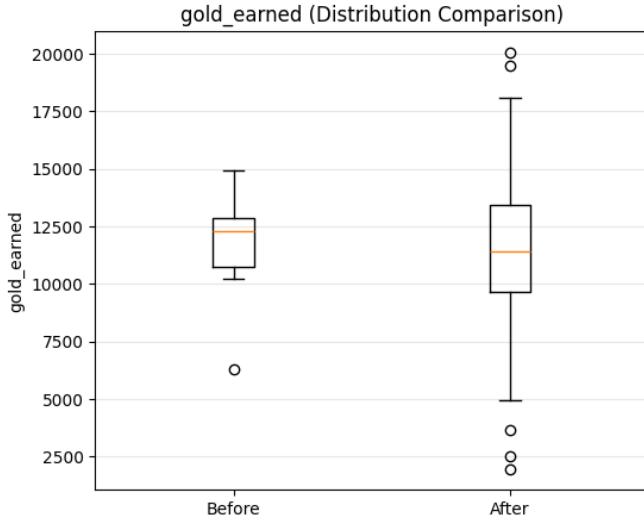


Fig. 9. Boxplot comparison of gold earned between periods.

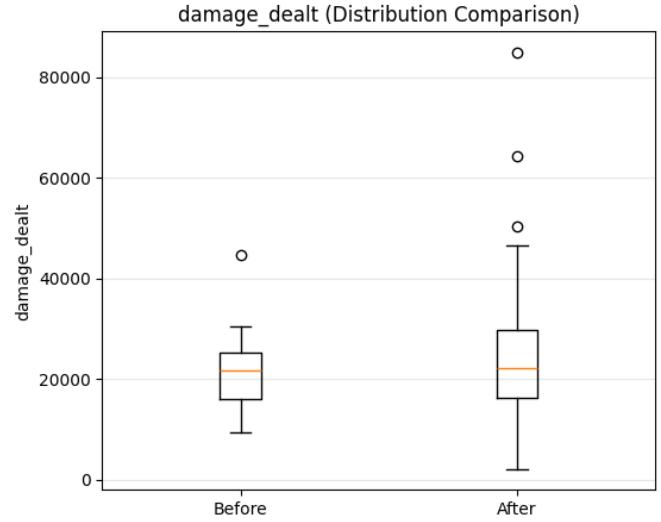


Fig. 11. Boxplot comparison of damage dealt between periods.

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.

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.

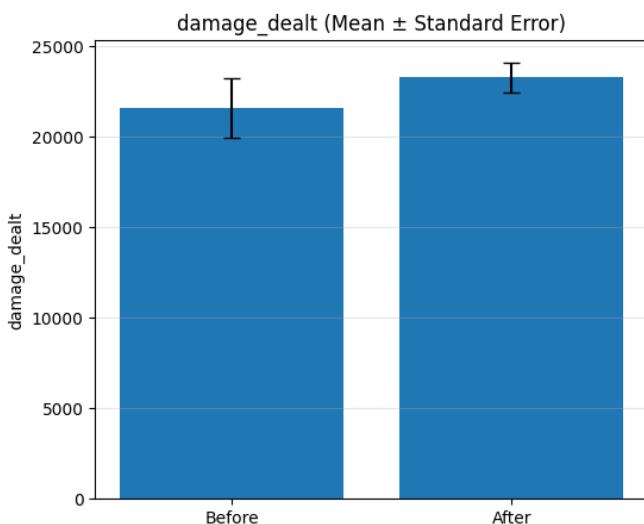


Fig. 10. Average total damage dealt before and after the project intervention. Error bars represent standard deviation.

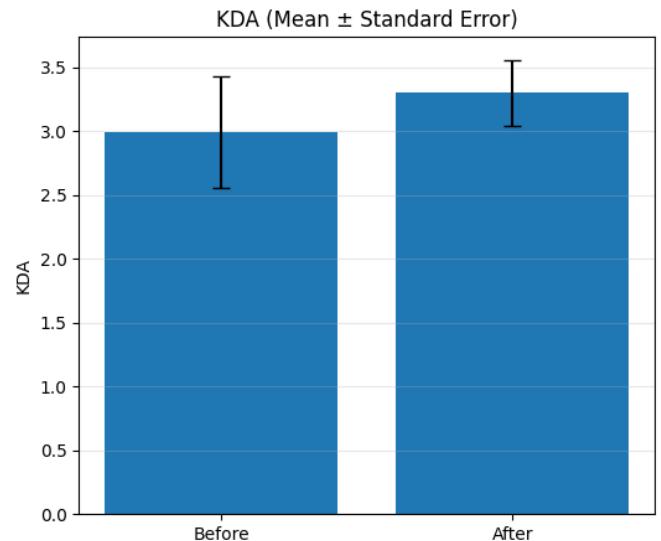


Fig. 12. Average KDA before and after the project intervention. Error bars represent standard deviation.

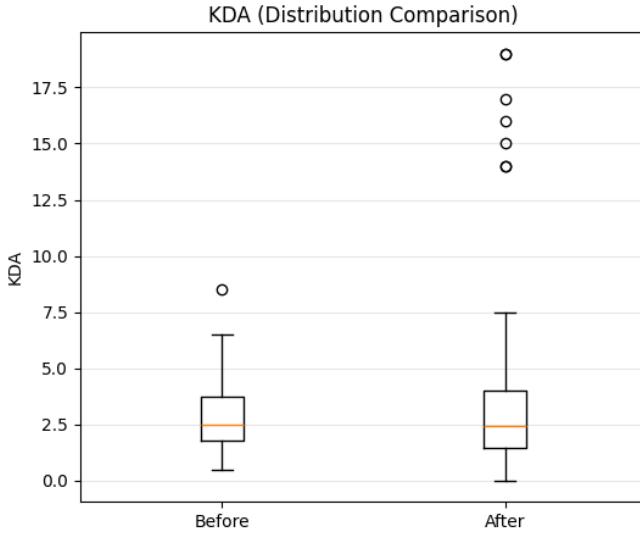


Fig. 13. Boxplot comparison of KDA between periods.

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

Correlation analysis examined the evolving relationships between individual performance metrics and match outcomes. While the pre-research period relied heavily on objective damage to secure victories, the post-research period reflects a shift where economy-related metrics—particularly CS per minute and gold earned—began to exhibit much stronger positive correlations with winning.

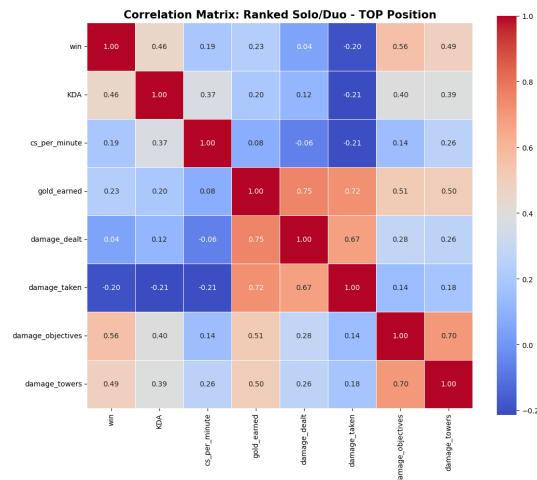


Fig. 14. Correlation heatmap illustrating relationships between performance metrics and match outcomes.

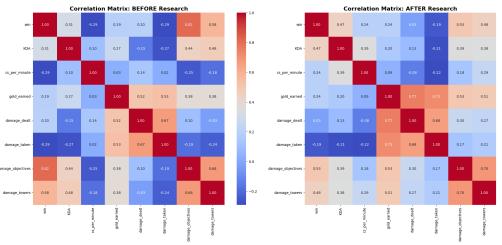


Fig. 15. Correlation heatmap illustrating relationships between performance metrics and match outcomes.

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

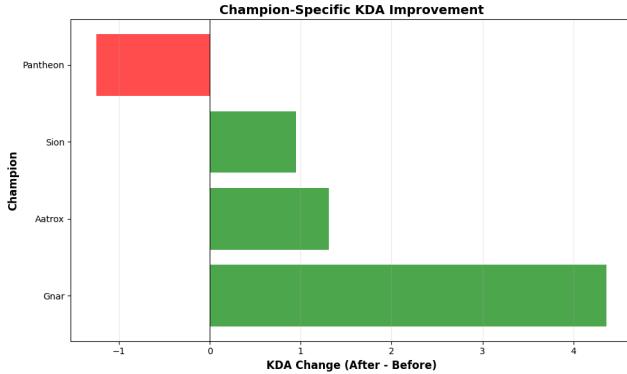


Fig. 16. Champion-specific KDA improvement between periods.

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 Result

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	0.223435	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 is explained by match duration: the player's more efficient resource extraction likely produced more decisive early-game advantages, resulting in shorter average match lengths and therefore less total time to accumulate gold. This transition from "chaos-driven" to "resource-driven" victories is corroborated by the shift in the CS-to-Win correlation from $r = -0.29$ to $r = +0.24$.

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. Win Rate as a Practical Outcome

Although the 8.8 percentage-point increase in win rate (40.9% to 49.7%) was not formally hypothesis-tested—because win rate is derived from a binary variable and requires a proportion-based test rather than a *t*-test—it represents a practically meaningful improvement. With only $n = 22$ matches in the pre-research period, any win-rate comparison carries high sampling variance and should be interpreted cautiously until replicated with a larger and temporally balanced baseline sample.

D. Statistical Power and Limitations

The primary limitation was the substantial sample size disparity ($n = 22$ vs. $n = 163$), which stems directly from the unequal observation windows: the pre-research period spanned approximately 3 months while the post-research period spanned approximately 4.5 months. The high variance inherent in team-based MOBAs compounds this problem, making it difficult to achieve statistical significance from a baseline of only 22 matches. This likely resulted in Type II errors (false negatives), where the practical improvement of +8.8 percentage points in win rate was not flagged as statistically significant.

Several limitations must be acknowledged. This study focuses on a single player, limiting generalizability. The analysis does not explicitly control for confounding variables such as opponent rank, champion matchups, or patch changes. Sample size constraints further reduce statistical power. 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

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. 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 applied data science techniques to evaluate longitudinal competitive performance in a top-lane League of Legends player by comparing gameplay metrics across two time periods of differing duration. Using match data retrieved

from the Riot Games API, the analysis examined economy-, combat-, and outcome-related metrics through descriptive statistics, correlation analysis, and hypothesis testing.

Descriptive trends suggest modest improvements in lan-

ing efficiency and combat contribution; however, inferential statistical tests did not detect statistically significant mean differences between periods. These findings highlight the challenges of measuring performance growth in high-variance, team-based competitive environments.

A. Future Work

Future work may extend this analysis with larger datasets, additional players, or longer time horizons to improve statistical power and generalizability. Crucially, future study designs should ensure comparison periods are of equal duration to enable valid statistical comparison. Advanced methods such as time-series analysis, mixed-effects modeling, or effect size estimation may provide deeper insight into performance trends. 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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