Role Synergy and Win Rate Determinants in League of Legends: A Mixed-Method Analysis

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ABSTRACT

This study investigates the factors influencing win rates in League of Legends, focusing on player skill, champion synergy, and role-specific dynamics. The combination of telemetry data and qualitative survey responses examines how bottom lane ADC (Attack Damage Carry)-Support pairings contribute to match outcomes. Qualitative analysis reveals that player skill significantly outweighs champion strength in determining win rates, while synergy within the bottom lane roles enhances team performance. However, chi-squared tests indicate no significant association between specific ADC-Support pairings and win rates, suggesting the impact of broader contextual factors, such as team strategy.

Limitations of this study include the dataset size, ethical constraints on participant recruitment, and the absence of real-time communication metrics. Future work should analyse larger datasets, incorporate professional-level matches, and explore the influence of game patches and meta-shifts over time. This research offers insights into the interplay between player behaviour, champion dynamics, and team synergy, contributing to role-based strategy optimisation in competitive games.

KEYWORDS

League of Legends, Player Skill, Champion Synergy, Telemetry Analysis, Win Rate

1 Introduction and Background

League of Legends is one of the most popular Multiplayer Online Battle Arena (MOBA) games, with millions of players worldwide. The game's dynamic revolves around strategic champion selection and team coordination across five unique roles. Understanding the factors influencing win rates is vital for game balance, ensuring competitive fairness. Prior research explored win rate determinants in League of Legends, suggesting disparities in these factors exist based on the game's state, with Junglers and Mid-Laners being more impactful in the early game, while ADCs and Supports play a greater role in the late game (as seen in work by Samford University [1]) However gaps remain unexplored in understanding synergy on a deeper level with specific role pairings and the relationship that player behaviour has with win rates. This study explores the unexplored dynamics of role synergy and player skill in win rates, providing a granular analysis of their influence. Through telemetry analysis and a user study, the findings offer insights for improving game balance, enhancing player experience, and informing future MOBA game design.

This paper is structured as follows:

- Section 2 underlines the methodology and findings of the telemetry analysis, encompassing findings on win rates and role synergy.
- Section 3 presents the UX user study, detailing the methodology, procedure and qualitative results on player skill.
- Section 4 discusses the implications of the findings, stating research limitations, and areas for future work.

2 Telemetry Analysis

This study investigates several research questions to guide the telemetry analysis. First, it delves into the relationship between champion pick and win rates, aiming to understand whether popular champions are more likely to achieve higher performance. Secondly, this study examines how lane distributions impact win rates, specifically focusing on the most frequent roles of the top 10 most popular champions. After gaining insights into role-specific influence on win rate, identifying how key gameplay metrics, such as gold earned or damage dealt, influence win rates would tackle how in-game performances correlate with winning outcomes. Lastly, this study explores the impact of role synergy on team performance and win rates, investigating how specific role combinations of champions influence overall team success. This aims to unravel the importance of inter-role dynamics in creating optimal team compositions and how they contribute to strategic victories.

2.1 Methodology

The League of Legends match data was explored using the Pandas library in Python, a versatile tool for data manipulation and analysis. This methodology focused on extracting key player performance metrics to establish a solid foundation for analysis.

The process began by isolating individual player data from the broader dataset to aggregate the data. Subsequently, the top 10 champions, ranked by pick rate, were identified based on player counts This foundation facilitated the creation of visualisations that illustrated the distribution and popularity of the top 10 champions, providing valuable insights into player preferences and trends whilst serving as a foundation for deeper telemetry analysis.

To analyse player performance, gameplay metric averages were aggregated, including player kills, player damage, gold earned, crowd control, and win rate. Correlation coefficients were calculated and aimed to examine the relationships between these average performance metrics. This analysis specifically focused on the most common role within the top 10 champions, providing insights into the typical performance patterns of these champions and the influence of these relationships with pick rates.

Multivariate regression was employed to analyse the relationship between average player metrics and win rates, further exploring how these metrics correlate to pick rate and other influencing factors. To assess the significance of these factors, T-tests were applied to the average gameplay statistics. This approach was vital for identifying metrics that significantly contribute to win rate trends, accounting for the diverse characteristics of League of Legends champions and the dynamic nature of MOBA gameplay.

A visual aid of role synergy was generated to better understand how interactions between roles contribute to optimal team compositions, highlighting the most effective role pairings. This visualisation provided actionable insights for understanding champion synergies in the bottom lane and their contributions to overall team success. These methods employed a comprehensive telemetry analysis framework, enabling a nuanced investigation of how popular roles influence team performance, with a focus on role synergy and champion interplay. The findings offer valuable insights for players optimising team compositions and strategies and for developers seeking to balance champions effectively.

2.2 Findings

Understanding the player counts and win rates associated with the top 10 champions was vital in identifying outliers between roles in League of Legends.

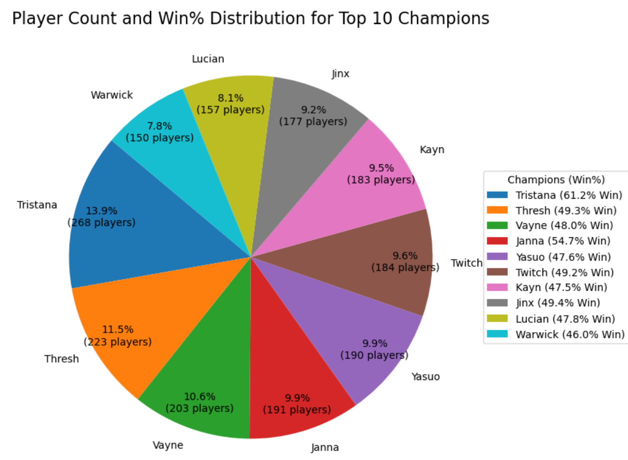

Figure 1: Player Count and Win Rate Distribution Among the Top 10 Champions in League of Legends

Amongst the top 10, there is a relatively balanced player count, with a few noticeable discrepancies, as seen in Figure 1. Tristana emerged as the most popular champion, accounting for 13.9% of the total sample with a significantly high win rate of 61.2%, indicating the champion's frequent selection and strong performance in-game. Champions like Vayne and Yasuo displayed mediocre win rates relative to their popularity, which could highlight the dependence on player skill in maximising the champions' usage.

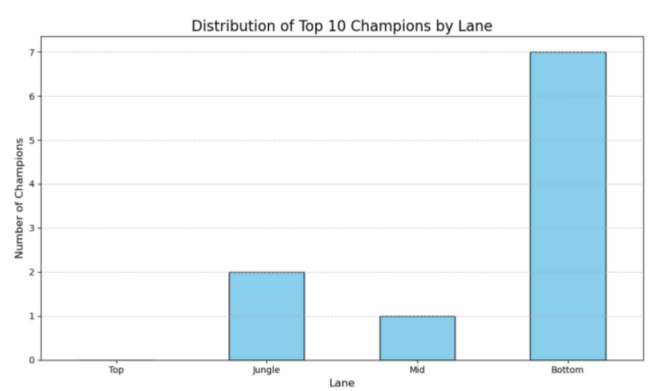

Figure 2: Lane Distribution of the Top 10 Most Popular Champions in League of Legends

The dominance of champions that are preferably played in the bottom lane is evident, with 7 out of the top 10, while the middle and top lanes are drastically underrepresented. As seen in Figure 2, the inconsistencies in this distribution could be attributed to the importance of the bottom lane for objective control, possessing the ability to influence gameplay dynamics and team outcomes. This observation highlights the interconnectivity between champion selection, popularity and performance, detailing a broader and more nuanced view of champion dynamics in League of Legends. Both Figure 1 and 2 serves as a foundation to investigate gameplay-specific metrics and contextual factors that may be at play influencing these outcomes.

2.2.1 Win Rate

This graph below focuses on the success rate of the bottom lane champions in conjunction with all the champions, visually highlighting the correlation between pick rate and win rate.

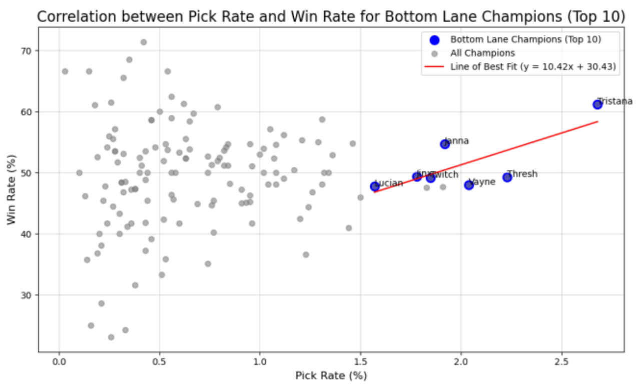

Figure 3: Correlation between Pick Rate % and Win Rate % (Bottom Lane Champions and All Champions)

Win rates for the bottom lane champions vary but remain above average (between 40-60%), emphasising their effectiveness. This variation implies that the bottom lane champions in the top 10 are consistent performers in contrast to all the champions in League of Legends, as seen in Figure 3. A Pearson's correlation coefficient was computed to assess the relationship between Pick Rate and Win Rate, which revealed a strong positive correlation coefficient (r=0.765) for the bottom lane champions, with a correlation that is statistically significant (p=0.044). Contrastingly, all champions showed a very weak positive correlation (r= 0.0903), which wasn't statistically significant (p=0.292) suggesting that the relationship is likely due to random chance, with no strong evidence of a meaningful relationship. This contrast further validates the bottom lane champions as pivotal choices in the game. These findings in conjunction with the earlier figures offer insights on how player preference doesn't always equate to success, with favoured champions like Jinx and Lucian exhibiting lower win rates. Players may pick popular champions because they are "meta", fun to play, or perceived as strong, but their win rate may suffer from the high skill ceilings of those champions and individual player skill. Player performance in roles in the bottom lane like ADC and Support heavily relies on team coordination to maximise effectiveness. Highlighting the importance of team synergy is key in determining factors that shape win rate.

2.2.2 Multivariate Regression

Multiple linear regression was used to investigate if key performance metrics, like average kills, average damage, crowd control, and average gold earned significantly predicted win rates for the bottom lane champions of the top 10. The correlation coefficients indicate the magnitude and direction of each metric's impact on win rates, whilst the p-values determine the statistical significance of these relationships.

	Coefficient	Standard Error	T-Value	P-Value
const	-1.36287	176.139	-0.00773746	0.994529
Average Kills	0.763162	22.5086	0.0339053	0.976032
Average Damage	-0.00167703	0.00766423	-0.218812	0.847096
Crowd Control	0.00332613	0.830682	0.00400409	0.997169
Average Gold	0.00658644	0.0148305	0.444114	0.70039

Table 1: Multivariate Regression Analysis Summary: Evaluating the Influence of Performance Metrics on Win Rates

The most significant variable that has an impact on winning was the Average Kills, with the highest coefficient (r=0.763), suggesting a moderate positive correlation with win rate, however, the high p-value (p=0.976) indicates that the result is not statistically significant, as seen in Table 1. Other determining metrics such as Average Damage, Crowd Control, and Average Gold Earned depict low coefficients and high p-values, suggesting that these performance metrics also offer minimal impact on win rates. The fitted regression model indicates that Average Kills, Average Damage, Crowd Control, and Average Gold collectively explain 36.9% (r^2=0.369) of the variation in Win Rate, however, the overall regression was not statistically significant (p=0.864 + r^2=0.369)

The model suggests that none of the analysed metrics significantly predict win rates for bottom lane champions, highlighting the complexity of win rate determinants in League of Legends. This model reinforces the interplay of other factors, such as role synergy, where player coordination and strategy in bottom lane pairings play a crucial role in shaping outcomes. Exploring champion pairings can provide deeper insights into these strategic factors and their impacts.

2.2.3 Role Synergy

Due to the importance of the champions occupying the bottom lane, this exploration in role synergy focuses on the ADC and Support. These two roles are highly interdependent, with the ADC responsible for dealing damage in the late game, while the Support provides utility and crowd control to protect and empower the ADC.

The figure below is a visualisation of the top 10 ADC-Support champion pairings. Rows represent ADC champions; columns represent Support champions and cell values indicate the win rate for the pairing.

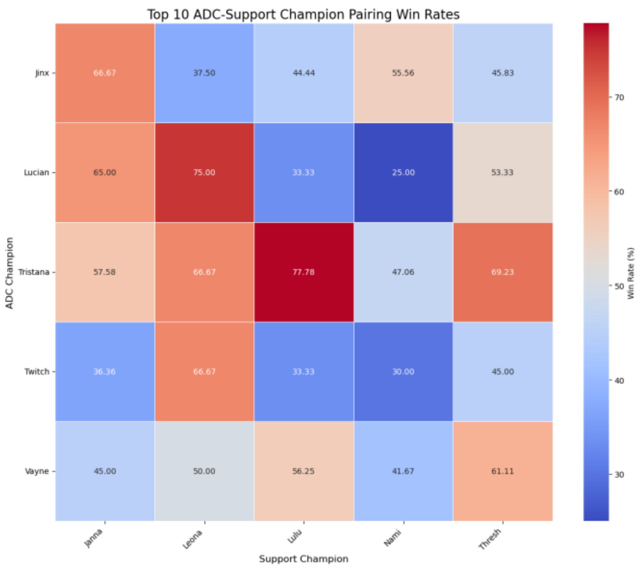

Figure 5: Heatmap showing Win Rates (%) of the top 10 ADC-Support Champion Pairings in League of Legends.

Significant synergy disparities exist, with certain combinations, like Tristana paired with Lulu or Thresh, and Lucian paired with Leona, noticeably achieving high win rates above 75%, as seen in Figure 5. Conversely, other pairings, like Twitch and Nami or Lucian with Nami, exhibit significantly lower win rates. This highlights the critical role of champion synergy in influencing match outcomes, emphasising how effective pairing choices can directly impact performance. To further validate these patterns, a chi-squared test of independence was conducted, showing there was no significant association between the ADC and Support roles and their win rates (p=1.000), resulting in a rejection of the null hypothesis, stating that ADC-Support pairings are independent of win rates.

These findings suggest that the differences in win rates observed in the heatmap could be attributed to random variation rather than meaningful champion synergy. Win rate disparities between parings may be influenced by external factors like player skill and strategy, rather than inherent champion synergy through their design. However, these insights could be limited by potential confounding variables such as the sample size and the lack of data regarding meta-shifts and the match data's patch version, although it still provides insights into the importance of player skill.

3 UX User Study

A qualitative user study was conducted with the intent of exploring player perspectives and behavioural factors of win rate, understanding the role of player skill in determining champion win rates and its interactions with other factors. This study investigates the following questions:

1. How does player skill influence a champion's win rate compared to the inherent strength of the champion?

2. How does the level of competitive play shape the impact that player skill has on win rates?

3. What are the perceptions of experienced players regarding the relationship between player skill and champion performance?

3.1 Methodology

3.1.1 Methods

An online survey was chosen for this user study due to its accessibility and convenience, allowing participants from diverse demographics to provide thoughtful, reflective insights. The survey featured open-ended questions, focusing on extraneous factors that may affect win rates, including player skill, a champion's strength and player perceptions of specific roles. For example, participants were asked whether player skill or a champion's inherent strength contributes more to win rates and why. Open-ended questions were better suited for this study as participants were able to express their thoughts freely without any constraints, which is particularly effective for exploring nuanced topics, like player skill and perception.

3.1.2 Participants

Participant selection followed Bruhlmann's [2] survey design approach, identifying the population as students who play League of Legends, and the sample as frequent players with a strong understanding of the game. Participants were recruited through a community Discord server and were constrained to final year BSc. Games Design students at Bournemouth University. A total of 6 participants were recruited, who consisted of experienced players that were predominantly male. The sample size allowed for a manageable data collection and analysis, whilst still providing enough insights by employing open-ended questions. Although rich insights were provided, the sample lacked demographic diversity, which may not fully represent the League of Legends player base.

3.1.3 Procedure

The survey was designed using Google Forms and included open-ended questions to encourage detailed responses. Pilot testing was conducted with 2 participants to help improve question clarity and the survey's flow. An invitation link was shared to students who actively play League of Legends after reviewing each participants answers about their gameplay experiences. This process was crucial in selecting experienced players, Due to the ethical restrictions on participants numbers. The survey was distributed online, and participants were free to complete it at their convenience. The survey completion process was straightforward, encouraging participants to read brief introductions on various topics and answer the following questions. Responses were exported from Google Forms for qualitative coding and analysis.

3.1.4 Analysis

Quantitative analysis initially began by eyeballing the data, to get a sense of emerging ideas and trends within the responses. Inductive coding was the method of choice as it allowed for a flexible discovery of unexpected insights, without the risk of forcing the data into predefined categories. This was ideal as it would acknowledge factors that may have been overlooked regarding determinants for win rates. Responses were broken down into short descriptive codes based on key points by coding them line by line. For responses focused on player skill, similar codes were grouped into themes, allowing for meaningful conclusions to be drawn.

Theme	Code	Definition
Player Skill as Main Factor	Player skill over champion strength	Player skill is the most important factor in determining win rate, regardless of champion strength.
	Skill compensates for champion difficulty	Even complex or strong champions can underperform if player skill is insufficient
	Skill is key	A skilled player can succeed with any champion.
Champion Strength as Contextual	Champion skillset impacts win rate	Champions with high skill ceilings appear weaker due to the challenge in mastering them.
	Overpowered champions are exceptions	Exceptionally strong champions can significantly influence win rates.
	Outdated champions struggle	Champions perceived with outdated designs are more vulnerable to counterplay, affecting win rates
Variability in Skill Context	Casual vs competitive differences	Champion skill becomes more relevant at competitive levels
	Skill variability in casual play	In less competitive modes, differences in player skill lead to greater variability in win rates.

Table 2: Theme Identification for Responses on Player Skill in Codebook Format

3.2 Findings

A significant portion of respondents believed that player skill was the most important factor in determining a champion's win rate, noticeably arguing that skilled players can carry any champion to victory, regardless of the champion's inherent skillset and strength. However, it is important to regard champion strength as a determinant, with respondents mentioning that some champions are powerful but difficult to master (e.g. Yasuo), resulting in low win rates for less skilled players. The interconnectivity of both player skill and champion strength determines win rates, with player skill determining the effectiveness of a champion's potential. The level of competitive play further dictates a champion's impact, as seen in Table 2.

4 Conclusions and Future Work

This study investigated the impact of role synergy and player behaviour on bottom lane win rates in League of Legends. The findings revealed that individual gameplay metrics, such as KDA and pick rate, did not significantly predict win rates. Instead, qualitative insights emphasised that player skill plays a dominant role, with champion strength as contextual depending on player proficiency. These findings highlight the complexity of win rate determinants and the variability in interconnectivity at different levels of play.

Despite these rich insights, the study faced limitations. Telemetry data was collected during a single patch, limiting the ability to account for variability in meta-shifts over time. Telemetry data also focused on quantifiable metrics and lacked contextual insights such as team communication and champion matchups. While the user study provided valuable qualitative data, the sample size and demographic of the user study were limited due to ethical and time constraints, which may limit the degree of generalisation of the findings.

Future work could address these limitations and enhance this research by analysing larger and more professional match data, such as through the Riot API. Incorporating real-time metrics, such as team communication could provide contextual insights into win rates. Further analysis could examine the effects of game patches on win rates over time, accounting for the volatility in champion strength. Additionally, expanding the scope to other roles may also provide a more holistic insight into role-specific factors of success. Combining qualitative data with richer telemetry data would offer a more holistic understanding of the interplay between player behaviour, champion strength, and strategy in League of Legends

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