Team Momentum: The Criticality of Resources in League of Legends

David Li[1]

[1]Westwood High School

ABSTRACT

Objective: This research investigates the impact of the early game and team resources on overall team performance in League of Legends, a Multi-player Online Battle Arena gaming environment. **Background:** The early game is typically defined as the first 10-15 minutes of the game. I hypothesize that a resource-based view approach fails to capture a holistic analysis of team performance, especially in the early stages of formation. **Methods:** The data set used in this research consists of data from the first 10-15 minutes of professional gameplay. **Results:** Binary ANOVA and visual graphing techniques are used to explore the data to answer the proposed research questions. Gold difference over time is used as an independent variable in developed models. Results show that gold difference has a significant impact on but cannot always explain team performance. **Conclusions:** This study demonstrates how data on teamwork may be used to model the performance of teams. The results highlight that a pre-emptive resource-based view may fall short in explaining team success and performance. **Application:** This research shows the value of reassessing a resource-based view to account for resource allocation and its effects on team performance.

Introduction

This research paper studies the flow of the early game and its effects on overall team performance by examining momentum and team resources over certain intervals of time in the Multi-player Online Battle Arena gaming environment—League of Legends. The work will particularly focus on the ways in which team performance is directly correlated to team resources.

Utilizing data from League of Legends, this paper will model team performance by examining resource accumulation over time. Contrary to current research on team performance in field environments, this type of study provides valuable insight into team functions without a high dependency on significant resources.

Data collected from professional League of Legends games will be analyzed through statistical analysis using logistic regression and binary ANOVA modeling. Results and models will be presented visually by utilizing various graphs. Finally, I will discuss the significance of the results and present recommendations for further research.

Background

The rising popularity of virtual gaming environments has opened up new possibilities for examining data related to teams and teamwork in relatively low-risk field settings. Mass datasets are increasingly open for interpretation and have reached the point where objective studies on teamwork can now be performed.

In League of Legends, detailed data is collected in publicly accessible servers through the Riot API. In the version of League of Legends studied here, two five-member teams work together to defeat each other by destroying the other team's Nexus. Computer-controlled defenses called structures defend the Nexus from destruction. Teams attempt to get to the Nexus by destroying these structures and killing their opponents. Each player on the team is given a role in which they perform certain duties and tasks to help their team win the match.

Each match takes place on a map called "Summoner's Rift." During the game, players occupy these physical locations as shown in Figure 1. The two teams are referred to by color. The team whose base is located in the bottom left corner of Figure 1 is referred to as the "blue" team, while the team whose base is located in the top right of the corner is referred to as the "red" team.

Figure 1. *League of Legends game map*

Before the game begins, each player selects a "champion" to play. Each "champion" has unique characteristics and playstyles that can benefit the team. Players pick their "champion" based off their role in the game. Each player occupies exactly one role on the team. Important roles include the top lane (able to perform well in fights), the mid lane (exerts map control), the ADC (Attack Damage Carry, able to output consistent ranged damage), the jungler (supports each lane and explores the map), and the support (provides utility for the team).

A team is defined as a "set of two or more individuals who interact interdependently and adaptively toward a common goal or objective" (Cannon-Bowers & Salas, 1998). While different teams may have various objectives by nature, they all share fundamental rules that govern the ways in which they function.

Although there are many ways to measure a team's performance, this paper will focus on the relationship between team success and team resources through a resource-based view theory.

A resource-based view (RBV) is a management strategy used to explain the growth of firms and corporations. A RBV is based on a company's resources and assets as the source of the organization's competitive advantages (Barney, 1991; Nair & Bhattacharyya, 2019).

The literature debate on a RBV is well over 30 years old. Since then, a RBV has been critiqued, assessed, and changed in studies relating to management literature.

Overall, proponents of a RBV indicate that it is sophisticated and developed enough to explain success in increasingly competitive environments.

However, critiques of a RBV show the limitations that arise from implementing such a theory. Past studies indicate the incompleteness and lack of clarity within a RBV framework (Priem & Butler, 2001). Priem & Butler noted the following five issues with the current theory: (1) lack of a solid conceptual foundation, (2) flawed assumptions about product markets, (3) exogenous variables to the theory itself, (4) overly inclusive definitions of resources, and (5) static approaches resulting in ambiguity (Priem & Butler, 2001).

Further research and analysis by Kaufman identifies further flaws with a RBV when theorizing strategic resource management (Kaufman, 2015). Similar to Priem & Butler, Kaufman identifies weaknesses and areas that are perhaps underdeveloped in RBV (Kaufman, 2015). Such research suggests that, although a RBV is a useful theoretical model that can explain performance to some extent, it cannot fully explain a company's success.

We can also examine a RBV through the lens of team performance. A RBV approach to analyzing team performance would suggest that a team's resources play a critical role in a team's overall success. Current work on the intersection between these two topics mostly conclude results that support the prevalence of RBV in a team-based environment (Smart & Wolfe, 2003).

However, my working hypothesis is that a pre-emptive and careless resource-based view approach fails to capture a holistic analysis of team performance. Team resources can often change drastically over time, creating inconsistencies when examining team performance. I do not dismiss RBV as a whole, but rather, I argue that it is often overemphasized when used to analyze team performance. This paper explores the following research questions:

RQ1: What is the impact of momentum on a team's resources over time?

RQ2: What is the impact of a team's resources on the outcome of team performance?

Methods

In this study, team performance is measured as a function of the binary outcome of the game, win or loss. Team resources are assessed as a function of a team's gold accumulation during a match. Gold allows players to gain additional power for their champion, which makes it much easier for a team to achieve their end objective—destroying the enemy Nexus.

Throughout the game, players can accumulate gold from various sources around the map. A few of the main ways a player can accumulate gold is through killing another player from the enemy team, securing map objectives, killing jungle monsters (monsters that spawn in the jungle areas of the map), and killing enemy "creeps" (minions that spawn periodically throughout the game).

Study data was gathered from records of professional matches from 2015-2018. Data was pulled from the North American major professional league, NALCS throughout their spring and summer seasons. The only criteria that was applied was that all matches had to be at least 15 minutes in length. All matches met this requirement, producing the final dataset of 7,620 matches.

Gold difference is calculated by subtracting one team's total gold from the other team's total gold. In the study data, the "blue" team's total gold is subtracted from the "read" team's total gold. For analysis, total gold of each team and overall gold difference is tracked at every minute increment throughout the match.

Data is also segmented according to the proportion of gold difference at a given minute interval in the game. A *Low* gold difference represents a number in the lowest range of gold differences (spanning into the negatives, if applicable). *Medium* gold difference represents a number in the middle range of gold differences (spanning into the negatives, if applicable). And a *High* gold difference represents a number in the highest range of gold differences (spanning into the negatives, if applicable). The exact range varies from minute to minute in order to ensure an equal distribution of values. Approximately one-third of the total dataset is distributed into each category.

A binary-ANOVA analysis is implemented to analyze the statistical significance of gold difference on the final outcome of the game. Individual models are developed for each minute interval from a selected timeframe (10–15 minutes) for all matches. Using a Low, Medium, and High gold difference as an independent factor and win/loss as a binary dependent variable, a logistic-ANOVA model was developed for each minute on the 10–15-minute interval.

Results

During the 10–15-minute interval, the average chance for a team with a *Low* gold difference to win was approximately 32.7% (SD 0.112), a team with a *Medium* gold difference was 72.5% (SD 0.137) likely to win, and a team with *High* gold difference had a 58.1% (SD 0.176) chance of victory (values are independent of each other). Summary statistics are outlined in Table 1.

There is a significant effect of gold difference on the outcome of the match for all minute intervals. Tables 2-7 highlight the model structures of each of the binary-ANOVA models at a certain time interval. Figures 2 and 3 show the changes in probability of team success when looking at proportional levels of gold difference.

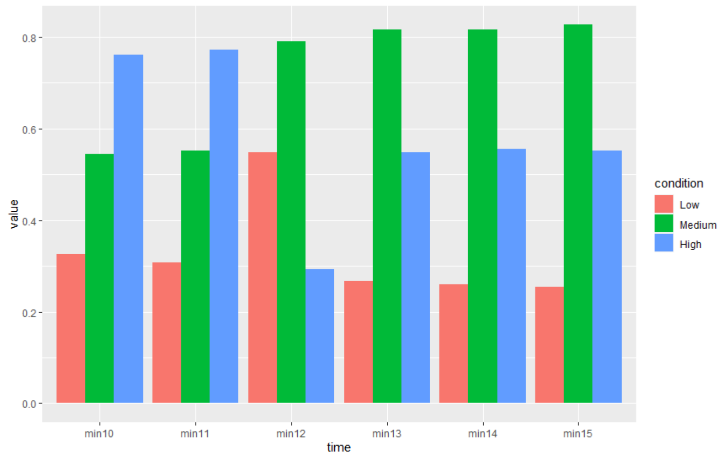

Figure 2. The likelihood of match win based on gold difference.

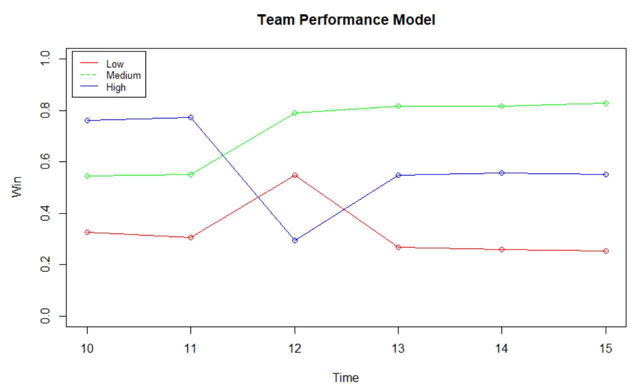

Figure 3. Team performance based on gold difference.

Table 1. *Statistics shown for team performance based on the relative gold difference for each minute interval from time 10–15.*

	Conditions		
Time Interval	Low	Medium	High
Minute 10	0.3258	0.5452	0.7612
Minute 11	0.3071	0.5517	0.7734
Minute 12	0.5478	0.7906	0.2938
Minute 13	0.2678	0.8165	0.5478
Minute 14	0.2597	0.8172	0.5554
Minute 15	0.2536	0.8271	0.5515
Average	0.3270	0.7247	0.5805

Table 2. *Summary statistics for team performance based on gold difference at time interval, t = 10. Coefficient significance is designated with asterisks such that, 0 < '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < ' ' < 1. A 'Low' gold difference is implicitly represented by the intercept. A 'Medium' gold difference is represented by the variable: 'goldcat_10medium'. A 'High' gold difference is represented by the variable: 'goldcat_10High'.*

	Model Structure			
Coefficients:	Estimate	std	z	Pr(>|z|)
(Intercept)	-0.727	0.04235	-17.2	<2e-16 ***
goldcat_10medium	0.90834	0.05813	15.63	<2e-16 ***
goldcat_10High	1.88646	0.06294	29.97	<2e-16 ***

Table 3. *Summary statistics for team performance based on gold difference at time interval, t = 11. Coefficient significance is designated with asterisks such that, 0 < '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < ' ' < 1. A 'Low' gold difference is implicitly represented by the intercept. A 'Medium' gold difference is represented by the variable: 'goldcat_11medium'. A 'High' gold difference is represented by the variable: 'goldcat_11High'.*

	Model Structure			
Coefficients:	Estimate	std	z	Pr(>|z|)
(Intercept)	-0.7270	0.04304	-18.9	<2e-16 ***
goldcat_11medium	1.02134	0.05866	17.41	<2e-16 ***
goldcat_11High	2.04178	0.06404	31.88	<2e-16 ***

Table 4. *Summary statistics for team performance based on gold difference at time interval, t = 12. Coefficient significance is designated with asterisks such that, 0 < '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < ' ' < 1. A 'Low' gold difference is implicitly represented by the intercept. A 'Medium' gold difference is represented by the variable: 'goldcat_12medium'. A 'High' gold difference is represented by the variable: 'goldcat12High'.*

	Model Structure			
Coefficients:	Estimate	std	z	Pr(>|z|)
(Intercept)	-0.8769	0.04357	-20.1	<2e-16 ***
goldcat_12medium	1.06877	0.05905	18.1	<2e-16 ***
goldcat_12High	2.20517	0.06539	33.72	<2e-16 ***

Table 5. *Summary statistics for team performance based on gold difference at time interval, t = 13. Coefficient significance is designated with asterisks such that, 0 < '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < ' ' < 1. A 'Low' gold difference is implicitly represented by the intercept. A 'Medium' gold difference is represented by the variable: 'goldcat_13medium'. A 'High' gold difference is represented by the variable: 'goldcat_13High'.*

	Model Structure			
Coefficients:	Estimate	std	z	Pr(>|z|)
(Intercept)	-1.0057	0.04482	-22.4	<2e-16 ***
goldcat_14medium	1.19668	0.05997	19.95	<2e-16 ***
goldcat_14High	2.50009	0.06813	36.71	<2e-16 ***

Table 6. *Summary statistics for team performance based on gold difference at time interval, t = 14. Coefficient significance is designated with asterisks such that, 0 < '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < ' ' < 1. A 'Low' gold difference is implicitly represented by the intercept. A 'Medium' gold difference is represented by the variable: 'goldcat_14medium'. A 'High' gold difference is represented by the variable: 'goldcat14High'.*

	Model Structure			
Coefficients:	Estimate	std	z	Pr(>|z|)
(Intercept)	-1.0478	0.04527	-23.1	<2e-16 ***
goldcat_14medium	1.27038	0.06035	21.05	<2e-16 ***
goldcat_14High	2.54512	0.06846	37.18	<2e-16 ***

Table 7. *Summary statistics for team performance based on gold difference at time interval, t = 15. Coefficient significance is designated with asterisks such that, 0 < '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < ' ' < 1. A 'Low' gold difference is implicitly represented by the intercept. A 'Medium' gold difference is represented by the variable: 'goldcat_15medium'. A 'High' gold difference is represented by the variable: 'goldcat_15High'.*

	Model Structure			
Coefficients:	Estimate	std	z	Pr(>|z|)
(Intercept)	-1.07928	0.04561	-23.66	<2e-16 ***
goldcat_15medium	1.28615	0.06059	21.23	<2e-16 ***
goldcat_15High	2.64447	0.06953	38.03	<2e-16 ***

Discussion

The results presented here show that, while gold difference has a significant impact on the overall outcome of the game, it cannot accurately predict or guarantee team success. The model summaries demonstrate that gold difference has a significant impact on team success. However, the statistics shown in Table 1 and Figure 4 demonstrate that a "High" gold difference only results in a match victory approximately 58% of the time, while a "Medium" gold difference results in a match victory 72% of the time.

Thus, other factors must also play an important role in determining team success. While a resource-based view seems to remain true to some extent, it cannot explain the gap in success for a "High" resource team and a "Medium" resource team. Although resource accumulation early on is important, it is often overemphasized when considering team success. Similarly, momentum is also less prevalent when considering the results shown. A team with "High" resources or a "strong" momentum may fail to properly utilize them effectively, resulting in a decrease in team performance.

Other factors such as team leadership, communication, and cohesion can prevent the effective allocation and use of resources. Maximizing the effectiveness of a resource-based view requires a broader focus on the prospects of team leadership and communication as a baseline for the distribution and use of resources. Allocation and distribution of resources is a prior question to considering the weight of the resources. If distributed incorrectly, a team can suffer negative consequences no matter how plenty their resources are.

Thus, although a resource-based view can be effective at its current state, it falls short of capturing all facets of a situation. The resource-based view has been widely considered to be one of the most powerful theories for explaining organizational relationships (Barney, Ketchen, & Wright, 2011). However, further development of a resource-based value must be pursued to ensure its effective implementation (Kaufman, 2015).

Instead of viewing resources as linear and strictly something to be consumed, a resource allocation lens allows for greater explanatory power. The way in which resources are distributed and allocated can greatly affect their effectiveness. Previous studies demonstrate that the effectiveness of distributed resources can change depending on the structure of a team. For example, it was found that the allocation of social capital towards the team expert often ended in a negative impact on performance. Whereas the team leader's social capital can have a larger impact on team performance than intellectual capital (Dissanayake, Zhang & Gu, 15). This study demonstrates the importance of resource allocation in a resource-based view. Without taking into consideration how resources are being distributed and used, a resource-based view will fall short in its ability to analyze and explain team success.

Conclusion

With the rising popularity of MOBAs, the ability to analyze and comprehend "big data" provides a valuable tool when assessing team performance. These large datasets provide in-depth analysis into areas of teamwork that are normally difficult to evaluate through traditional methods. Using MOBAs as a heuristic opens up new pathways for research and studies on teams and team performance.

While the research here focused on team performance in League of Legends, it can easily be generalized into a broader framework for other team research studies. Understanding the impact of team resources in League of Legends can easily be mapped to the importance of general team performance and effectiveness in the early stages of their functions.

Future research should further develop the relationship and intersections between a resource-based view and resource allocation. Developing a resource-based view in conjunction with a resource allocation perspective will allow for further explanatory power when analyzing and predicting team performance and success.

This study demonstrates the value of teamwork and team performance studies using League of Legends as a proxy. By providing insight into the complexities behind team functions, it can model and enable future studies in more critical field settings.

Limitations

One limitation to this study is the quasi-experimental methods that must be used because random assignment is not possible. The lack of control, therefore, is balanced out by the benefits of a large and detailed dataset.

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