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Variables related to the outcome of an esports professional tournament: Case study of 2019 League of Legends World Championship Series

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Abstract

The aim of this study is to analyse the possible relationships between variables that compose the game, their change and influence in achieving victory in esports, more specifically in the videogame League of Legends. To achieve this purpose, observation, and data extraction of 77 games from the final phase of the World Championship Series 2019 were carried out, recording data on variables related to the interactions of the players with the opponents and the map. A deep statistical analysis was made to find changing variables (*t*-test, Mann-Whitney U and Pearson´s Chi-square) and to generate a classification and regression model (CRT). Results obtained showed significant differences in several variables related to team structures, number of deaths, earned gold and neutral map targets. Specifically the squad that got the first Baron Nashor or main structures (>6) first had a much higher chance of victory. These findings could be important to develop new strategies and select the main objectives in the high-performance scene, but it is necessary to gather additional information from international tournaments to establish a predictor model which supports the game regardless of the patch.

Keywords: esports, performance, MOBA, outcome, gaming

Highlights

- Kills, towers, gold, inhibitors, drakes, Baron Nashor and first team to manage Baron Nashor were identified as changing variables according to the winner side.
- Towers, especially those obtained by read team, could be essential to build a game strategy to improve the chance to achieve the victory in international tournaments.
- A longitudinal research is necessary to establish if these variables are equally important with game modifications or in different regions.

Introduction

The video game industry is in a state of development and is experiencing exponential growth for some time now. Since 2013, diverse researchers (Hamari & Sjöblom, 2017; Reitman et al., 2020) have studied the development of the sector's income, and its population increase. According to these reports, in 2013, more than 70 million people engaged with videogames, and more specifically about its competitive aspect: esports. This increased to 143 million viewers in 2017 (Newzoo, 2017) and it is estimated to reach 250 million spectators in 2021. Despite the clear evidence of the rise of this industry (Yue et al., 2020), there is some controversy regarding the terminology of the area and the framework in which it is established.

The concept of esports has been a topic that has presented disparity in definitions (De Matías, 2014; Hamari & Sjöblom, 2017; Wagner, 2006). According to these definitions the term esport can show different characteristics by gender or videogame. To determine if a videogame is an esport or not, we can draw from series of criteria suggested by De Matías (2014) or Bornemark (2013). Due to this, it is considered necessary to learn about different variables that influence the development and/or outcome of the game. The characteristics and variables that could influence the development of the esport were previously studied, both before and during the game, for evaluative and predictive purposes (Hodge et al., 2017; Yang et al., 2016). Considering the different types of videogames that can be played at a competitive level, as well as the unique characteristics that each one presents due to their typology, there can be various influencing factors, due to the objectives, procedures and situations that arise may or may not be related, even between different eSports within the same genre.

For this study, League of Legends, a Multiplayer Online Battle Arena (MOBA), has been selected as it is one of the most prevalent genre within esports. This selection is based on its follow-up and participation data, achieving the first position in hours watched of live events, and second in terms of hours of game watched not belonging to tournaments (i.e., streamers and content creators; Newzoo, 2020). Several previous studies have attempted to generate predictive knowledge about the development of activities within the MOBA genre, however few examine League of Legends, instead focusing on other games such as Honor of Kings or Dota2 (Aryanata et al., 2017; Yang et al., 2020a; Yang et al., 2020b)

This paper presents the intention of creating knowledge about the influence of victory based upon several variables gathered in-game. Additionally, the relationship between variables and their presence when a team achieved the victory is studied with the purpose of detecting parameters that help us to objectively measure the performance of professional esports teams, in pursuit of the advancement and professionalism within esports.

After significant research, different variables were identified as conditions of the development of the game. These conditions or categories can explain the metagame, which is the way the game can change or be explained through those modifications. According to this, four categories can be identified to explain the metagame (Salen Tekinbas & Zimmerman, 2003, p. 482): what players bring to each game, what players take away from each game, what happens between games and what happens during a game. Related with last category, there are three moments that can be considered as the most influential (Wang, 2018): In-Game factors (Hodge et al., 2017; Yang et al., 2016), Champion Selection Phase (Ong et al., 2015) and Player Performance and Behaviour Analysis (Hodge et al., 2019). Solely In-Game will be study in this paper, for this reason variables which are analysed in this research are the main interactions with the environment and the opponent, picking up variables previously studied, such as gold earned (Gaina & Nordmoen, 2018; Todeschini de Souza & Nogueira Cortimiglia, 2017), kills,

structures and neutral objectives (Novak et al., 2019a; Wang, 2018) and adding others that could be important (such as first blood or first tower achievement) or from similar games (Aung et al., 2018). The aim of the study is to define several variables related with League of Legends, and to study the relationship between these variables and victory, focusing on changes produced by the outcome condition, and to generate a predictive model of the winning side based upon these variables.

Methodology

Sample

To carry out this research, the sample collected correspond to the 77 games that composed the final phase of the League of Legends Worlds Championship Series 2019, played in patch 9.19[1]. These games were played by a total of 16 teams from Asia, North America, Europe, and South America, representing the best international leagues after a Play-In process.

In this system, there are 12 teams directly qualified to the final phase of the tournament, according to their position in the regional league; and another 12 teams selected from the minor regions (wildcard) and the teams from large regions, but with a lower score than those directly qualified, compete for 4 places in the final phase of the tournament. In this case, the leagues that obtained representation in the final phase were the LEC (European League), LCS (North American League), LCK (Korean League), LPL (Chinese League), LMS (Taiwan League Macao and Hong Kong) and VCS (Vietnam League).

Regarding variables to be developed within the study, different variables were recorded within each of the games, which have been detailed in the following section.

Variables

The variables examined in this research were focused on the winning team; number of kills by team, total of gold earned by team, objectives achieved from opposite team, first team to achieve a neutral objectives and number of times which they achieved it, type of drakes and times of the main events. The observed variables are exposed on the Table 1.

Table 1 - Definition of variables examined in the study

Variable	Description
Phase	Tournament phase in which the game is played (group stage, quarterfinals, semi-finals, finals)
Type of match	Format in which the match is played (Best of 1/BO1, Best of 5/BO5)
Winner side	Winning team side (Red-Blue)
KillsBTeam	Number of blue side kills achieved
KillsRTeam	Number of red side kills achieved
FirstbloodBR	Team who managed first kill in game
TimeFB	Time of first kill
TeamFT	Team who destroyed first turret in game
LaneFT	Lane of the first turret destroyed
Min1Turret	Time of first turret eliminated
TurretsDestBT	Turrets destroyed by blue side
TurretsDestRT	Turrets destroyed by red side team

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[1] The patch is the update in which the game is developed, making changes periodically in terms of the selectable characters, items, solve possible weakness or strengths within the game.

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InhibDestBT	Inhibitors destroyed by blue side team
InhibDestRT	Inhibitors destroyed by red side team
GoldFinalBTK	Gold earned at the final of the game by blue side
GoldFinalRTK	Gold earned at the final of the game by red side
FirstDrake	Team who killed first drake in game
TimeFD	Time of first drake kill
DrakesBlue	Number of blue side drakes managed
DrakesRed	Number of red team drakes managed
FiredrakeBT	Number of blue side fire drakes managed
WaterdrakeBT	Number of blue side water drakes managed
EarthdrakeBT	Number of blue side mountain drakes managed
AirdrakeBT	Number of blue side wind drakes managed
FiredrakeRT	Number of red side fire drakes managed
WaterdrakeRT	Number of red side water drakes managed
EarthdrakeRT	Number of red side mountain drakes managed
AirdrakeRT	Number of red side wind drakes managed
ElderdrakeBT	Number of blue side elder drakes managed
ElderdrakeRT	Number of red side elder drakes managed
HeraldTeam	Side of the team who killed Herald and took it
TimeHerald	Time of Herald kill
FirstTeamNashor	First team to kill Baron Nashor
TimeFirstNashor	Time of first Baron Nashor killed
NashorBT	Number of blue side total Baron Nashor killed in all game
NashorRT	Number of red side total Baron Nashor killed in all game
TimeGame	Total time of the game

The Rift Herald is a neutral target located in the upper part of the river that divides the field. It appears in the 10th minute of play and remains in this space until the 20th minute that Baron Nashor appears. The player who collects the Eye of the Herald will be able to use it for the next 4 minutes to summon an ally that will launch against the closest target. Baron Nashor is a neutral target on the top of the river that divides the field, being one of the strongest neutral elements. It appears after 20 minutes and gives a reward of empowerment of minions and statistics to the team that defeated it for 3 minutes.

The drake is a neutral target located at the bottom of the river that divides the field. It appears in minute 5 and grants rewards to the team that defeats it depending on the type of drake it is: the water drake grants health regeneration, the earth (mountain) drake grants armor and magic resistance, the fire drake grants attack damage and power of skill and the wind drake grants cooldown reduction on the ultimate ability of each player on the team permanently in the game, thus being able to stack. The Elder Drake appears after the 35th minute and is one of the most difficult neutral targets on the map, standing at the bottom of it, at the same point as the rest of the dragons. The team that defeats it gains true damage and increased other drake stats for 150 seconds.

The towers are structures that protect the lane from the enemy team. Each team has 11 towers. 3 per lane and two in front of the nexus, attacking enemies that approach it. A tower cannot be attacked unless the previous one is destroyed. Inhibitors are structures at the base that protect the nexus. When a team destroys an inhibitor, during the next 4 minutes the nexus spawns super minions and can attack nexus towers and nexus. The nexus is the target to destroy in the game. Located at the base of the team, guarded by two towers. The team that destroys the nexus wins the game.

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Process

To collect these data on the variables, an observation of all games of the competition from its official page was carried out(by two independent observers), with a common record form. Then this data was cross-checked to correct possible mistakes (for which a third display was carried out to avoid erroneous data). Once this data collection was completed, the result was compared with the similar database provided by Sevenhuysen (2020) in which information on these variables were collected from RIOT API, with the purpose of triangulating data of these games obtained through two previous steps. This information was obtained from official sources from RIOT Developer Web and was used as the authoritative data in case of a mismatch between authors, except for specific variables such as lane of the first turret destroyed, inhibitors destroyed by blue and red side team and time of Herald kill, which were reviewed to reach an agreement.

Subsequently, the collected data was analysed using the Statistical Package for the Social Sciences (SPSS, IBM Corporation; Armonk, New York) program in its version 25.0. An a priori α level of 0.005 was set for all comparisons to determinate statistical significance. The variables were defined according to their nature and the distribution corresponding to the scale variables was viewed using the Kolmogorov-Smirnov test, meanwhile nominal variables were studied for a frequency distribution.

With all this, and considering these results, an independent *t*-test was carried out in the case of variables that followed a normal distribution. While, in case of the variables with a non-normal distribution, a Mann-Whitney *U* test was performed. In parallel, the relationship between the different nominal variables was observed using Pearson´s Chi - square test, using Fisher´s Exact Test (FET). Several correlations were carried out with Spearman correlation, in order to detect variables with a large correlation and avoid a possible multicollinearity error (Hinkle et al., 1979).

To calculate size effect, different classifications were followed. Cramer´s V was the measure for Pearson´s Chi – square, following Rea & Parker (1992), with an interpretation: <0,1 = Negligible association; ≥0,1 to <0,2 = Weak association; ≥0.2 to <0.4 = Moderate association; ≥0.4 to <0.6= Relatively strong association; ≥0,6 to <0,8= Strong association; ≥0.8 to 1 = Very strong association. Eta squared (η_2) (Morse, 1999) and *d* (Cohen, 1988) were considered on each relevant variable.

Finally, a classification and regression tree model (CRT) was, utilising a significance level of *p* < 0.05, a range of interaction 50 – 25 (maximum – minimum), the improvement measure should be higher than 0.001 and a cross-validation was conducted (the sample was randomly divided into 10 folds), using the 10% of the sample as a test sample.

Results

The frequency of each nominal variable is presented in Table 2 below. Differences were observed in variables related to the team who achieved first drake and destroyed first turret. Red side had greater percentage of victory (51.9%) than blue side (48.1%), and mid turret was eliminated less times than other lines (11.7 %, compared with top 46.8% and bot 41.6%).

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Table 2 - Frequency of each nominal variable

	B		R		NC		NO		Top		Mid		Bot	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Winner side	37	48.1	40	51.9										
FirstbloodBR	39	50.6	38	49.4										
TeamFT	34	44.2	43	55.8										
FirstDrake	31	40.3	46	59.7										
HeraldTeam	35	45.5	40	51.9	1	1.3	1	1.3						
FirstTeamNashor	39	50.6	34	44.2			4	5.2						
LaneFT									36	46.8	9	11.7	32	41.6

Legend: B = Blue side team, R = Red side team, NC = Done but not collected, NO = None, N = Frequency, % = Percent, Top = Top lane of map, Mid = Middle lane of map, Bot = Bottom lane of map. Please use Table 1 for full list.

Table 3 shows that the team who eliminated the first Baron Nashor ($\chi^2(2) = 43,44$; FET = 48,17; $p < .001$; $Vc = .751$) was not independent of the winner side. Following Rea & Parker (1992), the team who achieved first the Baron Nashor kill had a strong association with winning team based on the size effect. A higher percentage of victory from blue side was observed when the blue team obtained the Baron Nashor buff first in the game (82,1%), more than was expected by chance. The red team presented a lower percentage of victory (17,9%) when blue team achieved first Baron Nashor. In the case of red team as first squad managing first Baron Nashor, a higher percentage of victory was observed for red team (94,1%), and blue team presented a lower value than was expected (5,9%).

Table 3 - Cross tables with chi-square, degrees of freedom and significance

Variables		Winner side				
		B	R			
		N	N	X²	df	P Value
FirstbloodBR						
	Blue	22	17	2.21	1	0.14
	Red	15	23			
TeamFT						
	Blue	22	12	6.76	1	0.01
	Red	15	28			
FirstDrake						
	Blue	20	11	5.63	1	0.02
	Red	17	29			
HeraldTeam						
	Blue	18	17	2.01	3	0.57
	Red	19	21			
	None	0	1			
	Not Collected	0	1			
FirstTeamNashor						
	Blue	32	7	43.44	2	0.00
	Red	2	32			
	None	3	1			
LaneFT						
	Top	18	18	0.18	2	0.94
	Mid	4	5			
	Bot	15	17			

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Legend: B = Blue side team, R = Red side team, N = Frequency, Top = Top lane of map, Mid = Middle lane of map, Bot = Bottom lane of map, df = degrees of freedom

Regarding quantitative variables, frequency, standard deviation, mean and normal values are shown in table 4, after Kolmogorov-Smirnov test.

Table 4 - Average and standard deviation with Kolmogorov – Smirnov test

	N	M	SD	Kolmogorov - Smirnov Z	P Value
KillsBTeam	77	13.19	6.62	0.12	0.01
KillsRTeam	77	13.77	6.95	0.08	0.20
TimeFB	77	05:01	02:52	0.16	0.00
Min1Turret	77	13:56	02:11	0.09	0.08
TurretsDestBT	77	6.03	3.51	0.17	0.00
TurretsDestRT	77	6.22	3.88	0.19	0.00
InhibDestBT	77	0.84	0.95	0.28	0.00
InhibDestRT	77	1.08	1.21	0.23	0.00
GoldFinalBTK	77	59.52	12.84	0.07	0.20
GoldFinalRTK	77	59.55	12.93	0.06	0.20
TimeFD	77	08:51	02:02	0.10	0.07
DrakesBlue	77	1.88	1.35	0.14	0.00
DrakesRed	77	2.31	1.41	0.21	0.00
FiredrakeBT	77	0.47	0.68	0.40	0.00
WaterdrakeBT	77	0.45	0.68	0.38	0.00
EarthdrakeBT	77	0.58	0.78	0.37	0.00
AirdrakeBT	77	0.38	0.61	0.42	0.00
FiredrakeRT	77	0.60	0.83	0.35	0.00
WaterdrakeRT	77	0.64	0.87	0.35	0.00
EarthdrakeRT	77	0.58	0.77	0.35	0.00
AirdrakeRT	77	0.49	0.72	0.38	0.00
ElderdrakeBT	77	0.09	0.29	0.53	0.00
ElderdrakeRT	77	0.12	0.36	0.52	0.00
TimeHerald	75	12:34	01:31	0.11	0.02
TimeFirstNashor	73	25:19	03:32	0.11	0.02
NashorBT	77	0.68	0.70	0.29	0.00
NashorRT	77	0.70	0.81	0.29	0.00
TimeGame	77	32:39	05:56	0.08	0.20

In the case of the quantitative variables with a normal distribution, results found are shown in table 5. Significant differences were found in the kills achieved by the red team variable (t_{75}= 5, 89; $p <$,001; d = 1,34), with a large size effect and final gold achieved by both teams (B t_{75}= 3,51; $p <$,001; d = 0,80 / R t_{75}= 3, 46; $p <$,001; d = 0,79), with a large and moderate effect size respectively.

Table 5 - T-test for independence sample related with winner side.

Winner side									
	B			R			T-Test		Size effect
	N	M	SD	N	M	SD	t	df	P Value	d

KillsRTeam	37	9.73	6.39	40	17.50	5.17	5.89	75	0.00	1.34
Min1Turret	37	13:45	02:11	40	14:06	02:13	0.70	75	0.48	0.16
GoldFinalBTK	37	64.51	10.53	40	54.91	13.17	3.51	75	0.00	0.80
GoldFinalRTK	37	54.60	12.77	40	64.14	11.43	3.46	75	0.00	0.79
TimeFD	37	09:13	02:13	40	08:30	01:48	1.58	75	0.12	0.36
TimeGame	37	32:45	06:03	40	32:34	05:54	0.13	75	0.90	0.03

Legend: B = Blue side team, R = Red side team

With the quantitative variables that did not follow a normal distribution, a Mann-Witney U test was performed (Table 6) which are compared against the winning team. Variables related to enemy objectives, such as number of turrets destroyed by blue ($Z = 7,44$; $p < ,001$; $\eta2 = 0,73$) and red team ($Z = 7,53$; $p < ,001$; $\eta2 = 0,75$), number of inhibitors achieved by team (Blue team as winner side $Z = 7,19$; $p < ,001$; $\eta2 = 0,68$ and Red team as winner side $Z = 7,33$; $p < ,001$; $\eta2 = 0,71$) and number of kills managed by blue side team ($Z = 6,12$; $p < ,001$; $\eta2 = 0,49$).

As for neutral objectives, significant differences were found in the number of drakes achieved for each team ($Z = 5,38$; $p < ,001$; $\eta2 = 0,38$ and $Z = 4,9$; $p < ,001$; $\eta2 = 0,32$ for blue and red side as winner teams respectively) and number of Baron Nashor kills by blue ($Z = 6,16$; $p < ,001$; $\eta2 = 0,50$) and red side ($Z = 6,78$; $p < ,001$; $\eta2 = 0,60$).

Table 6 - Mann-Witney U test between variables with non-normal distribution and winner side

	Winning side						Mann - Witney U Test		Effect Size
	B			R					
Variable	N	M	SD	N	M	SD	Z	P Value	$\eta2$
KillsBTeam	37	17.95	4.16	40	8.80	5.31	6.12	0.00	0.49
TimeFB	37	05:00	03:01	40	05:02	02:46	0.42	0.67	0.00
TurretsDestBT	37	9.19	1.24	40	3.10	2.06	7.44	0.00	0.73
TurretsDestRT	37	2.59	2.05	40	9.58	1.17	7.53	0.00	0.75
InhibDestBT	37	1.59	0.76	40	0.15	0.43	7.19	0.00	0.68
InhibDestRT	37	0.16	0.44	40	1.93	1.07	7.33	0.00	0.71
DrakesBlue	37	2.73	0.99	40	1.10	1.15	5.38	0.00	0.38
DrakesRed	37	1.49	1.35	40	3.08	0.97	4.9	0.00	0.32
FiredrakeBT	37	0.76	0.80	40	0.20	0.41	3.4	0.00	0.15
WaterdrakeBT	37	0.62	0.79	40	0.30	0.52	1.88	0.06	0.05
EarthdrakeBT	37	0.81	0.88	40	0.38	0.63	2.27	0.02	0.07
AirdrakeBT	37	0.54	0.65	40	0.23	0.53	2.56	0.01	0.09
FiredrakeRT	37	0.41	0.76	40	0.78	0.86	2.29	0.02	0.07
WaterdrakeRT	37	0.49	0.80	40	0.78	0.92	1.55	0.12	0.03
EarthdrakeRT	37	0.35	0.54	40	0.80	0.88	2.28	0.02	0.07
AirdrakeRT	37	0.24	0.49	40	0.73	0.82	2.93	0.00	0.11
ElderdrakeBT	37	0.16	0.37	40	0.03	0.16	2.08	0.04	0.06
ElderdrakeRT	37	0.03	0.16	40	0.20	0.46	2.12	0.03	0.06
TimeHerald	37	12:39	01:38	38	12:29	01:26	0.33	0.74	0.00
TimeFirstNashor	34	26:06	04:01	39	24:37	02:55	1.46	0.14	0.03
NashorBT	37	1.16	0.55	40	0.23	0.48	6.16	0.00	0.50
NashorRT	37	0.11	0.31	40	1.25	0.74	6.78	0.00	0.60

Legend: B = Blue side team, R = Red side team

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Regression analysis has been conducted on the significant variables (Figure 1). It can be observed that turrets destroyed by the red team is the essential variable. If the team who plays on the red side can eliminate 7 turrets, they will have a high possibility of obtaining victory; but if they eliminate 6 or fewer, the blue side has a high chance of winning. This variable seems to be the most important one, with the classification and regression tree model accounting for 93.5% of total variance after the cross-validation analysis (estimation 0.065 ± 0.028), with a percentage of correctly classification of 96.1%.

Figure 1 - Classification and regression tree analysis of winner side
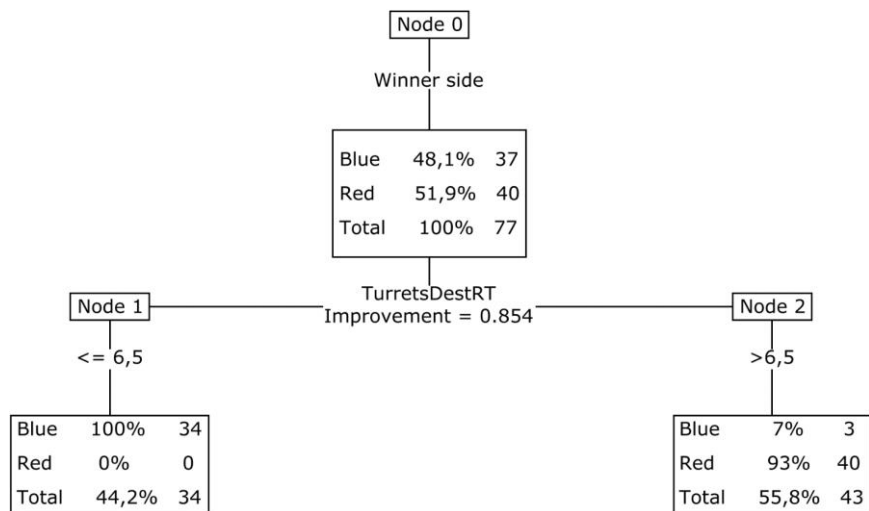
Additionally, correlation matrix between significant variables can be observed in the Table 8. The number of turrets destroyed presented a high number of correlations and an important value in correlations (ρ), in both sides.

Table 8 - Correlations between changing variables based in winner side.

	Kills BTeam	Kills RTeam	Turrets DestBT	Turrets DestRT	Inhib DestBT	Inhib DestRT	GoldFinal BTK	GoldFinal RTK	Drakes Blue	Drakes Red	Nashor BT	Nashor RT
KillsBTeam	1,000	-0,164	,753**	-,586**	,747**	-,548**	,619**	0,045	,547**	-,390**	,658**	-,471**
KillsRTeam		1,000	-,524**	,650**	-,463**	,664**	0,072	,666**	-,417**	,553**	-,341**	,654**
TurretsDestBT			1,000	-,743**	,886**	-,716**	,591**	-0,184	,681**	-,579**	,788**	-,645**
TurretsDestRT				1,000	-,699**	,897**	-,225*	,526**	-,573**	,641**	-,625**	,796**
InhibDestBT					1,000	-,715**	,517**	-0,186	,597**	-,540**	,718**	-,632**
InhibDestRT						1,000	-0,212	,511**	-,483**	,574**	-,575**	,829**
GoldFinalBTK							1,000	,612**	,447**	-0,021	,593**	-0,170
GoldFinalRTK								1,000	-0,165	,561**	-0,041	,490**
DrakesBlue									1,000	-,806**	,680**	-,466**
DrakesRed										1,000	-,472**	,533**
NashorBT											1,000	-,640**
NashorRT												1,000

$*$ = p <.05, ** = p < .01

Discussion

The main findings of this study were (1) variables such as structures, kills, gold and main neutral objectives presented changes considering the outcome of the game (in this case, winner side) with different size effects, and (2) the number of turrets destroyed by teams who played in the red side could be a good predictor of winner side, being 6 red-side-towers the key number for establishing a prediction.

Regarding the side that wins the game, we observe that the red side achieved more victories (51,9%) than the blue side (48,1%) in high performance players. This data is contrary to the thought that the team who plays on the blue side has an advantage over their opponent due to the preference in choosing characters in each game (De Matías, 2014). Worlds 2018 presented a 54,62% of win ratio in all tournament, including the Play–In phase (Novak et al., 2019b). In 2019 Summer Split of LCS, the blue side managed at 67% win ratio and LEC also had a higher blue side rate (53%), although this data is drawn from a limited sample size (15 games and 15 games respectively; . According to database Sevenhuysen, across the 2020 World Championship Series, in 76 games the red side achieved a 53,9% win rate.

Generally, first blood was obtained by one of the teams before achieving the first objective such as a tower or the Rift Herald. Following the line of the eliminations made, both sides have even averages, only half a point difference between blue team and red team (13.19 ± 6.62 and 13.77 ± 6.95, respectively). Moreover, at the end of the game, significant differences were found in the kills made by the team according to the side that wins the game, being higher when it is victorious side. In the same way, final gold earned was higher for the side that won.

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Focusing on neutral objectives, the red team collected the Rift Herald with more often (51.9%), although the first Baron Nashor kill was more often obtained by the blue team(50.6%). In comparison, Novak et al. (2019b) observed that blue team scored first Baron Nashor and Rift Herald most of the games. It is necessary to consider what happened with both Rift Herald and Baron Nashor in the studies. In Novak et al. (2019b) there were games discarded in which no elimination of these objectives was registered, or the Herald orb was not collected, even though a team was able to defeat him. Regarding the Baron Nashor, a strong association was found between the team that gets the first Baron Nashor and the team that wins the game, also achieving a higher number of kills when the same team obtains a victory.

To sum up, variables appear to stack onto each other leading to victory. It could be due to the fact of snowballing from an early game advantage, or an achievement of the main objectives throughout the game, bringing more benefits to the team which managed it, as gold, experience, or buffs. These differences can be observed in the Table 9.

Table 9 - Summary of changing variables of this study

	Winner side						
	B (*N* = 37)	R (*N* = 40)			Size effect		
	M ± SD	*M ± SD*	*P Value*	*Cramer´s V*	*d*	*η2*	*Interpreting*
KillsBTeam	17,95 ± 4,16	8,8 ± 5,31	,000			,49	Large
KillsRTeam	9,73 ± 6,39	17,5 ± 5,17	,000		1,34		Large
GoldFinalBTK	64,51 ± 10,53	54,19 ± 13,17	,000		,8		Large
GoldFinalRTK	54,6 ± 12,77	64,14 ± 11,43	,000		,79		Moderate
TurretsDestBT	9,19 ± 1,24	3,10 ± 2,06	,000			,73	Large
TurretsDestRT	2,59 ± 2,05	9,98 ± 1,17	,000			,75	Large
InhibDestBT	1,59 ± 0,76	0,15 ± 0,43	,000			,68	Large
InhibDestRT	0,16 ± 0,44	1,93 ± 1,07	,000			,71	Large
DrakesBlue	2,73 ± 0,99	1,10 ± 1,15	,000			,38	Large
FiredrakeBT	0,76 ± 0,8	0,2 ± 0,41	,001			,15	Large
DrakesRed	1,49 ± 1,35	3,08 ± 0,97	,000			,38	Large
AirdrakeRT	0,24 ± 0,49	0,73 ± 0,82	,003			,11	Medium
FirstTeamNashor							Strong
Blue (*N*)	32	7	,000	,751			
Red (*N*)	2	1					
None (*N*)	3	32					
NashorBT	1,16 ± 0,55	0,23 ± 0,48	,000			0,5	Large
NashorRT	0,11 ± 0,31	1,25 ± 0,74	,000			0,6	Large

Legend: B = Blue side team, R = Red side team

In terms of structures, the inhibitors presented the same pattern as the rest of the variables that correlated with the winning side. Towers destroyed could be considered an important part of the game, according to the obtained results, especially those managed by red team. These variables could be taken as an impact element on victory achievement, being able to develop a strategy for high performance teams guided to these kinds of structures, in order to increase their chances of winning a match. The results are on the same wavelength as Wang (2018), where turrets showed significant differences depending on the winning side, being greater when their side is the one that wins the game.

The results of this study are not surprising if we bear in mind that concurring with Novak et al. (2019b), when it is considered tower difference (between enemy and own turrets destroyed) and inhibitors taken as most important variables related to match outcome. A possible reason

for these findings could be the role of the towers, being the main defensive element for the nexus, as the only way to reach it is through the towers, being necessary to destroy at least 5 to be able to attack the enemy nexus.

We believe that the identification of these variables and the significant relationships with the result will be important when making decisions inside and outside the game, providing the technical staff of the professional League of Legends teams with elements to consider in the construction of a "game model" or game plan. These can be used not solely for a better knowledge of the metagame but also to create strategy guides to improve the chance to win, considering the correlations among them. Towers destroyed was highlighted as a good variable to develop a framework from.

As future lines of investigation, we propose using this data to consider key variables and build a model or a game-style, as well an analysis of differences between regional and international competitions, or to compare performance between teams. The vision score and the use of wards could be interesting for this area, as has been observed in other research (Pedrassoli Chitayat et al., 2020)

Study limitations

We must point out that League of Legends is an environment of constant change, so the modifications that are made can affect the importance of the variables, the inclusion of new variables and their relationship with the final objective. In this case, we are talking about patch 9.19, in which the tournament was played, but in the one corresponding to the following season, important alterations were carried out, such as the introduction of a second herald, and the changing requirements to achieve an elder dragon.

Finally, although it is true that studies on this topic are being developed recently, there is still a low number of studies in based upon the World Championship Series. Most research to date has focused on forecast analysis and chose regular leagues for develop main variables. These variables could be affected by possible changes, type of game (BO1, BO3 or BO5), evolutions in the game or own region style, which make difficult to specify key factors of the game and established a comparation between them.

Acknowledgments

Declaration of interest statement

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