Player Retention In League of Legends: A Study Using Survival Analysis

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ABSTRACT

Multi-player online esports games are designed for extended durations of play, requiring substantial experience to master. Furthermore, esports game revenues are increasingly driven by in-game purchases. For esports companies, the trends in players leaving their games therefore not only provide information about potential problems in the user experience, but also impacts revenue. Being able to predict when players are about to leave the game - churn prediction - is therefore an important solution for companies in the rapidly growing esports sector, as this allows them to take action to remedy churn problems.

The objective of the work presented here is to understand the impact of specific behavioral characteristics on the likelihood of a player continuing to play the esports title *League of Legends*. Here, a solution to the problem is presented based on the application of survival analysis, using Mixed Effects Cox Regression, to predict player churn. Survival Analysis forms a useful approach for the churn prediction problem as it provides rates as well as an assessment of the characteristics of players who are at risk of leaving the game. Hazard rates are also presented for the leading indicators, with results showing that duration between matches played is a strong indicator of potential churn.

CCS CONCEPTS

• **Applied computing** → **Computer games**; • **Information systems** → *Data mining*; • **Mathematics of computing** → Survival analysis;

ACSW 2018, January 29-February 2, 2018, Brisbane, QLD, Australia

ACM ISBN 978-1-4503-5436-3/18/01.
https://doi.org/10.1145/3167918.3167937

KEYWORDS

League of Legends, churn prediction, game analytics, esports, prediction, business intelligence, churn

ACM Reference format:
Simon Demediuk, Alexandra Murrin, David Bulger, Michael Hitchens, Anders Drachen, William L. Raffe, and Marco Tamassia. 2018. Player Retention In League of Legends: A Study Using Survival Analysis. In *Proceedings of Australalasian Computer Science Week 2018, Brisbane, QLD, Australia, January 29-February 2, 2018 (ACSW 2018),* 9 pages.
https://doi.org/10.1145/3167918.3167937

1 INTRODUCTION

Electronic sports (esports) has in the past decade emerged as a popular format for players as well as spectators, fostering a substantial industry and a developing field of research [19, 21, 25, 28, 37, 38]. While it is difficult to estimate the size of the esports market, Superdata Research predicted that the market will be worth $1.1 billion in 2017 and that there will be 330 million spectators by 2019 making esports an important research and development field across game academia and industry.

While there is no official definition, Schubert et al. [25] proposed that esports was any digital games played in a competitive context with an audience. Within esports, Multiplayer Online Battle Arena ("MOBA") games are an increasingly common form, with *League of Legends* ("LoL") being the most popular example. LoL possesses an international player base of approximately 100 million monthly players [15]. Like other MOBAs, LoL involves two teams of five players, each competing to destroy the opposing team's "Nexus", a physical structure located at the teams' bases. Each player is termed a "summoner" and controls a "champion", which is the player avatar for the battle. There are, at the time of writing, over 120 champions for players to select from. In addition to the opposing five team members, players must also battle computer controlled monsters. Defeating enemies gains the player experience and gold, the former allowing for more powerful abilities to be unlocked in the current match while the latter can be spent to buy items that increase strength and performance.

LoL is free-to-play, with revenue predominantly driven by micro-transactions, the price of which can range from US$2 to hundreds of dollars, which allow players to purchase items such as champions and champion skins. Given that these items have essentially zero marginal cost, LoL is able to be highly successful and profitable even with only a relatively small number of players making these optional purchases. In 2016, revenue for LoL reached US$1.7bn, the highest grossing of free-to-play-online games [30], despite recording the lowest average spend per player of US$18.88, relative to other MOBAs [29].

Given this, The MOBA business model relies on player retention so that there continues to be a body of players making these purchases. Even if only a fraction of the player base engages in micro-transactions, the more such players there are, and the longer they play the game, the higher the income to Riot Games, the publisher of LoL. In addition, there is evidence that in freemium games, the duration of player engagement appears correlated with the chance of purchases occurring [17, 39]. This adds further weight to the interest in fostering a player experience that leads to long-term retention.

The company's reliance on in-game purchases implies that an understanding of the predictors of the cessation of play is integral to the continued financial success of LoL and similar games. The ability to identify behaviour that is characteristic of a player close to leaving the game can assist a company with knowing when to strategically increase its services or cater more specifically to these individuals to prevent them from leaving [9, 23].

Thus, the contribution of this paper is to provide an initial investigation into key predictors of player disengagement (or "churn") in LoL. This is accomplished by considering the playing of a match of LoL as a significant event and using survival analysis to predict how much time will pass between an epoch (one game) and that event (another game) given a set of independent variables. Survival analysis is commonly used to analyse customer churn in a variety of industries but its use within games analytics is much rarer. Specifically, the work in this paper extends on previous work done in playtime measurement and survival analysis on mobile games [34, 36] and applies it to the more complex MOBA domain. To achieve this, three survival analysis techniques are applied and the results they produce compared: the Kaplan-Meier estimator, the standard Cox regression model, and the mixed effects Cox regression model. These are used with temporal player behaviour features that include recent average time of matches, recent average time between matches, and highest achieved season tier. These features are predominately agnostic to this specific game, making the approach to churn analysis presented here easily transferable to the wider MOBA genre.

The remainder of the paper is as follows: Section 2 provides more details on customer churn as it applies across multiple industries, as well as the use of survival analysis to identify key indicators of churn. Section 3 describes the survival analysis models that are used in this paper, while Section 4 introduces the data set used and the primary features that are used within the survival analysis models. Section 5 provides the results of the analysis with a more in-depth discussion of the interpretation of the results and avenues for future work provided in Section 6.

2 RELATED WORK

This research builds on a longer chain of investigation in games research, network science and machine learning, which originates in the efforts to manage network and server loads for Massively Multi-player Online Games (MMOGs). Representative of early work, Chambers et. al. [4] initially investigated server loads in online games via mining the client-server data streams. Tarng et. al [32] and others expanded this area by investigating why people where leaving games and how it related to playtime within a game. The early work investigating temporal patterns in MMOGs and other online games, usually a game or two at a time, led to more recent large-scale investigations such as Sifa et. al. [26] in which patterns where found between playtime and player churn across several thousand games. The discovery of patterns in playtime, including the importance of metrics such as inter-session intervals, session lengths, total playtime, etc., matched the increased adoption of Freemium business models in the games industry and introduced the idea of using behavioral telemetry to predict player behavior. This in turn has recently introduced the idea of performing predictive analysis on players behaviour in games [9, 17, 23, 27, 35, 39], including recently survival analysis [34, 36], and the insights that might be gained through this type of investigation. In the literature on these topics, player departure has been termed "churn" and departing players as "churners" [9], adopting terminology from the telecommunications industry.

In this section we first discuss recent work that has been done on analysing and predicting churn in video games. Highlighting the difference in available data and player behaviour between game genres and the variety of techniques used to address this. The use of survival analysis techniques in churn prediction within other industries is then presented to demonstrate its successful application in non-games context, while also noting its limited use for the player churn problem.

2.1 Churn Analysis in Games

The literature indicates that both behavioural and environmental factors are key components in determining the likelihood of churn. Research on player churn in online games goes back for at least a decade, for example Feng et. al. [7] who studied the issue in *Eve Online*, a science fiction Massively Multi-player Online Role-Playing (MMORPG) game, using traffic analysis to examine data from the early period of the game, 2003-2006. Amongst their conclusions were that player churn increases over time and that the time between play sessions was a reliable means of "identifying players that are about to quit" (i.e., churn). Kawale et. al. [14] examined the impact of social influence of other players on churn. Studied in the context of the MMORPG, *Everquest II*, it was found that a significant improvement in the accuracy of churn prediction was achieved through an analysis that combined a player's session length (behavioural) and network influence (environmental), compared to analysing either factor in isolation. A player's network influence was modelled using a vector quantity of two components, one being negative influence and the other positive influence, reflective of how much the player is inclined towards playing the game. They found that a Modified Diffusion Model was superior to both a Simple Diffusion Model and a classification approach based on Network and Engagement features. However, even their best variant had a precision of just over 50%, indicating that considerable improvements could be made to their approach. The importance of a player's social network was further explored in research conducted by SuperData [3]. That survey found that gamers tend to abandon games in groups, with 34% of churned players indicating that they had left a game because their "friends stopped playing".

Borbora et. al. [1] took an approach based on both data analysis and player-motivation theory to predict players likely to churn. Various game play features (such as rate of quest participation) were used in training a decision function as to whether a player would churn. They found the theory-driven approach to be almost as accurate as the data-driven alternative and claim that the former is more comprehensible by domain experts. They also found that a single classification algorithm may not be able to identify all likely churners. Runge et al [23] looked specifically at high value players of social games, where a high value player is defined as one who is within the top 10% of all paying players. They evaluated various approaches to churn prediction, including using a hidden Markov model and a neural network, using data sets from two games, *Diamond Dash* and *Monster World*. They found that a single hidden layer neural network, with some modifications, had the best performance in terms of predicting players likely to churn. They then used this, in the context of *Monster World*, to identify players likely to churn and applied strategies to dissuade them from leaving the game. This met with some measurable success.

2.2 Churn in Other Industries

Churn is not just an issue for online games. Customer retention is widely recognised as less costly than recovering churned customers [8] with Reichheld [20] stating that within the financial services industry "a 5% increase in customer retention produces more than a 25% increase in profit". Understandably, extensive research and analysis has been conducted on the topic of churn prediction and factors affecting customer retention. In a study of the online gambling industry, Coussement and De Bock [5] analysed both behavioural and demographic factors in their study on the online gambling industry using both a Random Forest model and Generalised Additive Model (GAM). A total of 30 drivers (27 behavioural and 3 demographic) were ranked according to predictive power on churn, with the top 3 variables being number of days since last bet, number of days since last net loss and number of betting sessions relative to the length of relationship.

Statistical models used to analyse customer attrition in areas such as the telecommunications industry and credit card provision include logistic regression and decision tree analysis, typically when encountering cross-sectional data [2], [11], [18], [33]. In the case of logistic regression, an arbitrary threshold (specific to the context) is typically selected as the point of churn, which results in a binary response variable indicative of a subject having churned. Independent variables are then used to predict the probability of the binary outcome. For decision tree analysis, historical data is organised into a hierarchical structure according to a set of conditions with a probability assigned to each node. Nie et al. [18] compared the usage of these two techniques in predicting churn using credit card data collected from a Chinese bank. The data analysed included customer, card and risk information, as well as transaction activity. It was found that superior performance was achieved using the logistic regression approach over the decision tree algorithm. Further, the different classes of statistical models used for customer retention modelling are often split between what is deemed 'static'and 'dynamic'depending on the type of data. Static models are applied to cross-sectional data and generally include logistic regression, linear regression and neural networks, whereas dynamic models tend to capture longitudinal data and include methods such as Bayesian and survival analysis [40].

2.3 Survival Analysis for Churn Prediction

When modelling longitudinal data, survival analysis is a common approach with usage prevalent across many industries. Lu [16] applied survival analysis techniques in his study on the "fiercely competitive" telecommunications industry. Specifically, the study applied a parametric regression model for the estimation of the survival and hazard function to provide information on customer churn rates, as well as for the identification of customers at high risk of churn. Kaminski and Geisler [12] used survival analysis to understand the retention of science and engineering associate professors at multiple US universities through analysing the time from original hire to departure. Further, through Zhang's [40] application of a Cox Proportional Hazards Model on retail banking customer data, he found that increases to customers'services usage, cross-buying, tenure experience and complicated product usage led to longer customer retention.

The application of Mixed Effects Cox Regression for churn analysis in the gaming industry appears somewhat less conventional, with little, if any, publicly available evidence of this being conducted. The objective of the current paper is to understand the impact of certain behavioural characteristics on the likelihood of a player continuing to play LoL. Specifically, through analysing factors affecting the rate of time until a subsequent match is played, behavioural characteristics associated with longer durations until the next match can be highlighted as leading indicators of potential churn. Through providing greater insight into the effects of match duration, time between consecutive matches and player skill on the hazard rate, esports companies will become better informed on how to introduce targeted strategies for players who exhibit these characteristics and are consequently at risk of churn. Given the dependency of Riot Game's - and other esports companies - business model on revenue generated via in-game purchases, these characteristics must be identified early so that the necessary actions can be pursued.

3 SURVIVAL ANALYSIS MODELS

When modelling longitudinal data, survival analysis is a common approach with usage prevalent across many industries. It is used to predict the amount of time that will pass before an event occurs, basing prediction on potential influencing features. In a traditional medical sense, this event is typically a reaction, remission, or death. The analogous negative event in our context may seem to be the churning of a player. However, there is no specific time that a "churn event" occurs and so for our purposes the analysis is inverted; the event is that of a player playing a match of LoL. This means that a player is said to have survived if they have not played a game between the epoch and the current time interval and so survival analysis is used to predict how long it will be until the player plays another match. Thus, if a player is predicted to "survive" for a long time, then it is likely that they have churned and are not returning or at least are disengaged with the game and will not return for a while.

Survival analysis calculates the survival function, which gives the probability of a subject surviving (not playing a game) past a certain time t: $S(t) = P(T \geq t)$. Inversely, the hazard function is used to give the probability of the event (playing the game) occurring at a specific time step given that it has not already happened, also known as the instantaneous failure rate: $h(t) = -\frac{\partial}{\partial t} \log S(t)$. The two quantities can be used to derive each other, and hence they are equivalent. However, this paper focuses on the hazard function, as a decrease in the hazard rate over time implies a decreasing probability of the player returning to the game. It can also be seen as the decreasing probability of a player returning to game of their own volition and therefore likely requiring incentives from the developer (Riot Games) to return.

We first use a Kaplan-Meier estimator to model the survival function at the population level. Then, we study the impact of behavioural variables using a Standard Cox Regression Model and a Mixed Effects Regression Model. All the models used are introduced in the next sections.

3.1 Kaplan-Meier Estimator

Survival analysis is often faced with difficulties related to the data. For example, some individuals do not experience the "event" during the study, so it is unknown after how long they experience it or if they experience it at all. Furthermore, some individuals may decide to quit the study before the end. These types of unknown data are termed *censored* data. The simplest method to calculate the survival over time despite these difficulties is the Kaplan-Meier estimator [13]. The survival probability is estimated according to the number of observations surviving past time t, divided by the total number of observations in the risk set for a given interval of time. Hosmer Jr and Lemeshow [10] summarises this with the following equation:

$$S(t) = \prod_{t_i \leq t} \frac{n_i - d_i}{n_i}, \tag{1}$$

where n_i represents the number of observations at risk of the event and d_i represents the observed number of observations who have experienced the event.

The main limitation of the Kaplan-Meier estimate is that it models survival at the population level. It is desirable, instead, to model survival as dependent of some features (e.g. behavioural features). The Standard Cox Regression Model, introduced in the next section addresses this need.

3.2 Standard Cox Regression Model

The Standard Cox Regression Model [6] can be used to explore the relationship between specific features and the rate of experiencing some defined event. The model assumes a functional form for the features (parametric), whereas no distribution assumption is required for the survival times (non-parametric). This makes this model advantageous over alternative statistical models, which require distributional conditions on the response variable.

The model assumes a hazard function of the following form:

$$h(t) = h_0(t)e^{\vec{\beta}^T \vec{x}}, \tag{2}$$

where $h_0(t)$ represent the baseline hazard function at time t (i.e., the hazard function when all explanatory variables are zero), $\vec{x}$ is the vector of explanatory variables and $\vec{\beta}$ is the vector of the coefficients. This model enables one to examine the effects of several independent variables on survival.

The key assumption for the Cox Regression Model is the proportional hazards assumption, which assumes that the hazard function for each individual inter-match observation is a multiple of the hazard function of any other inter-match time. That is, all players will have several hazard functions which are assumed to possess the same proportional shape, resulting in the features exerting a constant effect on the hazard rate over time.

Given the structure of the data we analyse, whereby consecutive matches are recorded per player, there is potential for the independence condition to be violated, as a result of the inherent correlation amongst an individual player's consecutive matches. Fitting a Cox Regression Model without accounting for this possible dependency within players, may result in inaccurate and misleading results.

Cox introduced [6] a way of estimating the model parameters in the standard Cox Regression Model via maximisation of the partial likelihood function with respect to β. We do not cover this as it is beyond the scope of the paper.

3.3 Mixed Effects Cox Regression Model

An extension to the aforementioned standard Cox Regression Model is the Mixed Effects Cox Regression Model [6], which gives the hazard rate for the j-th observation in the i-th cluster:

$$\lambda(t)_{ij} = \lambda_0(t)e^{\beta x_{ij} + b_i z_{ij}}, \tag{3}$$

where $\lambda_0(t)$ is the baseline hazard function, x_{ij} is a vector containing the fixed effects variables, β is a vector containing the fixed effects coefficients, z_{ij} is a vector containing the random effects variables and b_i is the random effect for the i-th cluster from a vector containing the random effects and is assumed to follow a normal distribution with mean 0 and covariance matrix Σ.

The model accounts for dependence amongst the player times via the addition of a random effect component. The use of the word "mixed" in the model refers to the combination of both fixed and random effects. This allows for heterogeneity in the population, where there are dependencies amongst clustered event times for a given individual. By introducing this random term, individual players who have a higher sensitivity will have an increased (or decreased) hazard rate.

The Mixed Effects Cox Regression Model mandates an additional assumption through the requirement that each subject belongs to

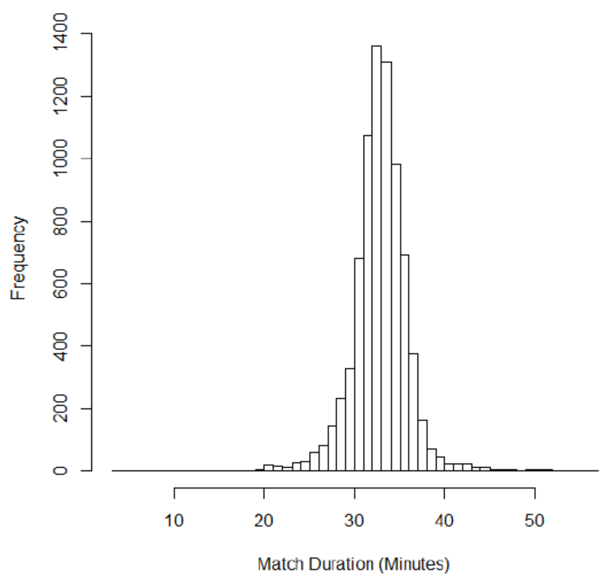

Figure 1: Histogram of the explanatory variable *Recent Average Match Duration*

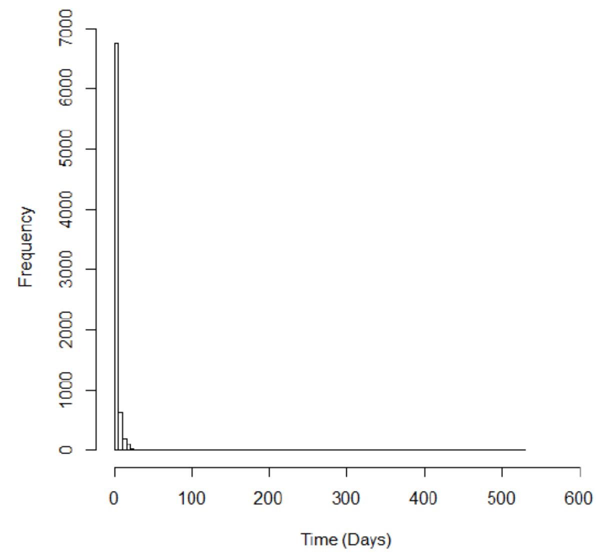

Figure 2: Histogram of the explanatory variable *Recent Average Time Between Matches*

only one cluster. The assumption is satisfied in our data whereby each time until the next match (subject) is unique to an individual player (cluster).

Ripatti and Palmgren introduced [22] a generalised approach to parameter estimation for the Mixed Effects Cox Regression Model using a penalised partial likelihood technique. We do not cover this as it is beyond the scope of the paper.[1]

4 DATA SET AND FEATURES

We analyse historical data to model and predict the probability of a player quitting the game. Our analysis is based on behavioural characteristics of players, namely *Recent Average Match Duration* (RAMD) and *Recent Average Time Between Matches* (RATBM), both being calculated over a 90 days period prior to the last event. We also use *Highest Achieved Season Tier* (HAST) as a proxy for the skill level of the player. The response variable we are interested in is *Time Until Next Match* (TUNM).

Our analysis is performed on data collected from the League of Legends API[2]. First, we randomly sampled 1000 players from the Oceania region among the 42,006 who participated in a public event in 2015. For each player, we collected match data between May 2014 and September 2016. Due to data restrictions, we could only download the data from 201 players, for a total of 7,842 matches. This, however, still gives a large number of data points.

The distribution of the variables of interests is shown in Figures 1, 2 (explanatory variables), and 3 (response variable).

The variable *Recent Average Match Duration* is approximately normally distributed. On the other hand, the variable *Recent Average Time Between Matches* is severely skewed, so we applied a logarithm

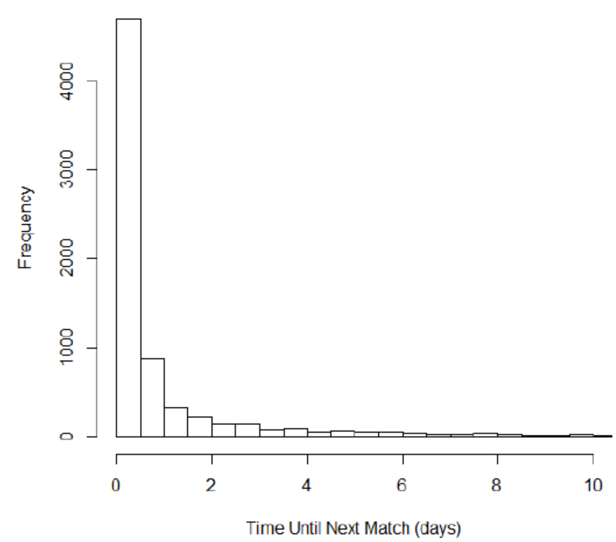

Figure 3: Histogram of the response variable *Time Until Next Match*

transformation to mitigate the problem. Figure 4 shows the distribution of the transformed variable. The response variable is heavily skewed (lower quartile is 4̃5m, median is 1̃h38m and upper quartile is almost 2 years) and has some extreme outliers. We excluded 2 observations where the players did not play for 12 months and then played a single game. Despite removing these outliers, the data still exhibits severe right-skewness. However, for survival analysis, no distributional assumptions are enforced upon the response variable, therefore no further data points will be removed.

[1]This is implemented in the `coxme` function in the `survival` package in R.
[2]https://developer.riotgames.com

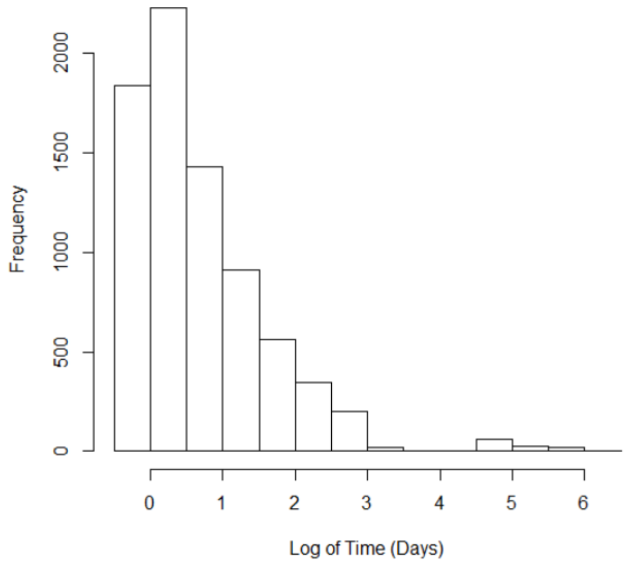

Figure 4: Histogram of the explanatory variable *Recent Average Time Between Matches* after a log transformation.

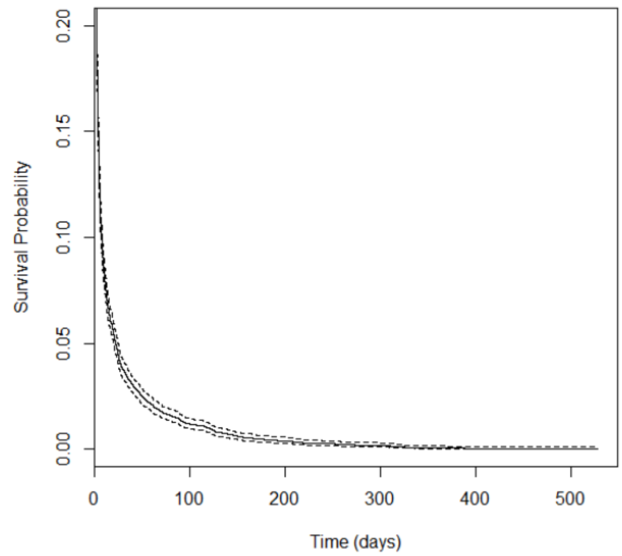

Figure 5: Kaplan-Meier Survival Function for Time Until Next Match with 95% confidence intervals.

Table 1: Median time until the next match and tier sample sizes. HAST is short for *Highest Achieved Season Tier* and TUNM is short for *Time Until Next Match*.

HAST	**Median of TUNM**	Sample Size
Challenger	0.030	2
Master	0.583	5
Diamond	0.169	7
Platinum	0.066	10
Gold	0.051	12
Silver	0.060	44
Bronze	0.074	89
Unranked	0.080	32

The median values and sample sizes for Time Until Next Match per Highest Achieved Season Tier are provided in Table 1 below. There does not appear to be a clear association or trend between the ordered tiers and time. However, sample sizes across the categories vary substantially with a much lower sample size for higher-tiered players, which may influence the reliability of results.

5 RESULTS

In this section we present the results of the analysis performed on the League of Legends data. The results of the three models, Kaplan-Meier and Standard/Mixed Effects Cox Regression Models are reported in the next sections.

5.1 Kaplan-Meier

An estimated Kaplan-Meier survival function for the response variable including 95% confidence intervals (dotted lines) is shown in Figure 5. The Kaplan-Meier estimator is a non-parametric approach to estimation of the probability of surviving beyond the event of interest, and which accounts for censored time-to-event data. Figure 5 depicts a decreasing rate of decline in survival probability over time after the initial severe drop. This indicates that as the time between a match increases the probability of a another consecutive match being played decreases. The curve begins to plateau around day 100 indicating that players with *Time Until Next Match* greater than 100 days have very low probability of returning to the game.

Given the sharp initial decline, the survival function is again plotted in Figure 6 over a period of 6 hours (0.25 days) given 58% of observations are below this threshold. It is easier to observe that the probability of the observations consisting of a match not yet having been played declines to around 50% after approximately 1 hours and 12 minutes (0.05 of a day). The initial plateau seen in this plot is representative of the time when all players are still playing the match associated with the previous event.

5.2 Standard Cox Regression Model

We fit a Standard Cox Regression Model which includes the two continuous variables and a categorical variable containing seven tiers with hazard ratios provided relative to the Challenger tier. The model treats all observations individually without accounting for the clustering of matches by player.

As introduced earlier, the proportional hazard assumption requires that the hazard functions across all features must be proportional over time. We run the Pearson product-moment correlation between the scaled-Schoenfeld [24] residuals and time to verify the assumption holds in the data. We found small p-values for *Recent Average Match Duration* ($p < 0.001$) and *Recent Average Time Between Matches* ($p = 0.030$), providing evidence of a violation of the proportional hazards. The result of the test for the categorical variable *Highest Achieved Season Tiers* is not significant ($0.627 \leq p \leq 0.899$),

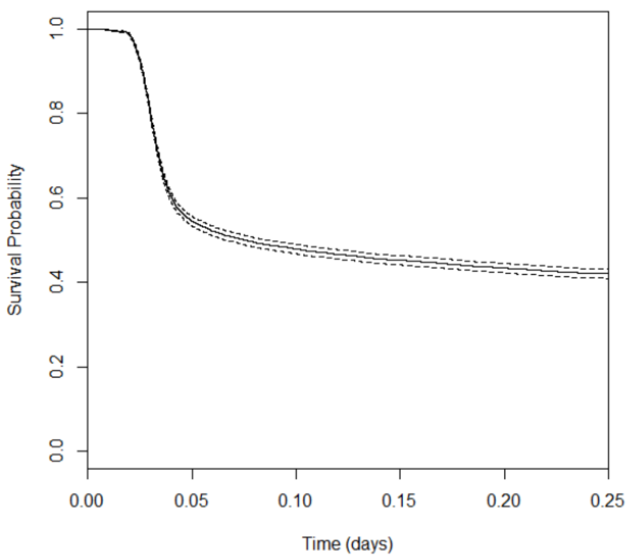

Figure 6: Kaplan-Meier Survival Function for Time Until Next Match with 95% confidence intervals over a quarter-day period.

Table 2: Standard Cox Regression Model output. RAMD is short for *Recent Average Match Duration*, RATBM is short for *Recent Average Time Between Matches* and HAST is short for *Highest Achieved Season Tier*.

Independent Variable		Parameter Estimates	Hazard Ratio	p-value
RAMD		-0.024	0.976	<0.001
RATBM		-0.002	0.998	<0.001
HAST	Challenger	N/A	1.000	N/A
	Master	-1.134	0.322	0.355
	Diamond	-1.509	0.221	0.133
	Platinum	-1.484	0.227	0.138
	Gold	-1.431	0.239	0.153
	Silver	-1.404	0.246	0.161
	Bronze	-1.443	0.237	0.149
	Unranked	-1.563	0.209	0.118

hence satisfying the proportional hazards assumption. The global test has a large chi-squared value, indicating that the overall model violates the proportional hazards assumption ($p < 0.001$).

Keeping in mind that some of the assumptions about the data are violated, the output of the Standard Cox Regression Model is reported in Table 2. Hazard ratios that are less than one are associated with longer time durations until the next match is played.

5.3 Mixed Effects Cox Regression Model

We fit a Mixed Effects Cox Regression Model to the data with the player ID as the random effect variable to accounts for within cluster dependency; i.e., the dependency between a player's various times. The output of the regression is presented in Table 3.

Table 3: Mixed Effects Cox Regression Model output. RAMD is short for *Recent Average Match Duration*, RATBM is short for *Recent Average Time Between Matches* and HAST is short for *Highest Achieved Season Tier*.

Independent Variable		Parameter Estimates	Hazard Ratio	p-value
RAMD		-0.027	0.973	<0.001
RATBM		-0.001	0.999	0.037
HAST	Challenger	N/A	1.000	N/A
	Master	-1.314	0.269	0.290
	Diamond	-1.561	0.210	0.120
	Platinum	-1.571	0.208	0.120
	Gold	-1.499	0.223	0.140
	Silver	-1.474	0.229	0.140
	Bronze	-1.492	0.225	0.140
	Unranked	-1.580	0.206	0.120

Hazard ratios that are less than one are associated with longer time durations until the next match is played. The output reveals a strongly significant effect for *Recent Average Match Duration* ($p < 0.001$). A hazard ratio of 0.973 indicates that a one-minute increase in recent average match duration decreases the hazard rate by 2.7% ($1 - e^{1*-0.027} \approx 0.027$). Equivalently, a 15-minute increase in recent average match duration is equal to a 33% decrease in the rate of time until the next match is played ($1 - e^{15*-0.027} \approx 0.333$). As such, as the duration of matches tends to increase for a player, the time until the next match decreases.

A significant effect was also found for *Recent Average Time Between Matches* ($p = 0.037$). Whilst this feature does not have as strongly significant of an effect as the match duration feature, the hazard ratio indicates that a one day increase in recent average time between consecutive matches, decreases the hazard rate by 0.1% ($1 - e^{1*-0.001} \approx 0.001$).

In terms of the highest achieved season tier, all tiers are insignificant at the 5% level (all $p \geq 0.12$).

5.4 Comparison of Models

A comparison of the hazard ratios from the Standard Cox Regression and the Mixed Effects Cox Regression Model are shown in Table 4. It can be seen that the ratios, with and without accounting for a random effect, are relatively stable. This suggests that there is little impact in fitting the random term on the overall model.

6 DISCUSSION

A Mixed Effects Cox Regression Model was used in this work to quantify the influence that player behaviour and skill exert on the rate of time until a subsequent match. It was found that as the length of play tends to increase, the rate of time until occurrence of the next match was found to decline. This may suggest that the player may have experienced a more challenging game. Without variables indicative of whether a player has won or lost a particular match, it is difficult to attribute longer match durations with a skill discrepancy between players, or whether a long ”lose” or long ”win” impacts on this decline. Over time, players may become discouraged or feel somewhat defeated and as a result, are less motivated to

Table 4: Comparison of hazard ratios. RAMD is short for *Recent Average Match Duration,* RATBM is short for *Recent Average Time Between Matches* and HAST is short for *Highest Achieved Season Tier.*

Independent Variable		Standard Cox Model	Mixed Effects Cox Model
RAMD		0.976	0.973
RATBM		0.998	0.999
HAST	Challenger	1.000	1.000
	Master	0.322	0.269
	Diamond	0.221	0.210
	Platinum	0.227	0.208
	Gold	0.239	0.223
	Silver	0.246	0.229
	Bronze	0.237	0.225
	Unranked	0.209	0.206

immediately recommence playing. As such, the availability of a variable indicating "win" or "lose" may have improved both model fit and interpretation of the results.

Similarly, increasing average time between sequential matches was found to be associated with a longer time period until the next match. Typically, one would expect that individuals who are becoming increasingly disinterested towards the game, would tend to be associated with longer gaps between subsequent matches. Again, it is difficult to draw conclusions without further information on aspects including the age of a player or a player's external environment. These factors are likely to provide more information around the particular circumstances of an individual's behaviour.

A player's highest previously achieved season tier (included as a proxy for player skill level) was not found to be associated with rate of match play. This may be due to the fact that Riot Games' have implemented targeted rules to discourage inactivity. For example, a Challenger-tiered player (highest ranking) can be demoted after 10 days of inactivity. A further incentive, League Points, sees points lost for Platinum, Diamond, Master and Challenger-tiered players after an inactive period of 28 days. It was anticipated that player skill level would exert some influence on the time until the next match. However, this variable did not significantly contribute to the likelihood of match play. It should be noted that this conclusion may be biased by the small sample sizes prevalent across the higher tiers, as highlighted in Section 4.

The selected observation period includes matches beginning in May 2014 until September 2016. Variations in both the length of the time period, as well as the selected observation period may influence results. Riot Games constantly attempts to improve the game by making changes to game-play and characters. Performing survival analysis at different periods in time, for example after a major patch or character rework, may provided deeper insight into their affects of player churn.

Furthermore, given this study conveys an online product, changes to technology may influence the user experience. It would be best-practice to continue using the most up-to-date LoL player data in order to keep the results relevant. New games are constantly being released which presents a risk that a game could be released in the future that replaces LoL and causes a mass migration away from this MOBA game.

Improvement to the analysis may also be achieved through incorporation of data such as level of player spend and frequency of player purchases. Coussement et. al. [5] incorporated monetary factors in their study of churn in the online gambling industry. Factors including number of bets placed during the preceding week, number of bets during the preceding month and total monetary amount of stakes were found to be significant drivers of churn. Incorporating these factors into the retention analysis would better facilitate Riot Games' ability to target players close to churn through analysing behaviours of players with a higher propensity to make in-game purchases. Note this data is current not available within the API and would need to be sourced from elsewhere.

7 CONCLUSIONS AND FUTURE WORK

As introduced in Section 1, and discussed in Section 2, the motivation for this analysis is driven by the business model adopted by Riot Games, which relies heavily on customer retention, and further contributes to an extensive topic in games research which focuses on behavioral patterns in player activity. LoL is unlike online games that require a subscription fee or an up-front cost for download. As such, the rationale for undertaking this study was underpinned by the importance of player loyalty in a game that generates the majority of its revenue from in-game purchases.

The findings on behavioural factors in this paper are consistent with prior research. As highlighted in Section 2, recent studies have found evidence supporting the association between player behaviour and churn [5], [14]. Inclusion of player behavioural characteristics, including average match duration and average time between subsequent matches, were found to be significant factors affecting the rate of time until the next match. The present study provides evidence of this association between player behaviour and the likelihood of match play. More specifically, the current study applies survival analysis techniques including a Mixed Effects Cox regression model with the results showing evidence of increasing rate of time until a player's subsequent match with shorter average match durations. Similarly, the results indicate that longer durations of time between subsequent match plays are associated with a decrease in the rate of time until a player's next match. This analysis, along with increasingly sophisticated methods will continue to contribute to understandings and insights into indicators of player churn. Given the reliance of ongoing player purchases as the key source of revenue, these insights will become increasingly more valuable.

In future work, we plan to extend this study to different regions in which LoL servers are hosted. This will remove a degree of population bias as a result of the inclusion of solely Oceania-region players. Additionally, extending this work into different regions will allow for comparisons of different hazard rates across regions, which may provide useful insight into location based influences on player churn. We also plan to perform survival analysis at different snapshots in time (i.e after a patch or character rework), to investigate how large changes affected player churn. This in analysis could provide insight as a predictor for player churn after changes or be used to direct future additions and changes to the game.

ACKNOWLEDGMENTS

The authors acknowledge support from ARC LP130100743. Additionally, this work is supported by the Digital Creativity Labs jointly funded by EPSRC/AHRC/InnovateUK grant EP/M023265/1.

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