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Chasing the Quitting Player

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Contents

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Declaration of scientific integrity

The author hereby declares that she has read and fully adhered the Code for Good Practice in Research of the University of Basel.

Abstract

Player churn is a key research area within games research, as understanding churn likely is a valuable resource to game developers designing customer retention strategies. It comes at no surprise that preceeding literature often focused on churn prediction based on behavioral metrics, as those are most easily available to developers. However psychological predecessors (e.g. motivation) of churn are not necessarily reflected in in-game behavioral data. Drawing from literature on athlete burnout in sports and the Self-Determination Theory framework, this study elaborates the relation between motivation, negative player experience, well-being and intention to quit in the context of Massive Online Battle Arena (MOBA) games. I present the results of a cross-sectional study with data from 203 players of *League of Legends*, a popular Massive Online Battle Arena (MOBA) game. Using binomial Logistic regression analysis, a predictive model based on psychological predictors, namely Amotivation, Exhaustion and Devaluation for the intention to churn is identified.

Keywords

• Motivational Regulation • HCI • Games • Churn • Retention • Persistence • Burnout • Well-Being • SDT

1 Introduction

Many people consider playing games a rewarding and motivating activity. In fact it has such a high appeal that the US game industry (“Economic Growth”, n.d.), has grown bigger than both the film industry and streaming services in terms of revenue in 2018 (“comeScore Reports 2018”, n.d.). Netflix for example considers one of the most popular game to be more of a threat to its business than Time-Warner’s HBO (“Netflix’s biggest threat”, n.d.). Non-surprisingly video games have received growing interest and were extensively studied in player experience (PX) research and also informed game analytics (e.g. Przybylski, Rigby, & Ryan, 2010; Lafreniere, Vallerand, Donahue, & Lavigne, 2009; Melhart, Azadvar, Canossa, Liapis, & Yannakakis, 2019; Tyack & Mekler, 2020). Until recently player experiences were mostly regarded as gratifying and pleasurable, due to the nature of player engagement being largely voluntary (Przybylski et al., 2010). In fact concepts with positive attributes such as intrinsic motivation and need satisfaction have been widely applied and can be considered core to the understanding of player experience and engagement (Tyack & Mekler, 2020). Meanwhile despite efforts from emerging games to create more long-lasting experiences, there is an increasing number of notions of negative gameplay experiences, player churn (a measure of the amount of players leaving a game, also referred to as "drop-out")) (e.g. Borbora, Srivastava, Hsu, & Williams, 2011; Kawale, Pal, & Srivastava, 2009) and of social factors having a detrimental impact on user retention (e.g. deviant behaviors) (Kwak & Blackburn, 2014; Shores, He, Swanenburg, Kraut, & Riedl, 2014; Tyack, Wyeth, & Johnson, 2016). This suggest that not all styles of gameplay foster positive outcomes. Yet, well researched motivational theories such as Self-Determination Theory (SDT) and Organismic-Integration Theory (OIT) have received limited attention in regards to churn. The same goes for self-reported player experience and well-being. Instead, preceeding research on player churn prediction is often conducted using various methods building on behavioral metrics or computational approaches to player motivation (e.g. Runge, Gao, Garcin, & Faltings, 2014; Liu et al., 2018; Edge, 2013). That is not by accident and can be explained by the fact that behavioral metrics are usually directly available to the developer and self-reported experience measures are not. Despite this clear disadvantage, using self-reported data might be beneficial in the process of churn prediction. Drawing from Self-Determination Theory (SDT) and literature on athlete burnout, previous research has shown, that churn can be considered to be a negative outcome rooted in negative motivational determinants (i.e. need satisfaction or motivational regulations)

(Przybylski et al., 2010; Sarrazin, Vallerand, Guillet, Pelletier, & Cury, 2002), experiences and well-being (e.g. burnout) (Hodge, Lonsdale, & Ng, 2008). As such, churn can be seen (amongst others) as the behavioral step following bad experiences, low well-being and/or low levels of self-determined motivation. Hence this work shifts the focus towards a self-report measure approach using the well established SDT framework applied to player churn. Furthermore it is unfortunate that within SDT game literature (e.g. Ryan, Rigby, & Przybylski, 2006; Neys, Jansz, & Tan, 2014) the concept of burnout has received limited attention, where well-being measures that cover the lower end (i.e. burnout measures) are likely connected to churn, as proposed previously in sport SDT literature (Lonsdale, Hodge, & Rose, 2009). Contributing to work on player churn prediction (e.g. Neys et al., 2014; Ryan et al., 2006; Borbora et al., 2011) I present results of a cross-sectional study with self-reported data from 202 players of League of Legends (LoL). This paper addresses short comings of preceeding literature by including burnout as a potential predictor of player churn and extends the body of knowledge of churn prediction with a new take on psychological predictors rather than behavioral ones. I identify three latent predictors of player churn (i.e. Amotivation (User Motivation Inventory), Exhaustion (Athlete Burnout Questionnaire (ABQ)), Devaluation (ABQ)) and discuss the validity of the presented binomial logistic regression model in terms of statistical measures and a qualitative insight of reasons for churn. Additional findings showcased that players having an intention to churn were distinguishable from those without intention to churn on a descriptive level. Specifically, players with intention to churn had an overall less positive experience, less derived well-being and lower self-determined motivation. These findings extend our understanding of the role of motivation, experience and well-being for churn in particular and for player-computer interaction in general. One must keep in mind that understanding player churn and being able to predict it, is likely highly valuable to not only applied sciences designing customer retention strategies but also informed money-acquisition of game-developers and game-studios (Runge et al., 2014; Van den Poel & Lariviere, 2004). Also, most multiplayer games rely upon member activity, hence churn in the form of stopping the activity poses a threat to the health of online communities (Karnstedt et al., 2010).

2 Related Work

Churn and Behavior based Prediction Churn is a measure of the amount of customers/players leaving or disengaging. Closely tied to churn is customer retention, which describes opposing mechanisms, processes or interventions to retain customers. For any business, churn is a prevalent problem with repeat customers as it is closely tied to revenue. An increase of 1% in customer retention rate was shown to increase revenue significantly (Van den Poel & Lariviere, 2004). Also the cost to acquire a new customer is up to five times higher than an additional sell to already existing customers (Slater & Narver, 2000). It is hence no surprise that churn has been analyzed in a wide range of industries, such as the telecom sector, retail business, banking, Internet service providers, service industries, P2P networks, insurance and also games (Borbora et al., 2011). In the games sector exceptional importance was given to churn prediction as a tool for player retention (e.g. Runge et al., 2014; Liu et al., 2018; Edge, 2013). The goal is to identify potentially churning players early and prevent it from happening. This is not only of interest for the company standing behind game development but also for the players themselves, as multiplayer games often rely upon member activity. Several researchers have looked into churning within various games using a wide-array of methodological approaches. Amongst others, temporal features found wide application in churn prediction. Borbora and Srivastava (2012) for example modeled player churn behavior by analyzing session activity of churners in the weeks before leaving the game and compared it with the activity traits of regular players. In this novel temporal based approach they identified distinct behavioral profiles between churners and active players. Most churners are characterized by little to no activity and some displayed a decrease in their activity levels in the weeks prior to churn. Non-churners did not show decreased activity levels. Yang et al. (2019) similarly assessed in-game time spending regularity for churn prediction, while achieving satisfactory prediction performance. Research by Feng, Brandt, and Saha (2007) further supported that the time between game sessions is a good discriminant to identify players about to churn. Castro and Tsuzuki (2015) proposed a more economical frequency analysis approach using only login records. Finally, Hadiji et al. (2014) combined multiple temporal predictors, specifically playtime, session length and session intervals to develop a broadly applicable churn prediction model, that yielded satisfactory prediction rates across five free-to-play games. In general the findings speak for a high importance of temporal features across diverse games. However temporal features are not the only behavioral measure that were applied in churn prediction. Weber, John, Mateas, and Jhala (2011) for example, identified game-specific attributes that are most influential in maximizing player retention. I abstain from listing these attributes, as they are too specific to the game in question. The use of game-specific attributes is overall a scarcity in churn prediction, potentially due to the lacking generalizability. Other research took a more holistic approach to churn prediction. More specifically both in-game, temporal and social features are incorporated into the prediction design. Lee, Hong, Yang, and Lee (2016) for example assessed an array of activity, purchase, transaction and social measures and identified "Number of Purchase" (a measure of in-game purchases) to be the most important behavioural feature for churn prediction. "Number of Times Attending Guild" (a measure of social interaction with fellow players) was also an important predictor and refers to the relevance of social relationship between players for player retention. Kawale et al. (2009) assessed player engagement as a function of time spent in game, and social influence using a social network analysis to predict churn. The results showed an improvement in prediction accuracy when predictors are combined. The importance of social relationship for player retention was also highlighted in the qualitative approach of Tyack et al. (2016). In contrary defiant behaviour of other players was found to be a major driver for churn in qualitative research (Shores et al., 2014; Kwak & Blackburn, 2014; Tyack & Mekler, 2020).

Churn and Self-determination Theory (SDT) player motivation Aforementioned literature commonly used behavior tied metrics such as in-game behavior, temporal features or "behavioral social measures" for churn prediction. Motivation as an important driver for behavior also received attention within churn prediction research. Rothenbuehler, Runge, Garcin, and Faltings (2015) for example took a slightly extended approach by modelling motivation of players using their changing activity levels. It was proposed that a low activity would represent a low motivation, and a high activity a high motivation. Modelling motivation in this way can be problematic as it lives from the assumption that activity can describe motivation directly. Brühlmann, Baumgartner, Wallner, Kriglstein, and Mekler (in press 2020) took an opposite approach of modelling motivation based on Self-Determination Theory (SDT) in order to predict both player experiences and behavior. Results showed that different motivational profiles (i.e. Amotivated, External, Intrinsic and Autonomous Profile) are linked to a wide variety of distinct experience and well-being measures but not so much in-game behavior (e.g. overall playtime). It is hence questionable to conversely derive motivation directly from behavioral measures such as activity. Some form of connection between interest, motivation and activity seems nonetheless existent. Bauckhage et al. (2012) for example proposed an underlying model of player interest for activity in games from observing playtime allocations across more than 3000 games.

This is of great value as it suggests that well-researched motivational frameworks might further explain not only experiential patterns, and interest (and with it somewhat activity patterns) in a game but also quitting behavior as a consequence. More profound and well researched conceptualizations of motivation can be found in the SDT framework and sub-theories like Organismic-Integration Theory (OIT) (Deci & Ryan, 2000; Ryan & Deci, 2000). OIT extends the conceptualization of motivation by motivational regulations that reflect the underlying reason (the why) of goal pursuit. Need Satisfaction on the other hand is described as an outcome of goal pursuit (Deci & Ryan, 2000). Specifically, the sub-theory differentiates six motivational regulation types, that distribute across a self-determination spectrum that ranges from non-self determined forms of motivation to fully self-determined motivation, as shown in Figure 1. On a more granular level, amotivation (AMO) describes a lack or absence of motivation. It depicts the least self-determined form of motivational regulations. The other end of the spectrum is occupied by intrinsic motivation (IMO), as the most self-determined regulation, where activities are pursued for their own sake. The remaining regulations are minor dimensions of extrinsic motivation. External regulation (EXT) describes the presence of a salient (un-)desired outcome that stands in relation to the activity (e.g. punishment in the form of pressure from other players or rewards). Introjected regulation (INJ) centers around self-control and self-esteem such as avoiding guilt or attaining feelings of self-worth. Corresponding behavior is only partially self-determined due to lacking acceptance. Behaviors regulated by Identified regulation (IDE) are accepted to be personally important and conscientiously valued, but the activity itself not necessarily perceived as pleasing. Integrated Regulation (INT) is the most self-determined form of extrinsic motivation and describes congruence between behavioral goals and already present values, goals and needs.

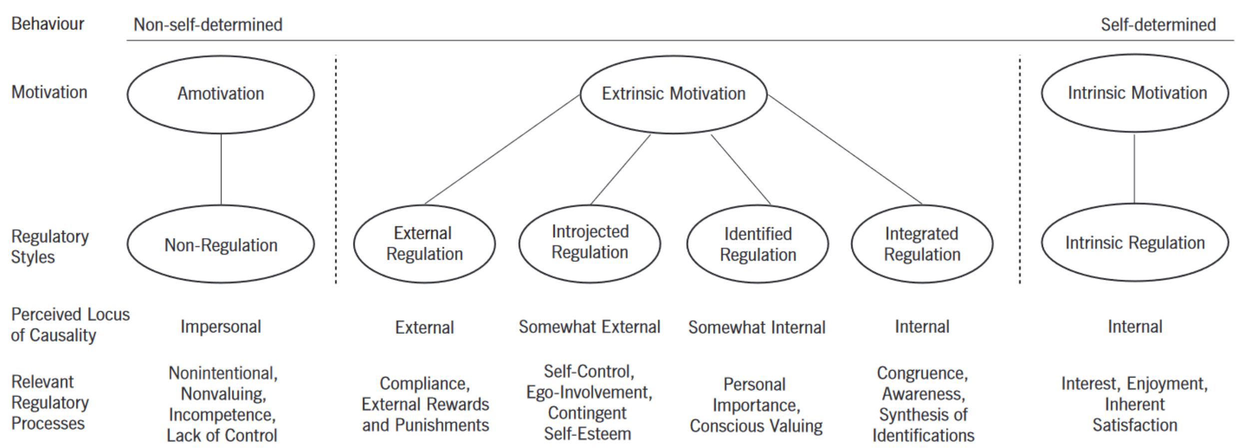

Figure 1: The six types of motivational regulation as posited by Self-Determination Theory. Ranging from the least self-determined (amotivation) to the most self-determined regulation (intrinsic motivation). Adapted from Tyack and Mekler (2020).

It is stated that pursuing behavior with self-determined motivation fosters higher need satisfaction and with it more positive experiences and higher well-being. Vice versa less self- determined forms of motivation are linked to lower need satisfaction, less positive experiences and well-being (Deci & Ryan, 2002). Correspondingly, findings in sport-motivation research showed that low levels of self-determined motivation (i.e. low levels of intrinsic and high levels of a-motivation) were also associated with intentions to drop-out, which in turn, predicted actual drop out behaviour almost 2 years later (Sarrazin et al., 2002). Hence, churn can be considered to be such a negative outcome rooted in predecessors such as less self-determined forms of motivation (Przybylski et al., 2010; Sarrazin et al., 2002), negative experiences and low well-being (Hodge et al., 2008; Przybylski, Weinstein, Ryan, & Rigby, 2009). This poses a promising approach to player churn prediction. Few studies took advantage from motivational theories to predict player churn. Borbora et al. (2011) for example investigates the problem of churn prediction using a conceptualization of motivation by Yee (2005) that later developed into the Online Gaming Motivations Scale (Yee, Ducheneaut, & Nelson, 2012). This empirical model of player motivation contains components such as Achievement, Social and Immersion and is hence different from an SDT and OIT approach. However the results support the importance of player motivation as a key factor in understanding churn behavior as their model was only slightly outperformed by a complex data-driven model. An other approach by Edge (2013) adapted the promising idea of the motivational framework of empowerment (Klyubin, Polani, & Nehaniv, 2005) to look at churn prediction within a single game instance (e.g. abort of a player versus player match, but continued interest in the game). This stands in contrast to churn in terms of stopping to play altogether, which is the focus of the current work. Additionally a computational approach to compute empowerment was used, why they had to hypothesize that this measure is a correlate to motivation. Other works discussed persistence and its relation to self-determination theory, (e.g. Neys et al., 2014; Ryan et al., 2006). Although somewhat related, it has to be noted that persistence is a different construct that is specifically bound to insufficient reward, whereas churn is not. No research to date to my knowledge has however looked at churn using the proposed SDT motivational framework in the context of games, whereas there is some comparable literature available in the domain of sport psychology, as mentioned before (e.g. Sarrazin et al., 2002).

Motivational Psychology and Burnout Multiplayer Online Battle Arena (MOBAs) pose a curious case, as they seem to induce extremes in both positive and negative interactions and experiences (Johnson, Nacke,

& Wyeth, 2015; Brühlmann et al., in press 2020). This suggests the potential to affect player motivation, enjoyment and well-being (Tyack et al., 2016) that might be reflected in player churn. Motivational concepts were repeatedly incorporated into study designs that aimed to look into persistence or churn (e.g. Ryan et al., 2006; Neys et al., 2014; Edge, 2013; Kawale et al., 2009; Borbora et al., 2011). Burnout as a measure of low well-being found however no application. This is unfortunate as the symptom-based definition of burnout by Raedeke and Smith (2001) provides a means by which the potential consequences of burnout, such as dropout could be explained (Lonsdale et al., 2009). Specifically, three sub-dimensions, namely emotional/physical exhaustion, reduced sense of accomplishment and devaluation form the latent athlete burnout construct Raedeke and Smith (2001). In the following parallels between physical athlete sports and E-sports are discussed briefly in conjunction to the aforementioned dimensions of burnout. Exhaustion is related to intense demands of training and competing. This might provide a lens for the intense demands of gaming, when considering how long enthusiast and hardcore gamer spend time playing a certain game. Additionally MOBA games are also highly competitive, where players strive towards winning games with their skills and knowledge. Reduced sense of accomplishment is similar in its terms of interpretation for both gamers and athletes. Similar to athletes, gamers might experience a reduced sense of accomplishment in terms of their skills and abilities. Raedeke and Smith (2001) describes devaluation to be a state ".. wherein athletes stop caring about what is important for athletes: sport and their own performance." (p. 283) . For the context of gaming and E-sports this translates to players stop caring about their performance and the game they play. Quite a few researchers looked into the connections between motivation, interest, burnout and drop-out in (physical) sports. Silva (1990) reported a loss of interest, lack of desire and lack of caring about sport for burned out athletes. Which is interesting along with the finding by Bauckhage et al. (2012) who stated interest to be an underlying mechanism for churn. In line with self-determination theory propositions Bartholomew, Ntoumanis, Ryan, Bosch, and Thøgersen-Ntoumani (2011) showed, that athletes perceptions of need thwarting (frustration of needs) respectively need satisfaction predicted outcomes such as burnout or depression. Results from Lonsdale et al. (2009) as well as Cresswell and Eklund (2005) provide further evidence of a consistent and strong relationship between amotivation, intrinsic motivation and athlete burnout. Lonsdale et al. (2009) additionally proposed a link between athlete drop-out and burnout. The latter proposition was however not further examined. Sarrazin et al. (2002) filled this gap using structural equation modelling. They predicted the intention drop-out based on need satisfaction and a condensed index of self-determined motivation. The index was formed using weighted motivational regulations. That way more self-determined motivation forms added to the index and less self-determined motivation subtracted from the index. The intention to drop-out itself then predicted actual athlete drop-out 2 years later. This work serves as a basis for the current research, as this approach has yet to be adapted to the context of games and to be extended with the burnout concept. Due to a not insignificant loss of information when using an indexed form of self-determined motivation, I instead integrate all motivational regulations individually. This research is furthermore driven by the need for more generalizable feature sets for game analytics and contributes new knowledge to prior research by a quantitative understanding of the intention to churn that is based on psychological markers rather than behavioral attributes. Derived from findings of preceeding literature, the hypothesis of this mostly exploratory study are as following:

- H1: **Churn is predicted by low levels of self-determined motivation.** This includes low levels of intrinsic motivation and high levels of amotivation.
- H2: **Churn is predicted by low levels of need satisfaction.**
- H3: **Churn is predicted by higher levels of burnout.**
- H4: **Churn is predicted by lower levels of interest-enjoyment.** This represents a loss of interest, representative for reduced player activity.

3 Method

3.1 Use Case: League of Legends

League of Legends (LoL) (Riot Games, 2009) is a Multiplayer Online Battle Arena (MOBA) game (henceforth referred to as MOBAs). Players choose and control a single character ("champions") with special abilities and attributes. They fight on three lanes, as illustrated in Figure 2. The game genre needs players to compete in two teams of five against each other with the goal to strategically gain map control and succeed over the enemy team by destroying their base. MOBAs provide both cooperative (within teams) and competitive (between teams) content.

Figure 2: An illustrative map of League of Legends with additional information on lanes. Adapted from Williams (2017).

3.2 Participants

As multiple game genres and level of gamers were considered relevant, the survey was advertised on different specific platforms and forums (i.e. subreddit). Also professional teams were contacted directly. 383 participants (39%) completed the survey out of a total of 982 people that started the survey. 174 participants were excluded, due to not meeting data quality requirements. Participants were tested for data quality using a mixed approach containing instructed response items, direct data-quality questions, long-string analysis to detect answering schemes and an analysis of the comments. Additionally, two participants showing incomplete data sets were removed as well. The four remaining players of DOTA 2 were removed, since no statistical conclusions can be drawn sample sizes this small. This data cleaning procedure resulted in a total of 203 participants. 23 participants did report as women, 177 as men, three as non binary. Age ranged from 18 to 33 years of age (Mean [M] = 21.5 years, Standard Deviation [SD] = 3.6 years). 16 participants were considered to be competitive/professional and 187 to be recreational/non-professional gamers.

3.3 Procedure

Participants received a survey link for the online study, where they were first introduced to the study objective and informed that their responses would remain confidential. Both a consent form and basic demographic information were asked (gender, age, game played (i.e. DOTA, LoL)). Depending on which game was chosen, they were subsequently asked to answer multiple scales in relation to this game, namely the User Motivation

Inventory (UMI), Player Experience Need Satisfaction (PENS), Intrinsic Motivation Inventory (IMI) and well-being measures (Athlete Burnout Questionnaire, Vitality, Satisfaction With Life Scale, Positive and Negative Affect Scale). Next participants answered questions on their intention to quit. Right after participants were asked to indicate whether they are a competitive / professional player or a recreational / non-professional player. All questions included can be found in the appendix. The sequence of the questionnaires was held constant, while the item-order was randomized. At the end of the online survey, participants were asked to give reference whether they answered the questions conscientiously. Upon survey completion participants were given the opportunity to participate in a lottery to win one of five Amazon gift cards, with a value of 20 Euros each.

3.4 Measures

Likert-type scales were used across the whole questionnaire, unless otherwise stated. Likert-type scales require respondents to specify their level of agreement or disagreement on a symmetric scale for a series of items. Detailed descriptive statistics, coefficient alphas, omegas are shown in Table 2. All tables are attached in **Appendix A** and a complete overview of used scales can be found in **Appendix B**.

3.4.1 User Motivation Inventory (UMI)

Motivation and motivational regulations were assessed using the User Motivation Inventory (UMI), an 18 item , 7-point Likert-type measuring instrument rooted in Self-determination Theory (Brühlmann, Vollenwyder, Opwis, & Mekler, 2018). It differentiates six distinct motivation types alongside an assumed spectrum of self-determination: *amotivation* (α = .89) referring to a lack or absence of motivation and non self-determined behavior; extrinsic motivation that is further divided into 4 motivational regulations: *external regulation* (α = .78), *introjected regulation* (α = .79), *identified regulation* (α = .69), *integrated regulation* (α = .80). *Intrinsic motivation* (α = .84) as the most self-determined form of motivation yields behavior that is pursued for its own sake. Subscale items were averaged to form scores.

3.4.2 Interest-Enjoyment and Pressure-Tension

Both the interest-enjoyment (α = .86) and pressure-tension (α = .81) dimension that derive from playing a game were assessed using an adapted 12-item version of the Intrinsic Motivation Inventory (IMI) using a 7-point Likert-type scale (McAuley, Duncan, & Tammen, 1989; Ryan, Mims, & Koestner, 1983). To use these measures as outcomes of need satisfaction is in line with prior research (Ryan et al., 2006). Previous research has shown the interest-enjoyment dimension to be linked to core need satisfaction measures (Ryan et al., 2006), however less literature is available for the pressure-tension dimension. In regards to the negative aspects of well-being connected to low-self-determined behaviors, it was though regarded as potentially important. Subscale items were averaged to form scores.

3.4.3 Player Experience of Need Satisfaction

Need Satisfaction were measured using a condensed version of the Player Experience of Need Satisfaction (PENS) scale (Ryan et al., 2006). Originally the PENS is a 21-item, 7-point Likert-type scale instrument with five sub-scales. However only relatedness (α = .82), competence (α = .85), autonomy (α = .73) were included in our study, as those reflect core need satisfaction measures, relevant to self-determination theory. Relatedness accounts for a sense of connectedness with other players. Competence refers to feelings of effectance and autonomy defines as a sense of volition or willingness (Johnson et al., 2015). Subscale items were averaged to form scores. The resulting 10-item instrument found application in previous studies (e.g. (Neys et al., 2014)).

3.4.4 Well-being

To get an insight on how different motivations affect well–being and as a starting point for implementing potential interventions in–game to benefit players' different measures of well-Being are collected to measure different aspects of it. This ensures a broader image on possible relations to motivation.

Positive and Negative Affect (PANAS) Players of MOBA games are prone to experience pronounced positive and negative affect (Johnson et al., 2015; Tyack et al., 2016). The PANAS by Watson, Clark, and

Tellegen (1988) was employed to assess positive affect (PA) and negative affect (NA). Items were rated on a 5-point Likert-type scale. Watson et al. (1988) states, that high positive affect does account for the extent to which individuals feel enthusiastic, active and alert, are fully concentrated and enjoy the engagement. Low positive affect on the other hand is characterized by sadness and lethargy. The second, negative dimension of affect concludes the presence of distress and unpleasurable engagement with subsequent aversive mood states, such as anger, contempt, disgust, guilt, fear and nervousness. Low negative affect being described as a state of calmness and serenity. This might allow to gather diverse insights into the emotional experiences of players.

Vitality State level vitality (α = .90) was measured as a closeness measure to well–being. A 7-point Likert-type scale was used with the 8-item vitality scale by Ryan and Frederick (1997). The wording was changed slightly to match the survey context, e.g., “When I play *LoL* I feel alive and vital”. Individuals vary in their experience of vitality as a function of both physical influences and psychological factors. That is for example the degree that one is unburdened by external controls (Ryan & Frederick, 1997).

Athlete Burnout Questionnaire (ABQ) Although the ABQ (Raedeke & Smith, 2001) is a measure that has primarily found application in SDT related (physical) sport studies, its dimensions are conveniently adaptable to the context of E-sports. The slightly adapted questionnaire (through minor word substitution) covers the three five-item subscales: emotional/physical exhaustion (α = .88), reduced sense of accomplishment (α = .76) and devaluation (α = .75) on a 5-point scale (Almost never - Most of the time). An example for an adapted item would be: "I don’t care as much about my LoL performance as I used to." The questionnaire has found to be positively correlated to amotivation and negatively to enjoyment and intrinsic motivation. Item scores were averaged within a subscale. The scale was adapted based on a conducted exploratory and confirmatory factor analysis that showed a better fit. The details are noted within the results section.

Satisfaction with Life Scale (SWLS) To measure global life satisfaction, the Satisfaction with Life Scale (SWLS) was used (Diener, Emmons, Larsen, & Griffin, 1985). Satisfaction with life (α = .91)is considered to be a state variable, that represents according to Pavot and Diener (1993) " ... a judgmental process, in which individuals assess the quality of their lives on the basis of their own unique criteria...” (p. 164). The five-item measure is rated on a 7-point Likert-type scale instrument. A score of 20 represents neutrality on the scale (neither satisfied nor dissatisfied), low scores (5–9) are indicative of extreme dissatisfaction with life, whereas scores above 30 display high satisfaction (Pavot & Diener, 1993; Vassar, 2008). Subscale items were summed up to form scores as suggested by Diener et al. (1985).

3.4.5 Intention to Churn

The present study conceptualizes churn as an outcome of other motivational determinants and experience measures, that is concerned with measuring the amount of players leaving a game. Due to the cross-sectional nature of the study churn was assessed using a single survey item: "Have you ever thought about stopping playing LoL?", as assessed in preceeding literature (Brühlmann et al., 2018). More specifically this operationalization assesses the behavioral intention to churn rather than observed behavior. (Ajzen, 1985) postulates in the theory of reasoned action, that a person's intention to perform (or not) certain behavior is an immediate determinant of that action. The link of behavioral intentions to actual behavior found repeated support (e.g. Sarrazin et al., 2002; Wilson, Mathews, & Harvey, 1975).

4 Results

The sample distribution across the variable intention to churn indicated that three quarters (n = 153) have had an intention to churn at least once. 50 Participants did not indicate to have had an intention to churn. This distribution is shown in Table 1.

Table 1: Absolute and relative (in percentage) sample distribution across the variable "intention to churn"

	League of Legends Players
No-Churn	50 (25%)
Churn	153 (75%)
Total	203 (100%)

Meanwhile descriptive statistics indicate in general high levels for positive connoted attributes such as intrinsic motivation (M_{G1} (with intention to churn) = 5.45, M_{G2} (without intention to churn) = 6.04), Enjoyment (M_{G1} = 5.18, M_{G2} = 5.70), Competence (M_{G1} = 5.02, M_{G2} = 5.15) and Autonomy (M_{G1} = 5.05, M_{G2} = 5.47) or positive affect (M_{G1} = 38.83, M_{G2} = 40.68). Lower values were observable for more negatively connoted measures, namely all ABQ measures, Negative affect (M_{G1} = 22.85, M_{G2} = 19.30), tension (M_{G1} = 4.03, M_{G2} = 3.41) or amotivation (M_{G1} = 3.30, M_{G2} = 2.09) Together this speaks for a mostly positive experience of the game. Nonetheless distinct values across most questionnaire scales between the group with respectively without intention to churn were observable. The group with intention to churn achieved consistently lower positively and higher negatively connoted values. The inferential statistic results are structured into three different sections. First, I review and adapt the measurement model of the burnout measures, since these have not been applied to the gaming context yet. In a second step, I report correlations between self-report player experience measures to gain an initial insight into the data. Third, a logistic regression analysis was conducted and the most relevant predictors identified. Lastly, reasons for churning are identified based on qualitative responses. Descriptive statistics for all self-report measures are presented in Table 2 and correlations in Table 3.

4.1 Step 1: Measurement Model - Confirmatory Factor Analysis (CFA)

To test the measurement model of the ABQ scale a confirmatory factor analysis (CFA) was conducted. All items were specified to load on their designated factor, and the loading of the first item was constrained to one. Multivariate normality was not given (Mardia tests: ABQ: χ^2 = 1028.40, p < .001, Z_k = 7.10, p < .001), hence a robust Maximum Likelihood Estimation (MLR) method with Huber-White standard errors and a Yuan-Bentler based scaled test statistic was used. The conducted CFA revealed multiple items with loadings below .3. Regarding the ABQ scale this might be due to the somewhat different application context than traditional sports. Consequently Exploratory Factor Analysis (EFA) and parallel analysis were run in order to identify items with bad or cross-loadings. Items with low or cross-loadings were removed one item at a time from each construct with the lowest among the low factor loadings deleted first. The subsequent CFAs indicated a better fit than the original models (ABQ: χ^2 diff. = 224.82, BIC diff. = 1808.6, AIC diff. = 1788.65). Three items of the ABQ scale were excluded: Item 4 " It seems that no matter what I do, I don't perform as well as I should." (ABQ: Accomplishment) was excluded due to cross-loadings, item 11 "The effort I spend in LoL would be better spent doing other things." (ABQ: Devaluation) did not show any loadings above a set cutoff of .3. Item 15 "I have negative feelings towards LoL." (ABQ: Devaluation) loaded on the wrong factor and was therefore removed as well. The adapted scale was used within this analysis. All tables and figures are based on the adapted scale.

4.2 Step 2: Correlation Analysis

Overall, there were several significant correlations between motivation, experience and well-being measures. Noticeably the pattern of correlations within the motivational regulations supports the notion of a self-determination continuum, with amotivation being the least self-determined and intrinsic regulation the most self-determined form of motivation. Amotivation shows highly significant negative correlations with need satisfaction measures such as competence (r = -.26, p<.001) and autonomy (r = -.41, p<.001). Relatedness is correlated positively to the more self-determined forms of motivation but shows no significant correlation to neither amotivation nor external regulation. Both positive affect and other well-being measures (i.e. Vitality and Satisfaction with Life) show an increasingly positive correlation the more self-determined the motivation dimension is. The correlations suggest significant positive relations of all ABQ subscales with amotivation and significant negative relations with intrinsic motivation additionally the correlations appear increasingly negative the more self-determined the motivation form is. Need Satisfaction measures are significantly correlated to reduced sense of accomplishment (ABQ) and devaluation (ABQ). Only autonomy is correlated significantly with exhaustion (ABQ) (r = -.33, p<.001). The correlation patterns remained mostly similar for both groups with/without intention to churn, with some exceptions (see Figure 5 and Figure 4 in Appendix B). Differences worth noting were observable for amotivation (UMI) and the exhaustion (ABQ). For the latter, correlations were different for vitality, autonomy (PENS), relatedness (PENS), enjoyment (IMI), intrinsic motivation and external motivational regulation (UMI), where there were stronger negative relations observable for the churn group. Also the correlation between reduced sense of accomplishment (ABQ) and exhaustion (ABQ) is higher in the churn group. For amotivation (UMI) stronger negative correlations with more self-determined motivation (UMI) as well as need satisfaction (PENS) and well-being measures (Vitality, SWLS) were observable in the churn group. Also reduced sense of accomplishment (ABQ) and devaluation (ABQ) show stronger correlations to amotivation in the churn group. For group comparisons and analysis on group differences these groups should be roughly equal. Note that some differences might be attributed to the unequal sample size. Nonetheless, results should be interpreted with caution, even though procedures to ensure data quality were in place.

Although correlation analysis offers an initial insight into the relations of the variables in question, it displays only bi-variate correlations between the individual metrics. In regards to the entangled conceptualization of motivation, experience measures and intentional behavior, an accurate estimation of all parameters is challenging and problematic due to potential multicollinearity (Pastor, Barron, Miller, & Davis, 2007). Dichotomous variables such as "intention to churn" could be interpreted via point-biserial correlation coefficients but the information content would be rather limited.

4.3 Step 3: Logistic Regression Analysis

To test the predictive value of the assessed variables for a binary classification of player churn, logistic regression was used. Logistic regression is a well suited procedure for testing hypotheses about relationships between a categorical outcome variable and one or more continuous/categorical predictor variables. It has the benefit that it takes only a few statistical assumptions. The assumptions are that the dependent variable is categorical; that little or no multicollinearity is present among the independent variables and that the linearity between the link function $(log(p/(1-p))$ and independent variables in the logit model is given. Hence this method is well suited for the current use.

Model Selection The latent predictor variables were tested a priori to verify there was no violation of the assumption of multicollinearity. Excessive correlation among explanatory variables, can complicate the identification of an optimal set of explanatory variables for a statistical model, as true relationships among variables will be masked if explanatory variables are collinear. Hence upon building a model, predictors were excluded based on a stepwise "variable inflation factors" (VIF) selection. The predictors showing the highest collinearity (highest VIF) were removed first. Setting the VIF threshold = 5 led to the exclusion of the Enjoyment (IMI) predictor. The resulting reduction in collineartiy is shown in Table 4: VIF5. In a second step predictors were selected using a stepwise Akaike information criterion (AIC) procedure, that incorporates a penalty for each additional predictor included. Lower AIC fit indices indicate a better model fit to the data.

This procedure led to the following three-predictor logistic model (AIC = 199.9):

$$logit(churn) = -1.88 + (.28) * Amotivation(UMI) + (.86) * Exhaustion(ABQ) + (.28) * Devaluation(ABQ)$$

A BoxTidwell test indicated no violation of the assumption of the linearity between the link function and independent variables in the logit model.

Overall model evaluation In general a logistic model provides a better fit to the data if an improvement over the intercept-only model (Null Model) is existing. An improvement over this baseline is examined using the likelihood ratio (χ^2 = 34.76, p < .0001) and the Wald tests (χ^2 = 23.29, p < .0001). Both tests yield the conclusion, that the logistic model was more effective than the null model. Also the decrease in residual deviance (how well the response is predicted by the model when the predictors are included) in this model (Residual Deviance = 191.9) compared to Null Deviance (how well the response is predicted by the model with nothing but an intercept) (Null Deviance = 226.6), indicates that the model has a better fit, when predictors are included. Statistics for the overall model evaluation are shown in Table 5.

Statistical tests of individual predictors The statistical significance of individual regression coefficients (i.e.,β) is tested using the Wald χ^2 statistic. All statistics can be found in Table 5. The latent predictor variables Amotivation (UMI) and Exhaustion (ABQ) in the logistic regression analysis were found to contribute to the model, with Amotivation (UMI) (β = .28, SE β = .14, Wald χ^2 = 4.22, p <.05) and Exhaustion (ABQ) (β = .86, SE β = .32, Wald χ^2 = 7.15, p <.05.) Whereas Devaluation (ABQ) (β = .28, SE β = .06, Wald χ^2 = 3.36, p >.05) does not contribute significantly to the model. One might consider excluding this predictor. However the prediction accuracy (66.9 %) was lower with this exclusion and pseudo R^2 measures showed lower values (Cox and Snell R2= .143, Nagelkerke R2 = .212, McFadden R2 = .139). The test of the intercept merely suggests whether an intercept should be included in the model or not (Peng, Lee, & Ingersoll, 2002). For the present data set the unstandardized Beta weight for the Constant (β = -1.88, SE β = .61, Wald χ^2 = -3.09, p = >.01) suggested that the intercept should be included. The odds of a one unit increase in the predictor Amotivation (UMI) (e^{β} = 1.33), Exhaustion (ABQ) (e^{β} = 2.37), Devaluation (ABQ) (e^{β} = 1.33) were positively related to the log of the odds of a player having the intention to churn. This means in other words that a player having a one unit higher score in Exhaustion (ABQ) being 2.37 times more likely to have an intention to churn than a player with a one unit lower score, while the other variables in the model are held constant. The same train of thought is applicable to the other latent predictors.

Goodness-of-fit Statistics Goodness-of-fit statistics assess the fit of a logistic model against actual outcomes (i.e., whether a player has an intention to churn) other than before comparing it to the null model (Peng et al., 2002). One inferential test (Hosmer-Lemeshow goodness-of-fit test) and four descriptive measures (CoxandSnell, Nagelkerke, McFadden, McKelvey & Zavoina) were used to evaluate the fit. The inferential Hosmer-Lemeshow goodness-of-fit test ($\chi^{2(8)}$ = 26.15, p <.001) compares the observed and expected frequencies of events and non-events to assess how well the model fits the data. A small and in this case significant p-value means that the model shows a poor fit to the data. As stated by Kramer and Zimmerman (2007) a significant Hosmer-Lemeshow test does not necessarily mean that a predictive model is not useful. It is thereafter suggested that additional information needs to be considered such as overall number of participants, the observed and predicted probabilities within each decile, and adjunct measures of model calibration. Apart from the adjunct measures, explanations for this result regarding the Hosmer-Lemeshow test are discussed in the limitations section. Four supplementary descriptive measures of goodness-of-fit are presented in Table 5. The pseudo R^2 indices, CoxandSnell (R^2 = .157), Nagelkerke (R^2 = .233), McFadden (R^2 = .153) and McKelvey & Zavoina (R^2 = .343) respectively are variations of the R^2 concept. They however do not render the meaning of variance explained (Peng et al., 2002; Scott Long, 1997). The closest approximation of variance explained is McKelvey & Zavoina's R^2 whereas the others tend to strongly underestimate the "true" R^2 for a model with latent variables (Veall & Zimmermann, 1996). All-together they indicate a mediocre fit to the data.

Validation of predicted probabilities In addition to a classification table to document the validity of predicted probabilities (Table 6), Kendall's Tau-b, Goodman-Kruskal's Gamma, Somers's D statistic (Table 5) are used to describe association or agreement between predicted probabilities and actual outcomes. For the prediction a cutoff was set at 0.73. This threshold was deducted from a cost analysis, as indicated in figure Figure 3). Both the false positive rate and the false negative rate were given an equal weight of 100. An equal weight means that a possible false classification of a player who has the intention to churn is as strongly weighted as a player who is falsely classified as not having an intention to churn. One might choose to adapt this weighting choice, depending on interest. Say for example you want that all players with a potential intention to churn are classified as churners with an error rate close to zero. In that case you want a higher weight bound to the false negative rate than the false positive rate. According to the classification table with the cutoff set at 0.73, the prediction for players who were not having an intention to churn (76.0% correct) was more accurate than that for those who were (68.6% correct). The false positive rate (1-Specificity) was 24.0% and false negative rate (1-Sensitivity) was at 31.4%. The overall prediction correction was 70.4%, which states an improvement over the chance level of 62.9%. The area under the curve (ROC) shows an accuracy of .761, which would be considered to be "fair" at separating players with the intention to churn from those without (Metz, 1978). This classification is based on a training set that is exactly equal to the test set. There are different cross-validation (CV) (e.g. leave-one-out approach (LOOCV), validation set approach, k-fold approach) approaches that circumvent this problem. They function all similarly, namely by holding out a subset of the training observations from the fitting process, and then applying the statistical learning method to those held out observations. In this paper a 3 times (multiple conducted k-fold cross-validation) repeated 10-fold cross-validation approach was applied to the dataset. For K-fold CV, observations are divided into k groups of approximately equal size. K-1 groups are regarded as training sets, while the remaining group is set as validation set. This procedure is repeated k times, with the validation set being assigned to a different group each time. The test statistics are then estimated by averaging the k resulting values. Results show an accuracy = .737. This is representative of an average level of correct classifications of 73.7%. Cohen's kappa coefficient (k = .13) is indicating a rather low inter-rater reliability, though higher than by chance. Further measures of association such as the Kendall Tau - b statistic (Tau - b = .389), Goodman-Kruskal's Gamma (γ = .747) and Somer's D statistic (D_{yx} = .523) suggest that the relationship between the prediction and the actual response is medium to high.

In the following I quickly want to highlight why the k-fold approach was chosen over the other cross-validation methods. The validation set approach can be described as a single split of the data set into a training and a validation set of roughly equal size. While this approach is simple, it has the problem of high variability in the test error and a tendency to overestimate the test error rate for the model fit. The "leave-one-out" approach (LOOCV) refers to an n times repeated division of the data set into a training set with n-1 observation, and a validation set that contains only that remaining observation. The LOOCV approach introduces another problem that is related to high variance, because each training subset is almost identical in its set of observations (except for one observation). Hence, depending on how often (one or n times) a data set is split, there is a trade-off in either test error bias or variance. The K-fold cross-validation balances this bias-variance trade-off and suffers neither from disproportionate bias nor from very high variance. For more detailed information on this topic you may refer to James, Witten, Hastie, and Tibshirani (2013) and Venturini (2016).

4.4 Step 4: Qualitative Responses for Churn

Most participants of the study (n = 190) took their time to respond to an open question regarding the reason they do play respectively why they had the intention to churn. Many players stated that the game is fun or things like "It's a good time waster" (P23). 57 People related their gameplay to being with friends. The manner that friends were related to gameplay differed. Some players stated that they love both the game and especially so when playing with friends, as expressed in "It's fun to play and I love playing it with friends." (P16) or "I enjoy the time I spend playing LoL and I would otherwise spend less time with my friends." (P28). This speaks for a high impact of social bindings surrounding the game. This is especially true for players that regarded the gameplay itself not as enjoyable and friends as one of the only reason to play "Background activity for talking with friends. I would never play this game alone." (P50) or "Friends don't play anything else" (P102). This way play behavior does not seem to be intrinsically motivated, but rather integrated into the goal of being with friends. The latter "category" of players are also the ones that are potentially to be related to intention to churn like this player stated "I still enjoy playing the game with friends, but I now understand the importance of taking a break when the game is no longer enjoyable." (P29) or "Because the friend I used to play with doesn't play as often as he used to." (P38). Another major factor mentioned repeatedly for quitting a game was toxicity "It's very stressful and the player-base is super toxic if you don't play perfect. ARAMs [1] are less toxic but it is still there. I often find myself questioning why I like to play a game with such a bad community." Further mentioned were life balance and addiction. Some players described to be addicted to the game and or that they are in need of a better balance between the game and life. "... but, like most things, I feel absolutely miserable if I do nothing but league. I guess I've figured

[1] Note. ARAM (All Random All Mid) is a PvP game mode in League of Legends, played exclusively on the Howling Abyss map. Players are not given the ability to choose their champion and fight solely on the mid lane. See: http://2018.wesg.com/en/

out ways to balance my life." (P192) or "I was about to quit LoL when i realised i was giving too much importance to it. Now i play in a much more relaxed way, and i actually enjoy playing it. I guess you just have to keep the right mindset." (P188). This seems to be a struggle for some players "I would like to stop playing and have taken long breaks (months) at a time. The game distracts me from real life goals." (P137). 13 people mentioned addiction in their responses. Certainly there are multiple qualitative reasons to quit a game. Despite the focus on churn it should be noted that many players regarded their gameplay currently as enjoyable.

5 Discussion

5.1 General Discussion

The goal of this exploratory research was to examine the relations of motivations, well-being and other experience measures to the intention of churn with players of League of Legends. More precisely the purpose was to test a prediction model using said measures. This approach is novel in various ways. First, motivation is not modeled using behavioral measures, instead the Self-Determination Framework is used as a game-unspecific, robust measure for motivation for churn prediction. Second, a symptom-based burnout measure was incorporated into the study design as a means to explain consequences such as player churn. To my knowledge, Self-Determination Theory (SDT), Organismic-Integration Theory (OIT) and Burnout have received limited attention in regards to churn in the context of games. This paper uncovered several interesting findings both on the descriptive as on the inferential level. For better comprehensibility I first discuss findings on a descriptive level before elucidating the binomial logistic regression model. A first insight into the distribution of players who indicated an intention to churn versus players who did not indicate an intention to churn reveals that the phenomenon of churn might be much more common than thought initially. Three quarters of the assessed population of League of Legends players indicated to have had the intention to churn at least once. Where there are some limitations to the operationalization of churn in the current work (as discussed in the limitations section), this finding is nonetheless reflected in the assessed descriptive measures. In other words players having an intention to churn were distinguishable from those without that intention on a descriptive level. Players in the "Intention to Churn" group reported lower overall levels of self-determined motivation. This includes both lower levels of intrinsic motivation and higher levels of amotivation than players in the non-churn group, supporting Hypothesis 1 (H1). Within the extrinsic forms of motivation the two more self-determined forms integrated and identified regulations yielded higher values within the group without intention to churn, while the less self-determined forms introjected and external regulations were higher for the churning group. This pattern although new in games research is in line with expectations. Preceeding work in sport psychology showed similar results (Sarrazin et al., 2002). The group with intention to churn also reported less interest and enjoyment (IMI) in conjunction to higher perception of tension (IMI). Hence players in the "Intention to Churn" group tend to derive less pleasure and more pressure in playing the game, supporting Hypothesis 4 (H4). When considering that player interest might reflect player activity (Bauckhage et al., 2012), the lower levels of interest and enjoyment (IMI) are indicative of reduced player activity in the group with intention to churn. For need satisfaction only a slight difference is observable for both groups in the perception of competence however the remaining need satisfaction constructs, namely Relatedness and autonomy show greater discrepancies between groups, with their respective values being lower in the churning group. This endorses Hypothesis 2 (H2). Deterding (2016) pointed out that autonomy defined as "perceiving oneself as the causal origin of one's actions" might provide a well-established construct for "voluntariness". The lower levels of autonomy experienced by the churning group do speak for less voluntariness in their gameplay. Previous evidence showed that forced game (or non voluntary) play results amongst others in negative affect (Heeter, Lee, Magerko, & Medler, 2011). Indeed players with intention to churn derive less positive but more negative affect than the non-churning group. Additionally Bartholomew et al. (2011) showed that athletes perceptions of "need thwarting" more consistently predicted outcomes such as burnout or depression. This is also consistent with current results, with the "Intention to Churn" group showing higher levels on all sub-dimensions of burnout and lower levels of well-being in general as indicated by Vitality and Satisfaction with Life Scale (SWLS). The differences in the ABQ scores signal support for Hypothesis 3 (H3). Taken together, the two profiles show that having an intention to churn is associated with overall more negative experiences, less self determined motivation, less need satisfaction and lower well-being. This is a contrast to the still very prominent belief that games are solely gratifying and pleasurable (Przybylski et al., 2010) and is concerning in extension to the discussion on MOBAs and their capability to induce both positive and negative experiences (Johnson et al., 2015). It raises the question whether or not gameplay for the majority of players of LoL might be considered to be a negative experience. Meanwhile, open responses indicated a mostly enjoyable gameplay experience. This difference might be explained via a social component of playing LoL. Many players relate their gameplay to being with friends and as such playing LoL is integrated into the goal of being with friends. Hence, while playing LoL itself might not be an intrinsic motivated activity, being with friends might be. This in turn may trigger some controversy within the perception of ones gameplay. While social factors were previously identified to be a major factor in player retention (Tyack et al., 2016) it is up to future research to further discuss this discrepancy between qualitative and quantitative data. Using binomial logistic regression and a stepwise Akaike information criterion (AIC) procedure, I identified Amotivation (UMI), Exhaustion (ABQ) and Devaluation (ABQ) to be the three major latent predictors for the intention to churn. A one unit increase in the score of Exhaustion (ABQ) increases the likelihood for intention to churn by the factor 2.36 (times). Exhaustion seems hence to be the strongest predictor of the identified set. For both Amotivation (UMI) and Devaluation (ABQ) a one unit increase on their respective scales equals out to an increased likelihood of 1.33 (times) with Devaluation (ABQ) being a non-significant predictor. Players without intention to churn were predicted correctly in 76.0% of the cases and those with the intention to churn in 68.6% of the cases. The model surpasses the level of chance (62.9%) with an overall prediction correction of 70.4%. A three times conducted 10-fold Cross-Validation indicated an even slightly higher correct classification rate of 73.7%. While this model is by no means carved into stone, and it does not outperform computational models, the reduction to these specific latent predictors is none the less very interesting. For one, it supports the importance of motivation and burnout as key factors in understanding churn behavior. Motivation was derived previously from behavioral patterns such as activity (e.g. Rothenbuehler et al., 2015) to predict churn. This form of assessement makes it however unclear the actual connections between self-reported player motivation and churn are. This work highlights that (self-reported) low self-determined motivation is related to intention to churn in LoL players. Unfortunately, no statements can be made about the relationship between motivation and player activity prior to churn. Preceeding literature proposed that players reduce their activity levels prior to churning (Borbora & Srivastava, 2012). Given the findings on higher Amotivation (UMI) increasing the likelihood for intentional churn, one would hypothesize that higher Amotivation (UMI) might stand in relation to reduced activity levels. While this relationship is subject to future research, SDT motivation might be used as an underlying model for player activity. Burnout on the other hand is a fairly new concept in relation to games. The logistic regression implies that especially the sub-dimension of

Exhaustion (ABQ) might be a core measure of well-being, that is closely related to intentional player churn. It is reasonable to assume that higher levels of Exhaustion (ABQ) and Devaluation (ABQ) are related to the aforementioned reduction of activity prior to churn.

Taken together, the model and its performance demonstrate that player churn can be considered to be a negative outcome rooted in less self-determined motivation and low well-being such as burnout, supporting hypothesis 1 (H1) "Churn is predicted by low levels of self-determined motivation" and partially hypothesis 3 (H3) "Churn is predicted by higher levels of burnout". These findings are consistent with inspected sport literature proposing the link between burnout and drop-out (Lonsdale et al., 2009) as well as the link between motivation and drop-out (Sarrazin et al., 2002). The model sheds some light on motivational, experiential and well-being aspects of churning players and as such proposes an alternative to computational behavioral approaches. As such, this work might facilitate future research on a self-report measure approach for churn prediction. Not all assessed measures found application within the logistic regression prediction model, hence not all hypothesis could be accepted in this exploratory study. One might want however consider that the hypothesis are nonetheless reflected in the descriptive data such as that **H1**: lower levels of intrinsic motivation can be found in the churning group; **H2**: the churning group is reporting overall lower levels of need satisfaction; **H3**: players with intention to churn have more reduced sense of accomplishment; **H4**: churning players achieve lower scores on the interest-enjoyment dimension. Hypothesis 4 (H4) is further discussed in the limitations section.

5.2 Limitations

There are several limitations to this study that are worth noting. The sample size to perform a logistic regression analysis is rather small in, although a recommended minimum ratio of observations to predictors of 10:1 is fulfilled (Peng et al., 2002; Lawley & Maxwell, 1973). The method of logistic regression was regarded to be best suited due to neither requiring a linear relationship between the dependent and independent variables nor to be normally distributed. The unequal sample distribution remains however a problem to some model evaluative measures such as the Hosmer-Lemeshow test, that would ideally require each group to have an equal number of observations (Peng et al., 2002). This might amongst others be an explanation for the poor model fit indicated by this test. Another point of discussion would be multicollinearity. The used constructs (i.e. motivation, well-being, enjoyment etc.) are often highly correlated in Self-determination Theory literature (e.g. Brühlmann et al., in press 2020), the same can be seen in the correlation analysis. Checking for multicollinearity prior to the logistic regression analysis revealed only Interest-Enjoyment (IMI) to have high multicollinearity as indicated by VIF. This exclusion is however very unfortunate as it prevents the examination of Hypothesis 4 (H4) "Churn is predicted by lower levels of interest". This would have been of great importance, as it was proposed previously that interest might be the underlying mechanism for player activity (Bauckhage et al., 2012), with player activity itself being one of the most prominent factors for churn prediction. Another limitation is that due to the already high complexity of model selection and the exploratory nature of the study, it was not appropriate to further complicate the the model by including interaction terms. This limits the meaningfulness of the present results. Considering the potential over-fit of the present data it was a necessary cutback on complexity.

Future research might look into interaction effects by only including the proposed reduced set of predictors. As mentioned beforehand the original focus of this paper was different from predicting churn, hence churn had only been of peripheral interest. This however raises some concern, when looking into the operationalization of churn in the current analysis. Intention to churn was asked using a single item: "Have you ever thought about stopping playing LoL?". One problem is rooted in the single item nature of churn, since single item measures are vulnerable to reliability issues (Wanous, Reichers, & Hudy, 1997). This is especially true as the intention to churn may or may not be linked to actual behavior (Sarrazin et al., 2002; Przybylski et al., 2010). For future research one might consider also rewording this item towards a more recent time frame (i.e. "Have you thought about stopping playing LoL in the last X days or weeks") , which might be an explanation in the current study why the intention to churn rate is very high. Matching the time frame of the churn item with the one of the predictors will likely result in a better fitting logistic regression model, where observed and expected frequencies of events and non-events are more congruent (Hosmer & Lemeshow GoF test). Further support for this is given by the open questions regarding churn. More people seem to currently have a joyful experience as would be expected by the the intention to churn rate. Alternatively the framework of reasoned action provides further possibilities for future research regarding the assessment of intention to churn. The theory specifically proposes a model using "behavioral beliefs", "outcome evaluation", "normative beliefs" and "motivation to comply" as latent predictors to asses behavioral intentions (Vallerand, Deshaies, Cuerrier, Pelletier, & Mongeau, 1992; Ajzen, 1985).

6 Conclusion

Prior works have provided several approaches to predicting player behaviour trends. Many of them are already able to provide promising prediction performance. None has however picked up the concepts of motivational regulations, burnout and other experience measures to predict churn. I present the results of a theory-driven exploratory approach towards understanding and predicting player churn in MOBAs (*LoL*). Using binomial logistic regression modelling I identify amotivation (UMI), exhaustion (ABQ) and devaluation (ABQ) to be predictors of player churn. Regarding the performance of the proposed logistic regression model, one might consider this work to be a solid basis for future prediction approaches and an alternative to computational behavioral approaches. The results shed light on the connections between churn and psychological predecessors, which might be of great value for informed retention strategy design in practice.

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Appendix A

Table 2: Means (M), standard deviations (SD), medians (Mdn), Cronbach's α, and hierarchical omega (ω) for all self-report measures. Group 1: With intention to churn, Group 2: Without intention to churn

	M	**SD**	**Mdn**	α	ω	**M(SD)** GROUP 1 N=153	**M(SD)** GROUP 2 N=50
UMI							
Intrinsic	5.59	1.18	5.67	0.84	0.85	5.45 (1.25)	6.04 (0.78)
Integrated	3.06	1.45	3.00	0.80	0.81	2.99 (1.48)	3.29 (1.36)
Identified	3.57	1.36	3.67	0.69	0.62	3.52 (1.36)	3.75 (1.35)
Introjected	2.16	1.36	1.67	0.79	0.80	2.19 (1.35)	2.05 (1.38)
External	1.86	1.15	1.33	0.78	0.78	1.89 (1.20)	1.76 (0.99)
Amotivation	3.00	1.73	2.67	0.89	0.89	3.30 (1.75)	2.09 (1.32)
IMI							
Interest-Enjoyment	5.30	1.06	5.43	0.86	0.88	5.18 (1.11)	5.70 (0.75)
Tension	3.88	1.31	3.80	0.81	0.81	4.03 (1.25)	3.41 (1.37)
PANAS							
Positive Affect	39.29	11.81	38	0.88	0.87	38.83 (12.05)	40.68 (11.03)
Negative Affect	21.98	8.31	21	0.82	0.77	22.85 (8.56)	19.30 (6.90)
PENS							
Relatedness	4.16	1.59	4.33	0.82	0.84	4.08 (1.59)	4.43 (1.58)
Competence	5.06	1.29	5.00	0.85	0.86	5.02 (1.31)	5.15 (1.25)
Autonomy	5.15	1.15	5.25	0.73	0.75	5.05 (1.18)	5.47 (0.97)
Vitality	4.21	1.35	4.29	0.90	0.90	4.11 (1.40)	4.49 (1.17)
ABQ							
Accomplishment	2.93	0.89	3.00	0.76	0.78	3.02 (0.90)	2.65 (0.80)
Exhaustion	2.00	0.88	1.80	0.88	0.88	2.16 (0.90)	1.50 (0.57)
Devaluation	2.78	1.30	2.67	0.75	0.76	2.96 (1.31)	2.25 (1.11)
SWLS	3.79	1.68	3.80	0.91	0.91	3.71 (1.71)	4.04 (1.59)

Table 3: Bivariate correlations between subscales. * p< .05, ** p< .01, *** p< .001

	UMI AMO	EXT	INJ	IDE	INT	IMO	**IMI** ENJ	TENS	**PANAS** PA
UMI									
AMO	1								
EXT	0.27 **	1							
INJ	0.19 **	0.22 **	1						
IDE	−0.35 ***	0.06	0.39 ***	1					
INT	−0.23 ***	−0.02	0.42 ***	0.75 ***	1				
IMO	−0.57 ***	−0.11	0.02	0.47 ***	0.41 ***	1			
IMI									
ENJ	−0.60 ***	−0.15	0.00	0.48 ***	0.40 ***	0.88 ***	1		
TENS	0.29 ***	0.21 **	0.27 ***	0.03	0.06	−0.13	−0.14	1	
PANAS									
PA	−0.40 ***	−0.14	0.19 **	0.53 ***	0.54 ***	0.57 ***	0.64 ***	0.01	1
NA	0.38 ***	0.25 **	0.35 ***	0.03	0.06	−0.19 *	−0.24 **	0.57 ***	0.09
PENS									
REL	−0.12	0.11	0.24 ***	0.37 ***	0.40 ***	0.27 ***	0.35 ***	−0.08	0.30 ***
COM	−0.26 ***	−0.12	0.13	0.35 ***	0.35 ***	0.41 ***	0.40 ***	−0.21 **	0.38 ***
AUT	−0.41 ***	0.03	0.14 *	0.45 ***	0.40 ***	0.63 ***	0.66 ***	−0.23 **	0.46 ***
VITALITY	−0.36 ***	−0.07	0.23 **	0.63 ***	0.63 ***	0.61 ***	0.63 ***	−0.05	0.71 ***
ABQ									
ACC	0.43 ***	0.14	−0.11	−0.49 ***	−0.45 ***	−0.41 ***	−0.47 ***	0.23 **	−0.47 ***
EXH	0.59 ***	0.28 **	0.22 **	−0.10	−0.01	−0.44 ***	−0.47 ***	0.39 ***	−0.20 *
DEV	0.31 ***	0.11	−0.13	−0.34 ***	−0.24 ***	−0.33 ***	−0.44 ***	0.01	−0.34 ***
SWLS	−0.32 ***	−0.10	−0.01	0.14	0.12	0.27 ***	0.27 ***	−0.14	0.30 ***

	PANAS NA	**PENS** REL	COM	AUT	**VITALITY**	**ABQ** ACC	EXH	DEV	**SWLS**
PENS									
REL	−0.03	1							
COM	−0.09	0.29 ***	1						
AUT	−0.17 **	0.43 ***	0.43 ***	1					
VITALITY	−0.06	0.37 ***	0.42 ***	0.52 ***	1				
ABQ									
ACC	0.20 **	−0.38 ***	−0.57 ***	−0.40 ***	−0.45 ***	1			
EXH	0.46 ***	−0.08	−0.13	−0.34 ***	−0.26 **	0.32 ***	1		
DEV	0.13	−0.19 **	−0.19 **	−0.31 ***	−0.30 ***	0.34 ***	0.38 ***	1	
SWLS	−0.07	0.18 *	0.20 **	0.29 ***	0.31 ***	−0.31 ***	−0.20 **	−0.15 *	1

Table 4: Collinearity amongst predictor variables as indicated by VIF values (Pre VIF). And VIF collinearity values after setting VIF treshhold = 5 (VIF = 5).

	UMI						**IMI**		**SWLS**
	IMO	INT	IDE	INJ	EXT	AMO	ENJ	TENS	
Pre VIF	4.88	2.91	3.06	1.62	1.29	2.39	6.43	1.75	1.29
VIF = 5	2.60	2.89	3.06	1.60	1.29	2.36	-	1.73	1.28

	PENS			**PANAS**		**Vitality**	**ABQ**		
	REL	COMP	AUT	PA	NA		ACC	EXH	DEV
Pre VIF	1.48	1.76	2.26	2.93	1.98	3.17	2.23	2.21	1.49
VIF = 5	1.44	1.75	2.16	2.72	1.95	3.16	2.22	2.21	1.44

Table 5: Logistic Regression Analysis of 203 League of Legends Players for the Intention to Churn

Predictor	Coef β	SE β	Wald χ^2	df	p	e^β (odds ratio)
Constant	-1.88	.61	-3.09	1	<.01	
Amotivation (UMI)	.28	.14	4.22	1	.04	1.33
Exhaustion (ABQ)	.86	.32	7.15	1	.01	2.37
Devaluation (ABQ)	.28	.06	3.36	1	.07	1.33

Test			χ^2	df	p	
Overall model evaluation						
Likelihood ratio test			34.76	3	<.0001	
Wald test			23.29	3	<.0001	
Goodness-of-fit test						
Hosmer & Lemeshow			26.15	8	<.001	

Note. Pseudo R^2: Cox and Snell R^2 = .157. Nagelkerke R^2 = .233. McFadden R^2 = .153. McKelvey & Zavoina R^2 = 0.343. Goodness-of-fit: Somers's D_{yx} = .523. Kendall's Tau-b = .389. Goodman-Kruskal Gamma = .747.

Table 6: The Observed and the Predicted Frequencies for Player Churn by Logistic Regression with a Cutoff of 0.73

	Predicted			
Observed	No	Yes	% Correct	Cohen's Kappa k
No	38	12	76.0	
Yes	48	105	68.6	
Overall % correct			70.4	
3 x 10-fold CV accuracy			73.7	.13
Expected % correct by chance			62.9	

Note. Sensitivity = 105/(105+48) = 68.60%. Specificity = 38/(12+38) = 76.00%. False positive rate = 12/(12+38) = 24.00%. False negative rate = 48/(48+105) = 31.40%.

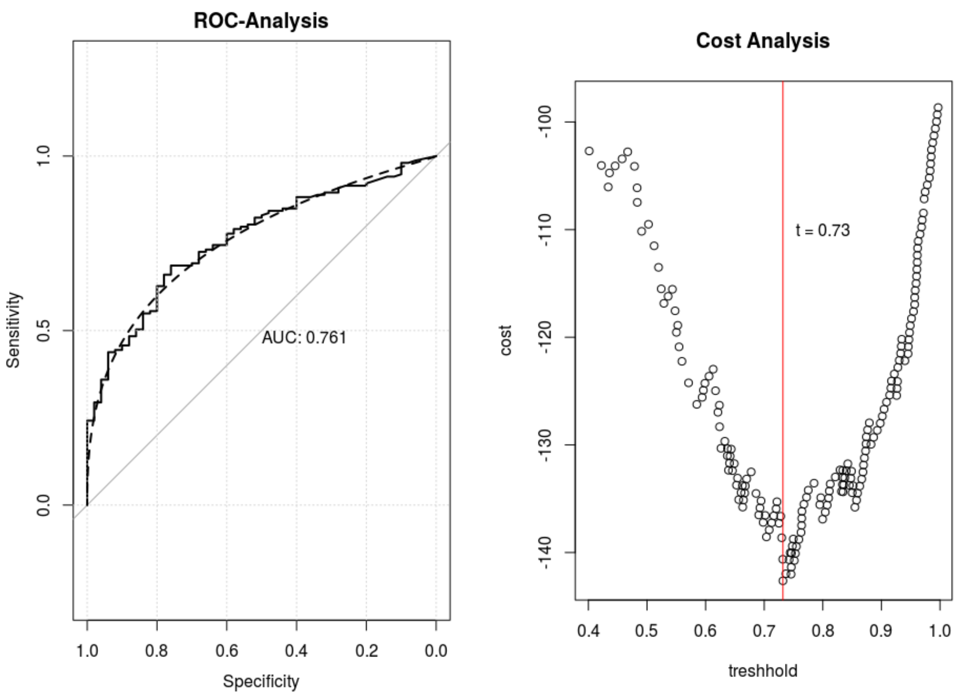

Figure 3: Roc Analysis and Cost Analysis for the Logit Funktion

Appendix B

Appendix B contains all supplementary plots or tables that might give further insight into the data. Also an overview of all questionnaire items is included.

Korrelationmatrix

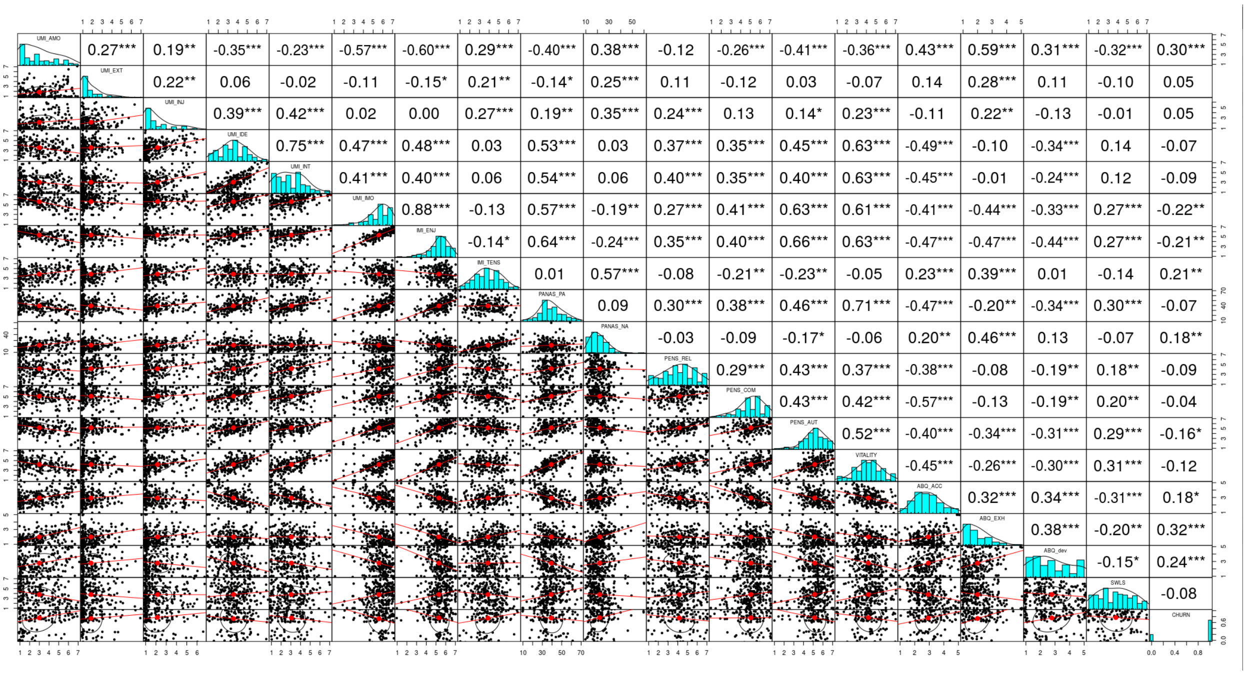

Figure 4: Correlation matrix and distribution table for the entire dataset.

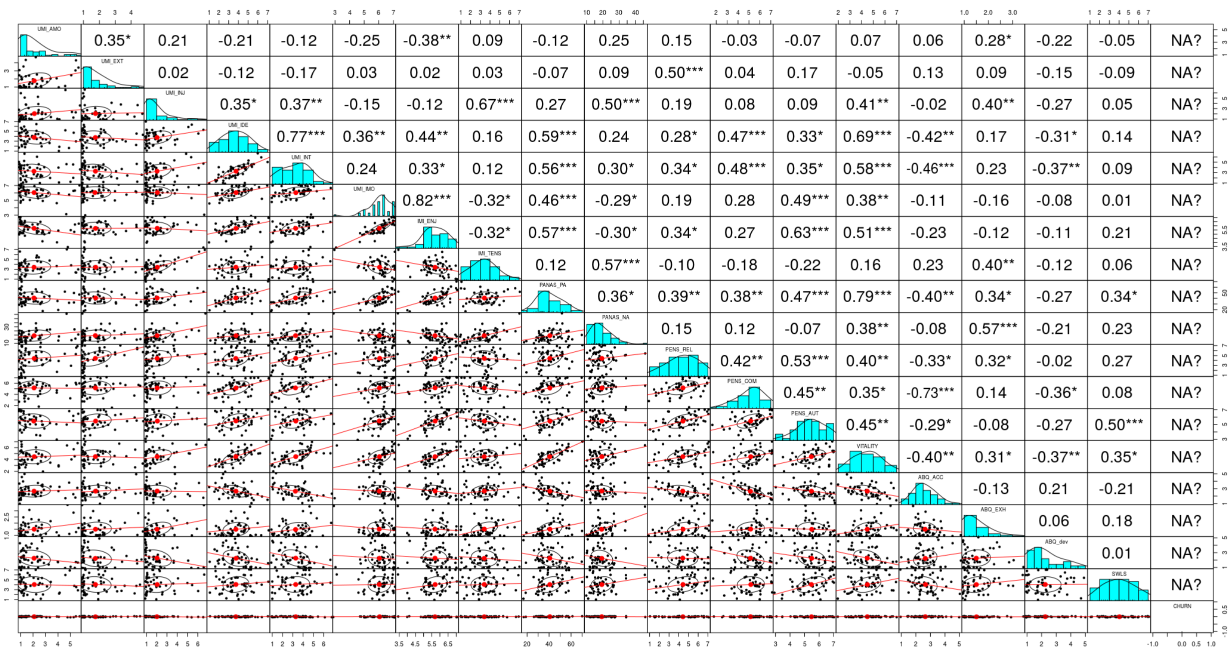

Figure 5: Correlation matrix and distribution table for the no-churn subsample.

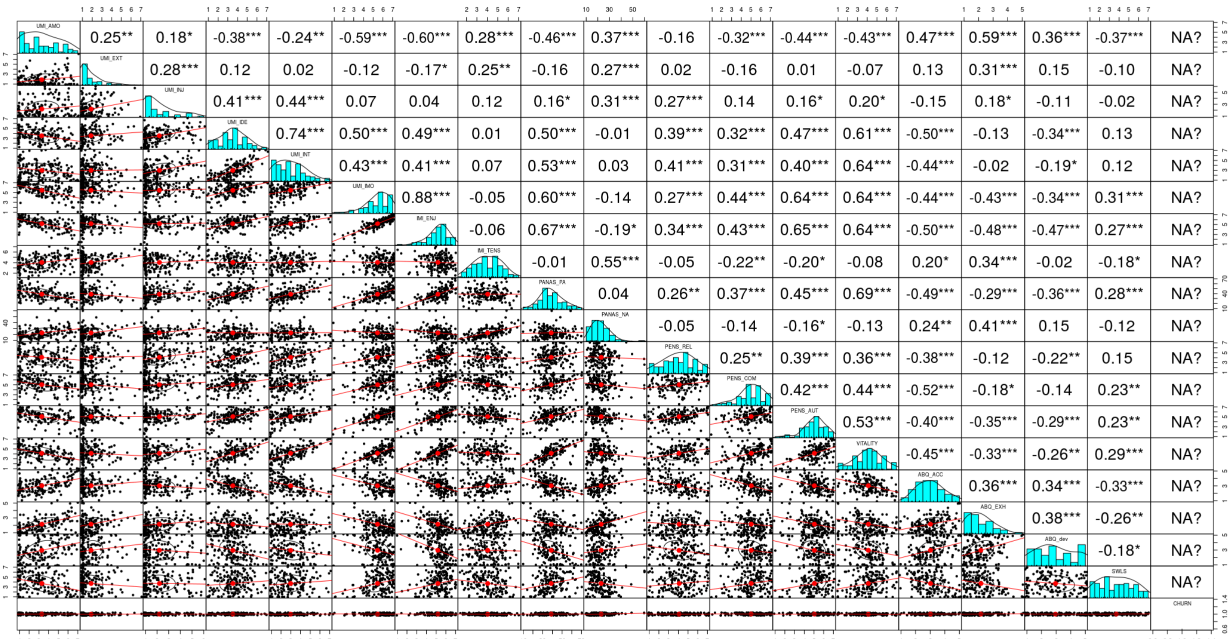

Figure 6: Correlation matrix and distribution table for the churn subsample.

Questionnaire Items

UMI

Variable Name	Dimension	Question / Statement Formulation
UMI_1	AMO	I play LoL but I question why I continue to play it.
UMI_2	AMO	I play LoL, but I wonder what is the point in playing it.
UMI_3	AMO	I play LoL, but I don't see why I should keep on bothering with it.
UMI_4	EXT	Other people will be upset if I don't play LoL.
UMI_5	EXT	I play LoL because others will not be pleased with me if I don't.
UMI_6	EXT	I feel under pressure from others to play LoL.
UMI_7	INJ	I would feel bad about myself if I quit LoL.
UMI_8	INJ	I would feel guilty if I quit playing LoL.
UMI_9	INJ	I would feel like a failure if I quit playing LoL.
UMI_10	IDE	Playing LoL is a sensible thing to do.
UMI_11	IDE	The benefits of playing LoL are important to me.
UMI_12	IDE	Playing LoL is a good way to achieve what I need right now.
UMI_13	INT	I play LoL because it reflects the essence of who I am.
UMI_14	INT	Playing LoL is consistent with my deepest principles.
UMI_15	INT	I play LoL because it expresses my values.
UMI_16	IMO	I play LoL because it is enjoyable.
UMI_17	IMO	I think playing LoL is an interesting activity.
UMI_18	IMO	Playing LoL is fun.

IMI

Variable Name	Dimension	Question / Statement Formulation
IMI_1	ENJ	I enjoy playing LoL very much.
IMI_2	ENJ	Playing LoL is fun.
IMI_3	ENJ	I think playing LoL is boring.
IMI_4	ENJ	Playing LoL does not hold my attention at all.
IMI_5	ENJ	I would describe playing LoL as very interesting.
IMI_6	ENJ	I think playing LoL is quite enjoyable.
IMI_7	ENJ	While playing LoL, I think about how much I enjoy it.
IMI_8	TENS	I do not feel nervous at all while playing LoL.
IMI_9	TENS	I feel very tense while playing LoL.
IMI_10	TENS	I am very relaxed while playing LoL.
IMI_11	TENS	I am anxious while playing LoL.
IMI_12	TENS	I feel pressured while playing LoL.

PANAS

This questionnaire is not included in the appendix due to impracticality of displaying the extensive amount of adjective pairs.

PENS

Variable Name	Dimension	Question / Statement Formulation
PENS_1	COMP	I feel competent at LoL.
PENS_2	COMP	I feel very capable when playing.
PENS_3	COMP	My ability to play LoL is well-matched with its challenges.
PENS_4	AUT	LoL provides me with interesting options and choices.
PENS_5	AUT	I could always find something interesting in LoL to do.
PENS_6	AUT	I did things in LoL just for the fun of it.
PENS_7	AUT	I experienced a lot of freedom in LoL.
PENS_8	REL	I find the relationships I form in LoL fulfilling.
PENS_9	REL	I find the relationships I form in LoL important.
PENS_10	REL	I don't feel close to other players, who also play LoL.

Vitality

Variable Name	Dimension	Question / Statement Formulation
VITALITY_1	-	When I play LoL I feel alive and vital.
VITALITY_2	-	I don't feel very energetic when I play LoL.
VITALITY_3	-	When I play LoL sometimes I am so alive I just want to burst.
VITALITY_4	-	When I play LoL I have energy and spirit.
VITALITY_5	-	When I play LoL I look forward to each new day.
VITALITY_6	-	When I play LoL I nearly always feel awake and alert.
VITALITY_7	-	I feel energized when I play LoL.

ABQ

Variable Name	Dimension	Question / Statement Formulation	Discontinued (Y/N)
ABQ_1	ACC	I'm accomplishing many worthwhile things in LoL.	
ABQ_2	ACC	I am not achieving much in LoL.	
ABQ_3	ACC	I am not performing up to my ability in LoL.	
ABQ_4	ACC	It seems that no matter what I do, I don't perform as well as I should.	Y
ABQ_5	ACC	I feel successful at LoL.	
ABQ_6	EXH	I feel so tired from playing LoL that I have trouble finding energy to do other things.	
ABQ_7	EXH	I feel overly tired from my LoL participation.	
ABQ_8	EXH	I feel "wiped out" from LoL.	
ABQ_9	EXH	I feel physically worn out from LoL.	
ABQ_10	EXH	I am exhausted by the mental and physical demands of LoL.	
ABQ_11	DEV	The effort I spend in LoL would be better spent doing other things.	Y
ABQ_12	DEV	I don't care as much about my LoL performance as I used to.	
ABQ_13	DEV	I'm not into LoL like I used to be.	
ABQ_14	DEV	I feel less concerned about being successful in LoL than I used to.	
ABQ_15	DEV	I have negative feelings toward LoL.	Y

SWLS

Variable Name	Dimension	Question / Statement Formulation
SWLS_1	-	In most ways my life is close to my ideal.
SWLS_2	-	The conditions of my life are excellent.
SWLS_3	-	I am satisfied with my life.
SWLS_4	-	So far I have gotten the important things I want in life.
SWLS_5	-	If I could live my life over, I would change almost nothing.

Churn / Quitting Behavior

Variable Name	Dimension	Question / Statement Formulation
CHURN	-	Have you ever thought about stopping playing LoL?
CHURN_OPEN	-	Please explain why you continue to play LoL, or why you want to stop playing.

Appendix C

A full documentation of the R code used in this master's thesis and the anonymous survey data of this study can be accessed under the following link:
https://drive.google.com/open?id=1a-D5xwpunMiiGWTJH3L3Z8ujoMQLCivK.