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MSc in Economics and Business
Master Thesis

Customer Defection Prediction in the Entertainment Product Industry: The Role of Product Usage Motivations in Defection Decisions

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Foreword

With this thesis, the final part of my master study is finished. Although it has been a long, and at sometimes even frustrating process, it was also one of the most instructive and interesting tasks during my bachelor and master studies. Not only did I learn a lot about performing academic research, I also gained new insights in my own interests. I will consult this new knowledge during all of the choices I will face in the future. All of this would not been possible without the help of certain people, which I would like to thank through this channel.

First of all, I would like to thank my supervisor, Vijay Hariharan, for motivating me by continuously extending my ideas, suggesting possible options and improvements for data transcription and analysis methods and for always showing interest in the topic.

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Finally, I would like to thank my parents. For offering me the opportunity to go to university, for supporting me throughout my studies, offering help when needed, for offering constructive feedback and for always showing interest in my choices. I will always strive to make you proud. Thank you for always being there for me.

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Abstract

Customer relationship management (CRM) is an increasingly important issue in competitive markets. One of the most important aspects of CRM is increasing customer retention. Within the entertainment product industry, several factors seem to motivate consumers in their product usage: habits, extrinsic rewards, immersion and product mastery. The current study introduces a fifth feature: social interaction. While prior research has identified factors affecting customer defection in many industries, the role of product usage motivations are not studied. The primary goal of the thesis is to bridge the gap between customer defection prediction literature and product usage literature, by proposing a defection prediction model using the factors of product usage motivation.

Data on actual product usage is obtained from a novel dataset containing usage and defection decisions of consumers of a popular online game. Using logistic regression, the effect of these product usage features on consumer defection is tested. The results suggest that (the lack of) product usage habits and social interaction are the most important predictors of customer defection. Product mastery and reward seeking are also factors that show predictive power, however these effects seem to be mediated by product usage habits.

Managerial insights are provided based on these results and prior literature, which are applicable to a broad range of product categories within the entertainment industry.

Keywords: *Customer Defection, Customer Relationship Management, Logistic Regression, Online Gaming, Product Usage*

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1. Introduction

As markets evolve and become mature, Customer Relationship Management is becoming increasingly important. It seems acquiring a new customer is five times as costly as retaining an old one (Fornell & Wernerfelt, 1988). Rosenberg and Czepiel (1984) even mention that an average company spends $118 to acquire a new customer, while the costs to keep a current customer satisfied are $20. Therefore, it is highly attractive to increase efforts of enhancing the relationship with current customers, instead of competing for new ones with competitors. However, to be able to manage customer retention, companies will need an effective and accurate customer-defection model (Coussement & Van den Poel, 2008). One way to increase loyalty to the product is to offer consumers incentives for a higher rate of product usage (Nevskaya & Albuquerque, 2012). When using a product –especially entertainment products – consumers experience certain factors that motivate their product usage. Nevskaya and Albuquerque (2012) describe these factors as habit formation, complexity of tasks, usage mastery and extrinsic rewards. Though studies have been conducted that use these factors to describe product usage (Douglas & Hargadon, 2000) and test their effect on product adoption (Shang et al.,2005), no studies exist that explore the effect of these factors on actual customer defection. My study attempts to close the gap between customer defection research and product usage research. Furthermore, literature on online game behavior mentions another factor that is not described in product usage literature: social interaction among consumers (Debeauvais et al., 2011). My study attempts to introduce this social factor to the intrinsic product usage motivations, as well as test its effect on customer defection.

To explore the effect of the factors on customer churn, my study will empirically test the factors using a panel dataset from the online game 'World of Warcraft'. Using data from online gaming is an appropriate method, as online gaming has become one of the most popular uses of the internet (Chen et al., 2005). Studies even show that more than 50% of internet users are also online gamers, making the online gaming industry worth approximately $8 billion by 2014 (Lee et al., 2011). The business model of online game developers hugely relies on players buying subscriptions to be able to play the game, or to get access to a larger part of the game (Alves & Roque, 2005). For game developers, gamers leaving the game (which means they unsubscribe or do not renew their subscription) directly affect their profits (Tarng, Chen & Huang, 2009). A model which can predict a game player's intentions of leaving or continuing the game would therefore benefit developers greatly, as such a model would give insights in the most important factors affecting defection decisions. By using these insights, remedial actions can be taken. To the best of my knowledge there are no studies estimating such models with intrinsic usage motivations in online gaming yet. Tarng, Chen and Huang (2009) have done a short study on the predictability of gamers leaving the game, but do not estimate a clear model, nor do they uncover factors influencing a customer's intentions. Debeauvais, Schiano and Ducheneaut (2011) use weekly play time and the duration of the relationship with the firm as predictors. Product usage motivations are not found in literature on retention in online gaming. The results of this study are applicable to other entertainment industries outside online gaming, such as television series, computer software, smartphone applications and leisure activities (Nevskaya & Albuquerque, 2012).

In my thesis, my goal is to estimate the proposed model in order to find factors which influence a consumer's intentions about leaving the product. I expect 'defectors' to show similar patterns of behavior in their product usage, which indicate a defection in the near future. Managers can use the results to identify consumers intending to leave the product and try to change the consumer's mind by making him or her special offers.

The main research question will be:"Can customers' intentions to defect from a product be predicted based on product usage behavior?"

Several questions will be researched to assist in answering the main question.

- "Why do companies put effort in Customer Relationship Management?"
- "How can customer retention be increased?"
- "How is product usage depicted in online gaming?"
- "Are there similar and typical types of behavior of gamers in an online environment?".
- "What are factors affecting defection decisions of gamers in an online environment?".
- "Based on the factors in online gaming, how do the product usage factors affect customer churn?"

Managerial and Academic Relevance

The relevance of this thesis is twofold. Firstly, it contributes to fill the gap between research on product usage and research on customer defection. As product usage can increase customer loyalty and retention, insights in the effect that the motivations for product usage have on customer retention is of significant importance. However, to my knowledge there are no studies on this subject yet. My study also adds a new motivation for product usage that is not discussed in prior literature: the social component of product usage. In product usage literature, factors concerning interaction among customers are not found. Such factors are found in research describing online behavior, but these studies are not aimed at forecasting customer defection.

Furthermore, while several churn prediction models have been developed and applied to many industries, there are no churn prediction models using actual behavior in the online game industry yet, despite its size and forecasted growth. My study will be the first to develop such a model.

The results can be used by managers of companies in entertainment product industries to find out which factors of product usage motivation are the most important when one is interested in finding out whether a consumer is likely to defect. There might be several factors that could affect a consumer's affection to a product, but this does not necessarily mean that each and every one of these factors increases the likelihood of defection. By exposing the most important factors, managers can design personalized offerings to consumers showing behavior that indicates a likely defection in the future.

Structure of the Thesis

The current section introduced the topic and describes the relevance of my thesis. In the next section, existing literature is reviewed on customer relationship management, customer retention, customer churn prediction, behavior and retention mechanisms in online gaming and product usage. This section is followed by a review of previously exposed factors that influence defection decisions in online gaming. Hypotheses for the current research are formed based on this review. Section four describes the data used in the thesis and the methodology of the data analysis. The data collection, transcription and computation are discussed, after which the most important issues of the analysis techniques are presented. This section is followed by the analysis of the data. The general assumptions of the analysis techniques are checked and several models are estimated here. The discussion of the analysis results is in the next section. Based on the discussion, the hypotheses are evaluated in the sixth section, followed by a summary of the study, a discussion of the limitations of the study and points of thought for future research.

2. Theory and Literature

2.1 Customer Relationship Management

As markets saturate, firms realize that traditional strategies of mass-marketing become increasingly less effective. Over the past several years, more and more firms realize that their current customers are a more valuable asset compared to the acquisition of new customers (Coussement & Van den Poel, 2008). The concept of relationship marketing – where firms focus on creating long-term relationships with customers – is becoming more popular. In order to effectively pursue a relationship marketing strategy, firms have to adopt a customer-centric approach, in which customer lifetime analysis and customer retention play a prominent role (Reinartz & Kumar, 2003). For this customer lifetime analysis, Customer Lifetime Value (CLV) can be used (Gupta et al., 2006). Furthermore, CLV allows for differentiation between customers, by deciding which customers are more profitable than others. Customer Lifetime Value can be formally expressed with the following formula:

$$CLV = \sum_{t=0}^{T} \frac{(P_t - c_t)r_t}{(1+i)^t} - AC$$

Where,
- P_t: the price paid by a customer
- c_t: the direct cost of serving the customer
- r_t: the retention rate (which depicts the fraction of customers that stay with the company at period t)
- i: the discount rate
- AC: the cost of acquiring the customer
- T: the time horizon.

A customer's lifetime value is thus positively related to the price paid and the retention rate, while it is negatively related to serving costs, acquisition costs and discount rates. Increasing the retention rate is thus a means of increasing a customer's profitability.

Traditionally, a firm's results are allocated to the *offensive* marketing efforts by the firm; sales were thought to be the results of offensive marketing efforts like advertising and promotional activity (Rust & Zahorik, 1993). However, during the late 1980s and early 1990s, a shift in view started arising, as it seems acquiring a new customer is five times as costly as retaining an old one (Fornell & Wernerfelt, 1988).

Companies strive to attain a high retention rate (the amount of customers that continue the relationship with the company per year), as this is one of the most important aspects of Customer Relationship Management (CRM) (Hoekstra, Leeflang & Wittink, 1999). Companies can boost profits by roughly 75% if they can achieve a retention rate increase of only 5% (Reichheld & Sasser, 1990). Most companies use systems that focus on current period costs and revenues, while ignoring potential cash flows that customers might generate over the years. In general, profits per customer increase over the relationship with the customer. When customers leave the company, all the increasing profit potential is lost. Another important aspect of long-term customer relationships, as depicted by Reichheld & Sasser (1990), is the free advertising loyal customers provide. This could either include Word-of-Mouth, or referrals. The final reason for managing customer retention by tracking possible defectors that Reichheld & Sasser (1990) propose is the insights defecting customers provide. Customers are able to provide a view of the company's business that is unavailable or unobservable to the ones inside the business. Whatever caused the customer to leave might lead to a stream of other customers to also leave. Defectors can thus be used as an early warning signal; information of defectors can be used to improve the business.

2.2 Increasing Customer Retention

2.2.1 Loyalty Programs

A way of rewarding loyal customers is by offering complementary services or price discounts. However, loyalty reward programs have become a more popular incentive in certain industries (Bolton, Kannan & Bramlett, 2000). The goal of these programs is to increase customer retention for profitable customers by increasing the value to these customers. Indeed, Verhoef (2003) confirms that offering loyalty programs with economic incentives lead to increased customer retention rates. Bolton and colleagues (2000) note that the mere membership of a loyalty program does not necessarily increase retention. However, members of a loyalty program generally experience a higher value proposition by the company, which makes them more likely to strengthen the relationship with the current company, instead of switching to a competing company. Therefore, loyalty programs are a means of building longer and stronger relationships with customers. According to Verhoef (2003), the effects of economically incentivized loyalty programs are long-run effects. While the results on the short-run are relatively small, the programs allow for an increased relationship age and the resulting customer share.

2.2.2 Switching Costs

Switching costs, as perceived by the customer, can be an effective means for retaining customers, even when customers aren't satisfied with the company (Jones et al., 2007). Because of switching costs, customers get 'locked' into the relationship with the company. Though this might increase repurchases, it can also have negative long-term effects. Jones and colleagues describe that customers who become locked into a relationship with a company, which they prefer not to be, could become hostile. Over time, this will result into negative effects such as negative Word-of-Mouth (WoM). There seem to be three general types of switching costs (Burnham, Frels & Mahajan, 2003):

- Procedural switching costs: time and effort put into finding and establishing the relationship
- Social switching costs: potential loss of personal bond or friendship with provider
- Lost benefits costs: losing benefits or special deals from the current provider

Jones and colleagues define two types of switching costs: positive switching costs (including Social and Lost benefits costs as these costs are derived from positive constraints) and negative switching costs (including procedural switching costs as these costs are derived from negative constraints). Altogether, these switching costs affect a customer's commitment to the company. This commitment can either be affective (affection because customers wants to retain relationship) or calculative (affection because customer feels like (s)he has to retain relationship). Jones and colleagues (2007) found out that strategies based on creating affective commitment (through positive switching costs) will be an effective means of increasing positive emotions and repurchase intentions and decreasing negative WOM, while strategies based on calculative commitment will increase negative WOM, while in some cases increasing repurchase intentions. Therefore, the most effective means for increasing customer retention for a company is by creating perceived social switching costs and lost benefits switching costs. The social switching cost seems to be the most important type for online game developers. Choi and Kim (2004) describe that game players need a social connection to the game, in order to obtain an optimal experience. Based on this finding, individual social switching costs will decrease when a player loses friendships in the game. Procedural switching costs apply to online gaming because of the high amount of time players usually spend playing the game (Debeauvais et al., 2011), while lost benefits costs apply because a player might lose access to bonus content that is achieved, when quitting the game (Choi & Kim, 2004).

2.3 Customer Churn Prediction

Customer churn prediction models have been applied to many industries, including personal retail banking (Garland, 2002), the telecommunications industry (Khan et al., 2013; Huang, Kechadi & Buckley, 2012), subscription newspapers (Coussement, Benoit & Van den Poel, 2009) and financial services (Larivière & Van den Poel, 2005). An overview of customer churn prediction models in literature is shown in table 1.

Table 1
Overview of churn prediction models in literature

Literature	Industry	Objective	Techniques	Explanatory variables
Trubik & Smith (2000)	Banking	-Examine factors to identify leaving customers to introduce data analysis in banking industry	Logistic Regression	Demographics, products owned, Time with bank, Discounts and payments
Garland (2002)	Personal retail banking	-Investigate Juster scale's performance -Identify customers about to switch banks	Juster's probability scale	Customers' self-reported likelihood to close all accounts at current bank
Van den Poel & Larivière (2004)	Financial services	-Combine several types of predictors in one model -Analyse customer churn behavior using longitudinal data	Cox proportional hazard method	Customer behavior predictors, customer demographic predictors, macroenvironment predictors
Song et al. (2004)	Online Game Site	-Identify defectors from past behavior data -Propose personalized method for preventing defection	Self Organizing Map	Total Session Time, Total Number of Sessions, Total Number of Congestion, Average Session Time
Larivière& Van den Poel (2004)	Financial Services	-Investigate customer retention and profitability outcomes -Compare Random forests' and regression forests' performance with Logistic regression and Linear regression	Random Forest, Regression Forest, Logistic Regression, Ordinary linear regression	Past customer behavior, Customer demographics, Intermediary variables
Buckinx & Van den Poel (2005)	Grocery Retail	-Identify partial defection by behaviorally loyal customers instead of complete defections -Compare several classification techniques	Logistic regression, ARD neural network, Random forests	Purchase variables, Payment variables, Timing variables, Demographics. Promotions
Coussement & Van den Poel (2008)	Subscription newspaper	-Build churn prediction model with higher predictive performance -Compare two parameter-selection techniques	Logistic regression, random forests, SVMs	Client-company interaction, Renewal-related variables, Socio-demographic variables
Seo et al. (2008)	Telecommunications	-Explore factors driving customer retention behavior -Explore moderating effect of demographics	Logistic Regression, Hierarchical linear model	Length of relationship, Dropped-calls, handset sophistication, Service plan complexity, Demographics

Table 1. Continued

Literature	Industry	Objective	Techniques	Explanatory Variables
Coussement et al. (2009)	Subscription newspaper	-Identify risky customers -Compare Logistic regression with General Additive Models	Logistic Regression, General Additive Models	Client-company interaction, Renewal-related variables, Subscriber- variables, Subscription-variables
Huang et al. (2012)	Telecommunications	-Present a new set of features for land-line churn prediction -Compare several modeling techniques	Logistic Regression, Linear Classification, Naïve Bayes, Decision Tree Neural Network, SVM, Evolutionary Data mining	Demographics, Grants, Accounts, service orders, Segments, Telephone line information, Complaint info, Bills and Payments, Call details, incoming call details
Khan et al. (2013)	Telecommunications	-Develop effective and efficient model -Apply GP to predict churn	Genetic Programming	Demographics, Billing, Call information

Some of the previous churn prediction models follow a similar context compared to online gaming. As most online games require a subscription fee to be able to fully enjoy the game, the context of online gaming can be compared to subscription service businesses. Telecommunications and newspaper industries are therefore in a similar context as online gaming. The variables that are used in the studies mentioned in the table above generally include customer-to-company interactions, as well as product information, payment methods and demographics. Variables that depict actual product usage are rarely used. Some telecommunications use call details, which can be seen as product usage information, but other than that, such variables are scarce. Song and colleagues (2004) apply a churn prediction model to an online gaming site. While the context in this study is very similar to online gaming in general, this study only used variables about the amount of time the product is used. Compared to the studies in a similar context, my study differentiates itself by using several product usage variables, as well as variables that depict usage time and social interactions.

2.4 Product Usage

When a consumer chooses to start using a product, she derives some utility from this usage. This utility is driven by the intrinsic motivation to use the product, as well as the emotions experienced during the usage and the external rewards received during usage (Novak et al., 2003; Nevskaya & Albuquerque, 2012). Other factors that describe the motivations for product usage are usage mastery, external cues, habits and the complexity of the tasks of usage. These elements of product usage motivation are common in entertainment product categories like digital games, television shows, computer software and leisure activities (Nevskaya & Albuquerque, 2012).

Product usage motivation can be driven by several factors. First of all, Wood and Neal (2007) describe that consumers can repeat previous product usage behavior, which ultimately forms a habit for the usage. It is expected that consumers with a high habit of usage show a higher involvement for the product. When consumers use a product, they gain experience in the usage itself. Nevskaya and Albuquerque (2012) describe this as usage mastery. The effect of this mastery can be twofold. While mastering the usage process, consumers might experience other intrinsic utility of the product usage, while it may even give consumers access to more features of the product. Furthermore, by gaining expertise in the usage of the product, the product becomes more easy to use for consumers. This greater ease of use allows consumers to either get more tasks done, or to conduct a variety of tasks (Teo et al., 1999). However, when a product starts demanding a higher expertise of the user, consumers might find it hard to enjoy the product. Therefore, an increased mastery of the usage, accompanied with more difficult features of the product, might also reduce the intrinsic utility derived from the product. Motivation for using a product might also come from the usage of the product itself. When using a product, consumers might experience a certain 'flow' of the product usage. This flow can be described as a psychological state in which a consumer feels highly involved with the product, yielding a feeling of efficiency, motivation and happiness (Shang et al., 2005). Mastery of the product is also at hand here, as Shang and colleagues (2005) argue that consumers' flow states are optimal when their skills in using the product are high, and the tasks of using the product are challenging enough. Another factor influencing states of flow is the immersion of the product usage (Cowley et al., 2008). By immersing with the product, greater engagement is created, increasing the pleasure derived from the usage (Douglas & Hargadon, 2000).
After using a product for a while, consumers might obtain extrinsic rewards (Nevskaya & Albuquerque, 2012). The prospect of a new reward in the near future might be an incentive for consumers to continue using the product. Rewards are not necessarily features of the product to be obtained. Teo and colleagues (1999) argue that another extrinsic reward can be that fact that the product usage can lead to the accomplishment of certain goals consumers have before using the product. In their study, the use of computers and the internet have the intrinsic motivation of increasing productivity, which is one of the main motivations for using these products. One means of offering extrinsic rewards to consumers who frequently use a product is by offering the earlier mentioned loyalty programs. After using the product for a certain amount of time, consumers might get access to better service or even to monetary incentives such as special discounts (Bolton et al., 2000; Verhoef, 2003).

The motivations for product usage are to some extent controllable by firms. Firms can change the rate at which cues are provided to consumers, depending on the amount they think is necessary to attract a consumer to use the product again. As individual consumers respond differently to cues, a firm has to carefully consider the right amount of cues per consumer. Nevskaya and Albuquerque (2012) state that the response of the consumer depends on the consumer's habit of using the game. Another aspect firms can influence is the amount and importance of external rewards received. For example, firms can alter the amount of extra content that becomes available from a certain amount of usage by a consumer. Furthermore, firms can alter the complexity of the product as the consumer masters the product. A careful consideration is needed, as a greater complexity might also demotivate more experienced consumers.

Within entertainment product categories, insights in product usage can be very beneficial. By identifying attributes that are relevant to the product usage, firms can decide on whether to offer the product on multiple formats (Koukova et al., 2012). Koukova and colleagues (2012) describe that products are used for product-related goals. For each of these goals, the choice for the product depends on the usage situation. Certain products, as well as certain formats of the same product, provide the consumer with different benefits. By identifying the benefits the consumer seeks, the firm can offer multiple formats of the product. Koukova and colleagues (2012) describe that offering multiple formats can also draw attention to new usage situation, therefore increasing the product usage by the consumer. When offering multiple formats, firms must realize that their communication of the format has to highlight the unique benefits that each format delivers. If this is not done, consumers will regard the multiple formats as substitutes. By highlighting the right benefits, firms can induce consumers to buy bundles of the product formats. Examples of these bundles include printed copies of a newspapers and online version of the newspapers. Directions for bundling in online gaming can include offering a mobile application of the game, which consumers can use to maintain their progress even better in the game.

2.5 Behavior and Retention Mechanisms in Online Gaming

Since the data used for this study is obtained from an online game, insights in retention mechanisms and behavior in online gaming will be helpful for a better interpretation of the data and the results. Although research modeling gamers' intentions of unsubscribing is scarce, plenty of research has been done on different patterns of behavior affecting a gamer's affection with a game. Suznjevic, Dobrijevic and Matijasevic (2009) for example show that the social component of gamers (i.e. written and vocal communication among players) is an important factor determining a game's popularity. Suznjevic, Stupar and Matijasevic (2011) propose a model for online gaming behavior in World of Warcraft. Though they do not measure the influence of this behavior on a gamer's affection, the study gives a general overview of the actions players can undertake in the game and the sequence of these types of behavior to form certain patterns of play. The actions they describe are *Trading, Questing, Dungeons, Raiding* and *Player-versus-Player*.

Chen, Huang and Lei (2009) investigate the effect of the quality of the game's network (such as delays) on a gamer's intention to continue playing or depart. It seemed that delayed networks tend to drive gamers out of the game, suggesting there are more factors outside a gamer's behavior that might be able to predict a gamer's intention to unsubscribe. Chen and Lei (2006) found out that players tend to have longer gaming sessions the higher they are involved with social interaction (e.g. communicating or team-playing). They recommend developers to encourage (or even force) players to communicate or play together, increasing the *stickiness* of the game (e.g. longer gaming sessions).

Feng, Brandt and Saha (2007) traced the activity on a popular Massively Multiplayer Online Role-Playing Game (MMORPG) during the first three years of its existence. Concerning gamer retention, they found a negative relation between the length of the player's time since his first subscription and the retention rate. Overall, this means the longer a player has been with the game, the lower the probability of a new subscription becomes.

Debeauvais et al. (2011) studied mechanisms that influence play time in World of Warcraft. They explored several aspects connected to the game, including player motivations (Yee, 2007), Guilds, Connections to real life and demographic factors. They found out that achievement as motivation has a predictable impact on play time. World of Warcraft seems to have a balanced reward system, which attracts and retains several sorts of players. They also found out that Guilds (which are self-formed groups of players that interact and collaborate for an extensive period) are the most important part of the sociality in the game. Being part of a guild, as well as the affection and rank in the guild, increase weekly play time. Furthermore, connections to real life (like having real-life friends, family or spouse to play with) increase play time. World of Warcraft designer Blizzard has already leveraged this connection by offering bonuses to players who refer and recruit new players to the game. By offering these bonuses, as well as increasing the real-life connection for gamers, Blizzard utilizes these findings to increase the player retention.

Choi and Kim (2004) studied underlying factors that positively influence customer loyalty in an online gaming environment. As they propose, digital contents (like online games) are primarily experience goods. Therefore, the focus of their study was on factors that increase the quality of a customer's experience. They found out that interaction is the most important feature related to an optimal experience in online games. They distinguish interaction between the user and the system (personal interaction) and interaction between users (social interaction). By providing gamers with these two forms of interaction, developers can realize higher customer loyalty. Next, Choi and Kim (2004) proposed design features, which can be used by game developers to implement the right features in their games to efficiently provide personal and social interaction in games. Yang, Wu and Wang (2009) studied the most influential factors on loyalty to an online game. The three most important features they propose are increasing the hedonic value of a game (offering challengeable tasks and rewards), shorten the transaction time, asking an acceptable price for the game and service and offering a high quality online game service. Song and colleagues (2004) study the predictability of gamers defecting by examining the game-session times of players who defected in the past and current players. Based on their model, they propose a personalized defection prevention campaign, which offers players a personal offer based on the factor which makes them defect most likely (e.g. offering players who spend too little time in game sessions free of charge usage time). They conclude that by offering players an individual defection prevention procedure, game developers can effectively alter a player's in-game behavior, which makes the player retain to the game for a longer period. Based on this study, it seems offering personalized bonuses is an effective means of increasing retention.

It seems there are some underlying categories of factors that influence the defection intentions of gamers. First of all, basic login features such as playing time, session times and logins seem to have an effect. Translating this to product usage motivations, these factors depict the product usage habits. There also seems to be a social factor that influences the intentions. Communication with other players, as well as being part of a guild (in which people socialize, interact and collaborate) and ranks in the guilds fall under this social factor. Another identified factor is based on individual achievement. Obtaining rewards in the game or completing tasks are examples of achievements that might influence defection intentions. The factors depict the extrinsic rewards in product usage motivations. Activity in the game, such as traveling, questing and trading are other factors. These factors depict the immersion of product usage. Finally, demographic factors related to the game, like family members who also play the game, seem to influence defection intentions. In the next section, these factors are investigated further to form hypotheses about factors that influence gamer retention.

3. Hypotheses

There aren't a lot of researches identifying behavioral factors that affect the gamer's intention to defect (Tarng et al., 2008; Debeauvais et al., 2011). However, there are some studies that explore individual factors to describe online game behavior (Song et al., 2004; Choi & Kim, 2004; Yee, 2007). Combined with the literature on the effect of the factors of product usage motivation, several effects can be expected from the data.

Song et al. (2004) studied the effect of game sessions on defection intentions by comparing current player behavior to the behavior patterns of past defectors. They found that either a low amount of total session time, a low amount of session or a low average time per session increase the likelihood of defection. This means that a low amount of play time or a low average session length can be moderated by a high amount of logins. If a gamer spends more time playing the game, each time he or she logs on to the game, it can logically be seen as higher affection. This would mean the gamer has a higher probability to stay with the game in the future, thus indicating a higher retention. So, longer game sessions will be followed by longer retention. This hypothesis is supported by Tarng, Chen and Wang (2008), who found a positive correlation between game session time and consecutive days of playing the game. Finally, Song and colleagues (2004) find that a higher amount of daily returns to the game increases the likelihood of retention. Wood and Neal (2007) describe that a continuous usage of the product might lead to a habit for using the product. The factors described above all depict a form of continued product usage and can thus be considered as habit factors. Since all the habit factors seem to have a positive effect on the affection to the product, I expect product usage habits to have a positive effect on customer retention.

H1: Product usage habits have a negative effect on customer defection

If a consumer shows a high level of communication with other consumers, this might indicate he has (be it virtual) friends in the product used. This phenomenon is seen in other product categories such as social networking sites, where the amount of consumers to socialize with drives the product usage (Kaplan & Haenlein, 2010). Prior research has shown that communication in gaming can be seen as the social aspect of the product which is an important factor of the game's popularity. Chen and Lei (2006) found out that more communication leads to longer retention. The best metric of communication in online gaming seems to be the fact whether or not a player is part of a guild (Debeauvais et al., 2011). Debeauvais and colleagues (2011) state that being in a guild increases play time. As a higher amount of play time seems to increase the likelihood of retention, I hypothesize that communication has a positive effect on retention.

H2: The amount of communication has a negative effect on customer defection

When consumers get more experienced with using the product, they become able to use the product more efficiently, giving them higher pleasure of using the product (Nevskaya & Albuquerque, 2012). Because of the higher efficiency, consumers are also able to get more tasks done by using the product, which is experienced as rewarding (Teo et al., 1999). As long as the product usage does not become more complicated as consumers become more experienced, this product mastery is expected to increase the likelihood of customer retention.

H3: Product mastery has a negative effect on customer defection

Nevskaya and Albuquerque (2012) argue that the prospects of rewards in the near future increase the motivation to use a product. From this finding, it is logical that consumers who show a higher level of product usage have attained access to a larger amount of rewards, and should thus show a higher affection to the product. Choi and Kim (2004) concluded that players of online games will stay with the game longer when their loyalty to the game increases. In order to attain higher loyalty, they will need to have an optimal experience in the game. One of the factors that increase their experience is the possibility to achieve certain goals during the game. One possible goal, as described by Tarng et al. (2008), is advancing to new levels. Yee (2007) confirms that leveling is indeed an achievement that motivates players to stay with the game. Based on these studies, I expect that a higher amount of rewards gained during the product usage will increase the likelihood of retention.

$H4_a$: The amount of rewards gained during the product usage has a negative effect on customer defection

When consumers reach the highest level of product usage possible, they might attain the highest possible reward (Blizzard, 2014). During the studied period, World of Warcraft maintained a maximum level to achieve of 70. The effect of the achievement of the highest level can be two-fold: it grants the consumer a big reward, but it also cancels out the prospect of future rewards by reaching higher levels. The effect of this achievement is thus dubious.

$H4_b$: Reaching the highest level possible in using the product can either increase or decrease the likelihood of customer defection.

Immersing with the product increases the likelihood of reaching an optimal state of flow. An optimal state of flow increases the affection with the product (Douglas & Hargadon 2000). Besides gaining levels in the game, there are several other actions players undertake during the game. Suznjevic et al. (2011) identified several 'action categories': trading, questing, dungeons, raiding and Player versus Player combat. However, these actions are not freely observed (Lee et al., 2011). Yee (2007) describes 'Immersion' as a motivation to play MMORPGs. One of the components of Immersion is exploration (e.g. traveling in the game to explore new areas). As Choi and Kim (2004) state that a higher amount of activity increases the optimal experience to the game and thus increase the likelihood of retention, I expect that a higher amount of traveling will increase the likelihood of retention.

H5: Immersion with the product has a negative effect on customer defection

Table 2
Overview of hypotheses and supporting literature

Product Usage Motivation	Supporting Literature	Hypothesed Effect on defection
Habits	Song et al. (2004) Wood & Neal (2007) Tarng et al. (2008)	-
Communication	Chen & Lei (2006) Debeauvais et al. (2011)	-
Product Mastery	Teo et al. (1999) Shang et al. (2005) Nevskaya & Albuquerque (2012)	-
Rewards	Teo et al. (1999) Nevskaya & Albuquerque (2012)	+ & -[a]
Immersion	Douglas & Hargadon (2000) Cowley et al. (2008)	-

[a]While the prospect of rewards in the near future are expected to have a positive effect on retention, reaching the highest level possible in the product means that there are no level-related rewards to be attained in the future. In World of Warcraft, reaching the highest level also mean attaining the largest reward of the game. Therefore, the effect of reaching the highest possible level can be twofold. The analysis should make the effect more clear.

4. Data and methods

4.1 Dataset

Collecting detailed data on individual consumer behavior is a hard task. Personally tracking a sufficient amount of consumers will be tremendously time consuming and hard to assess. Detailed data are also hard to obtain from firms directly, due to privacy and confidentiality reasons (Huang et al., 2012). Therefore, not all factors discussed in the second and third session can be collected. Some factors, such as family connections in the game, are not even needed in this study, as these data are not available to most firms. Therefore, these factors will never be used in a professional defection detection model. This study relies on data publicly available. Fortunately, there is a large dataset containing fairly detailed trackings of a large amount of characters from the MMORPG 'World of Warcraft'.

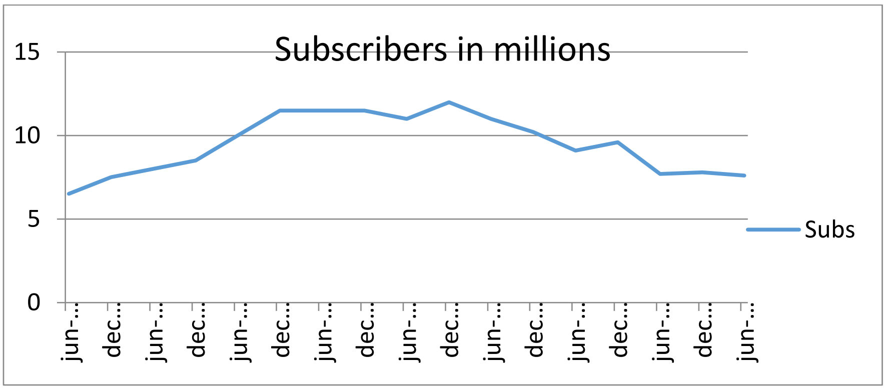
4.1.1 Introduction to World of Warcraft

World of Warcraft is a subscription-based MMORPG created in 2004. It is developed by Blizzard Entertainment, Inc., an American video game developer. As of March 2014, World of Warcraft has 7,6 million subscribers, down from an all-time highest amount of twelve million (Williams, 2014). In 2009, Blizzard won the Guinness World Records Most Popular MMORPG award (Langshaw, 2009). According to Digital Battle, World of Warcraft is also the highest grossing video game to date, grossing over ten billion dollars in 2012 (Douglas, 2012). Figure 1 shows the subscription numbers from June 2006 to Jun 2014. To celebrate the tenth anniversary this year, Blizzard has released an infographic containing a series of data points. This infographic has revealed that as of January 2014, one hundred million accounts have been created in World of Warcraft; not to be confused with one hundred million actual players (Blizzard, 2014).

The game's beginner's guide describes the beginning of the game (Blizzard, 2014). In World of Warcraft, a consumer takes on the role of a fantasy hero. As a player advances, the character takes on quests, learns new abilities, collects virtual goods and earns (and spends) virtual money. When creating a character, the consumer chooses the faction, race and class of the character. The faction depicts the 'side' the character is on: it either part of the 'Alliance' or the 'Horde'. In-game communication with other consumers is only possible within the same faction. The race of the character depicts a social choice, as it merely affects the appearance of the character, while the class depicts a game-play choice that determines the possibilities of the character. Besides belonging to a faction, consumers can communicate and cooperate with other consumers using the 'chat' and 'party' options. The chat option is a text-based communication tool. The party option allows players to cooperate during the game. While parties are temporary, 'guilds' are persistent groups of characters who regularly play together and usually have similar playing styles or even personalities. This way, guilds offer consumers a continuous access to communication with other players. World of Warcraft is available for free as a trial version. Afterwards, in order to continue playing the game, a subscription fee is required. Subscriptions can be bought for periods of one, three or six months. Upon subscribing for the first time, the player is required to submit basic personal information, such as name, date of birth, contact information and country. World of Warcraft finds itself in a changing industry, as free-to-play MMOs are becoming more popular, while World of Warcraft's graphics fall behind on competitors' and similar games fragment the market (Sun, 2014). Given the large amount of roughly 500 free-to-play MMOs available out of roughly 700 available MMOs (MMORPG.com), Blizzard can feel the constant threat of losing subscribers to free competitors. Given these circumstances, Blizzard could thus use a model for customer retention management. Screenshots of the game, showing the chat channel and overworld, can be found in the appendix.

Figure 1

Amount of Wold of Warcraft subscribers over the years (adapted from Williams, 2014)



4.1.2 World of Warcraft Avatar History Dataset and Transcription

The dataset used for this study will be the World of Warcraft Avatar History dataset (Lee et al., 2011). This dataset contains information about Avatars' (each avatar depicts one gamer) play time and character. The dataset includes information over a three-year period (January 2006 to January 2009). The authors created one character in World of Warcraft, which they used to collect data through the 'who' command. Using this command will ask the game server to provide a list of all avatars currently online. The authors used a scripting language to keep the data collection avatar online throughout the three year period, while it automatically collected the online avatars every ten minutes. The server returns information for each observed avatar (from now on: 'observation'), which the authors' script then formats into standardized data. The data is then stored in the World of Warcraft Avatar History Dataset as the following string: "Dummy, Query Time, Query Sequence Number, Avatar ID, Guild, Level, Race, Class, Zone, Dummy, Dummy". The meaning of the dummy variables remains unknown. For a description of the remaining variables, consider table 3 below.

The text files included the data string described above in a time period of 10 minutes, as a result of the scripting the authors of the dataset used. The data are saved per day, making each folder contain 144 files. The 1170 days in which the data collection took place thus add up to 168480 files. An example of a separate file can be seen in figure 2.

Table 3
Overview of data strings in the World of Warcraft Avatar History dataset (adapted from Lee et al. 2011)

Field	Values
Query Time	Time of tracking between January 2006 and January 2009
Query Sequence Number	An integer > 1
Avatar ID	An integer > 0 to identify each unique avatar
Guild	An integer > 0 to identify each unique guild
Level	An integer within [1,70] to depict the avatar's current level during the tracking
Race	Avatar's Race to be chosen before creating the avatar; either Blood Elf, Orc, Tauren, Troll or Undead
Class	Avatar's Class to be chosen before creating the avatar; either Death Knight, Druid, Hunter, Mage, Paladin, Priest, Rogue, Shaman, Warlock or Warrior
Zone	Current Zone the avatar is located in during the tracking, either one of the 229 zones in World of Warcraft world

The 'Persistent_Storage' contains the observations per character, while the meaning of 'RoundInfo' is not described by the author. These data are still very raw and require editing before one can analyze behavior per character.

Figure 2

Example of a separate datafile in the World of Warcraft Avatar History dataset

```
Persistent_Storage = {
    "0, 07/01/08 00:03:52, 1,58188, , 9, Orc, Warrior, Durotar, WARRIOR, 0", -- [1]
    "0, 07/01/08 00:03:52, 1,72060,365, 30, Orc, Warlock, Stranglethorn Vale, WARLOCK, 0", -- [2]
    "0, 07/01/08 00:03:52, 1,71537,189, 35, Orc, Warrior, Stranglethorn Vale, WARRIOR, 0", -- [3]
    …
    "0, 07/01/08 00:08:04, 50,35304,271, 70, Blood Elf, Mage, Thunder Bluff, MAGE, 0", -- [405]}
RoundInfo = {
    "0, 1, 6, 57", -- [1]
    "0, 2, 3, 50", -- [2]
    …
    "0, 50, 15, 50", -- [50]}
```

In order to edit the data, I needed to transcribe the relevant data – the text strings included in the 'Persistent_Storage' – into Microsoft Excel. To create a manageable workload, I decided to limit the transcription to three months of observations. I wanted to use the three most recent months, however I noticed the last few months in the original dataset used a different observing period of 15 minutes. Therefore, the most recent months using the 10 period timeframe were selected, which were July, August and September 2008.

To do so, an ETL (Extraction, Transformation and Load) tool was used. The ETL tool extracts the data from the original text files into the used system. In this system, all rows of the text files were transformed into one big list of rows and columns, including the unusable 'roundinfo' data. Fortunately, the roundinfo data included empty columns in the system, while the relevant data didn't. Based on the empty columns, the roundinfo data could be filtered out of the system. After only the relevant rows and columns were left in the system, the system loaded the rows and columns into a .csv file. After three months of data were transformed, the final amount of rows added up to roughly 3,2 million rows. Microsoft Excel cannot process files with more than 1,5 million rows, so the data were loaded into six different .csv files. While the data were listed chronologically before they were extracted by the tool, the final data were mixed. Therefore, the data needed additional processing, which was done after the sample was determined.

4.1.3 Sample Selection and Data Collection

After three months of data were transcribed into Excel, I randomly selected 500 out of 12.823 unique Avatar IDs found in these three months to use as the sample to study. After selecting 500 IDs, each character's observations had to be aggregated into individual Excel files. This required me to manually copy each selected character's observations from the six Excel files into a unique Excel file per character. Because this copying required me to check each character individually, I was able to refrain from adding a character to the dataset if thought to be appropriate. As World of Warcraft offers a free trial, only characters who actually buy a subscription will be of interest. During the studied period, the free trial was available for one month. If, during the collecting of individual data, I noticed a player that started the free trial and did not buy a subscription afterwards, I did not collect this character's data and randomly selected a character to replace the character in the final dataset. When a character's first observation in the World of Warcraft Avatar History dataset was at level 1, and the character did not show activity for longer than 1 month, I assume this character is a trial version character. Furthermore, some characters barely showed activity (which is noticed by the very low amount of observations in the original dataset). As these characters do not contribute to the variance in the data (e.g. due to lack of play time and therefore biased variables), I decided not to collect data from character with less than three observations. If such a character was discovered, I randomly selected another character to replace it. After I had 500 characters, I listed all their observations in individual files, to create individual variables later on (see next paragraph). The individual variables where then aggregated into a final dataset.

To ensure that the estimated model is able to generalize well, it is advisable to evaluate the model on a test set (or: forecasting set) (Coussement & Van den Poel, 2008). Therefore, I collected the data of an additional 50 characters. The 500 characters described above will function as the calibration set for the model. Based on their data, coefficients for the parameters in the model are estimated. Data from the 50 characters in the forecasting set will be entered into the estimated model from the calibration set. Afterwards, the performance is evaluated. This method increases the external validity of the model, given it a greater managerial reliability.

4.1.4 Variables

From the coded data from the downloaded dataset, I copied and constructed several variables to use for my study. Character IDs, as well as Race and Class, are copied in a new dataset to differentiate between unique characters. I also included a variable to depict the observed month. Data is constructed at the monthly level, and some Characters are not observed in each of the explored months. Formatting the data as a panel tackles this problem, as each month is treated as a different observation per Character. Further variables are created based on the coded data from the downloaded dataset. Figure 3 shows a sample of the data coding in the final dataset.

- ***Defection*** is the main variable of interest. This variable depicts whether or not a character has decided to stop playing the game. This variable will be denoted as '1' when a character is not tracked in the World of Warcraft Avatar History Dataset for 29 days. Tarng, Chen & Huang (2008) studied game play days of World or Warcraft player using the same Avatar History dataset. According to them, it is very unlikely (roughly 3%) for players to return to the game after an 'Off'-period (a period without playing the game) of 30 days. Using this finding, I assume that players in my sample who aren't observed for 29 days have quit the game. I use 29 days instead of 30 days so that players who decide to quit the game on September 1st 2008 are also observed as 'defectors'. Besides the study by Tarng and colleagues, 30 days of non-activity seems like a logical criterion for defection, as World of Warcraft is based on monthly subscriptions.

$$Defection = \begin{cases} 1, & if\ player\ is\ not\ observed\ within\ 29\ days \\ 0, & otherwise \end{cases}$$

- ***Play Time*** depicts the amount of actual time spent playing the game. The program used by Lee et al. (2011) to create the World of Warcraft Avatar History dataset collects a list of players every ten minutes. If a player logs out of the game within these ten minutes, his activity is not observed within consecutive snapshots. To calculate actual playing time, I summed all consecutive observations within a month and multiplied these by 10 minutes. This way, immediate logouts are not included as play time. The total play time is divided by 60 to measure the parameter at the hourly level. This way, the parameter values will not get inflated.

$$PlayTime = \frac{(Total\ Observations - Total\ Short\ Sessions) * 10}{60}$$

Where

Observation = 1 for each observation within a month

$$\text{Short Session} = \begin{cases} 1, & if\ observation\ is\ not\ consecutive \\ 0, & if\ observation\ is\ consecutive \end{cases}$$

- ***Average Session Length*** depicts the average amount of time within login and logout per month. To compute this variable, first the amount of sessions is constructed. If an observation is not consecutive to the previous one, it is considered as the beginning of a new session or a login. If the observation is consecutive to the previous one, it is considered as an observation within a session. Next, the time per session is computed. If an observation is consecutive to the previous one, the time between the two observations is calculated. This time will always be roughly 10 minutes, since the observations are made every 10 minutes. Finally, the total amount of time between consecutive observations is summed and divided by the total amount of sessions per month.

$$Average\ Session\ Length = \frac{Total\ Time\ between\ observations}{Total\ Amount\ of\ Sessions}$$

Where

$$\text{Time between observations} = \begin{cases} 10, & if\ observation\ is\ consecutive \\ 0, & if\ observation\ is\ not\ consecutive \end{cases}$$

$$\text{Session} = \begin{cases} 1, & If\ observation\ is\ not\ consecutive \\ 0, & If\ observation\ is\ consecutive \end{cases}$$

- ***Guilded*** depicts the relative amount of time the character is observed while being part of a guild. I chose a relative amount of time because some characters enter or leave guilds during the month. Therefore, a dummy variable for being in a guild would not be suitable. To compute this variable, the amount of guilded observations per month is divided by the total amount of observations per month.

$$Guilded = \frac{Guilded\ observations}{Total\ observations}$$

- ***Levels Gained*** depicts the amount of levels a character has gained per month. Whenever the level of a character during one observation is higher than its level during the previous observation, the observation is counted. To compute the Gained levels variable, these observations are summed per month.

$$Level\ Gained = \begin{cases} 1, & if\ level\ during\ t > level\ during\ t-1 \\ 0, & otherwise \end{cases}$$

Where

t = Current observation

t – 1 = Previous observation

- ***Average Level*** depicts the average level of a character during the observed month.
- ***Traveling*** depicts the relative time spent traveling between zones in the game. Whenever a character is located in a different zone than during the previous session, the character has switched zones (traveled). To compute this variable, the amount of observations where the character has travelled is divided by the total amount of observations per month.

$$Traveling = \frac{Total\ Traveled\ Observations}{Total\ Observations}$$

Where

$$\text{Traveled Observation} = \begin{cases} 1, & if\ Zone\ at\ t\ \neq Zone\ at\ t-1 \\ 0, & if\ Zone\ at\ t = Zone\ at\ t-1 \end{cases}$$

- ***Short Session Amount*** depicts the relative amount of short sessions per month. When an observation is not consecutive to the previous one, and the next observation is not consecutive to the current one, the observation is seen as a short session (or immediate logout). This is not included in the Actual Play Time, so a variable relative to the total amount of observations is included.

$$Short\ Session\ Amount = \frac{Total\ Short\ Sessions}{Total\ Observations}$$

Where

$$\text{ShortSession} = \begin{cases} 1, & \textit{If observation is not consecutive and not followed up within } 15 \textit{ minutes} \\ 0, & \textit{If observation is consecutive or followed up within } 15 \textit{ minutes} \end{cases}$$

- ***Days Played*** depicts the amount of unique days the character is observed in a month.
- ***Endgame*** depicts whether or not the character has reached the highest level possible (level 70) during the month. Whenever at least one of the characters observations includes the character being level 70, the character is classified as 'endgame'.

The following table summarizes the variables, as well as their description and the product usage motivation category they belong to based on prior literature.

Table 4
Variables used in the study

Product Usage Motivation	Variable	Description
-	Character ID	ID used to identify unique avatars
	Race	Avatar Race, chosen at creation of avatar
	Class	Avatar Class, chosen at creation of avatar
	Month	Describes observed month (Jul, Aug, Sep)
	Defection	Depicts whether character quit the game (1) or not (0)
Product Usage Habits	Play Time	Depicts actual play time in minutes per month
	Average Session Length	Depicts average time between login an logout in minutes per month
	Short Session Amount	Depicts relative amount of observations that are not part of actual play time (immediate logouts)
	Days Played	Depicts amount of unique days the character is observed during month
Communication	Guilded	Depicts relative amount of time spent being part of a guild
Product Mastery	Average Level	Depicts average level of character during month
Rewards	Levels Gained	Depicts the amount of levels the character gained each month
	Endgame	Depicts whether or not character has reached highest level possible during month
Immersion	Traveling	Depicts relative amount of observations in which character is in a different location compared to previous observation

Figure 3
Dataset example

Character ID	Race	Class	Period	Defection	Play Time	Guilded	...	Endgame
1108	Undead	Warlock	1	0	20	1	...	0
1108	Undead	Warlock	2	0	90	1	...	0
1108	Undead	Warlock	3	0	50	1	...	0
1163	Troll	Rogue	1	0	240	0,09	...	0
1163	Troll	Rogue	2	1	10	0	...	0

4.2 Descriptive Statistics

For an overview of the data, descriptive statistics are generated.

Table 5

Dataset observation statistics

Dataset Trace		Month	Observations	Defections
Start Date	01-07-2008	July	435	117
End Date	30-09-2008	August	380	122
Observed Characters	499	September	320	22
Total observations	1135			
Total Defections	261			

The observed period covers the first of July until the 30th of September. The sample consists of 500 characters, of which a single character somehow had incomplete data and was removed from the dataset. These 499 characters resulted in 1135 observations over a 3-month period. Each observation depicts a decision concerning defection and 261 defection decisions were observed. Of these defections, 117 were observed during July, 122 during August and 22 during September. From these observations, it is clear that relatively far less defection decisions are made in September. A very plausible reason for this is the fact that most defection decisions made in September aren't observed with the applied coding (using the criterion of 29 days of inactivity). Because there is no data transcribed for October, defection decisions during September are only observed during the first and second day of September, even though character may also have decided to defect during later days in the month. It is highly likely that this inconsistency in defection classification biases the data. Therefore, only observations from period 1 and 2 are taken into consideration during analyses.

When looking at the activity variables, it is noticeable that Endgame players show different levels of activity than non-endgame players (see table 6). Endgame players tend to have a higher amount of play time per month, have higher session lengths, spend more time in guilds, travel more, play more days per month and tend to have less short session than non-endgame players. Based on the hypotheses, it thus seems logical that endgame players are retained longer.

Table 6

Activity comparison between endgame and non-endgame characters

	Did not reach level 70	Reached level 70	Total
Count	741	394	1135
Play Time	998,79	2236,65	1428,49
Average Session Length	42,34	53,88	46,34
Percentage of Time in Guild	0,6	0,86	0,69
Percentage of Zone Switches	0,23	0,35	0,27
Days Played per Month	8,72	14,01	10,56
Percentage of Short Sessions	0,34	0,24	0,31

The difference between endgame players and non-endgame players became clear when looking at the data. However, as this study attempts to explain the difference between defectors and retained characters, checking for differences in the data among them might already indicate certain differences (see table 7). Because period 3 might show biased data, this period is not included in these descriptive statistics.

Table 7
Activity comparison between retained and defected characters

	Retained characters	Defected characters	Total
Count	576	239	815
PlayTime	1725,61	353,31	1323,18
AverageSessionLength	47,88	36,22	44,46
Guilded	0,72	0,53	0,67
LevelsGained	3,38	1,36	2,79
AverageLevel	51,13	41,30	48,25
Traveling	0,27	0,25	0,27
ShortSessionAmount	0,28	0,40	0,32
DaysPlayed	12,78	4,08	10,22
Endgame	0,36	0,19	0,31

The descriptive statistics all follow the formed hypotheses: Defected characters show a lower average values for habit parameters, communication parameters, product mastery, extrinsic reward pursuit and immersion. Defected characters also show a higher average amount of short sessions.

4.3 Method

4.3.1 Model and Assumptions

To test the relationship between the proposed factors and customer defection, logistic regression is used (Seo et al., 2008). As can be seen in table 1, logistic regression is one of the most used models for predicting customer churn. Logistic regression is seen as an appropriate technique for modeling customer defection because it handles a binary dependent variable (Trubik & Smith, 2000). Furthermore, logistic regression is relatively easy to use, while it provides quick and robust results compared to other techniques (Coussement & Van den Poel, 2008). While one can expect to lose performance due to the easy nature of the model, the model performs fairly well and can perform even better than more sophisticated techniques (Neslin et al., 2004). Random forests seem to be able to outperform logistic regression (Coussement & Van de Poel, 2008). However, Buckinx and Van den Poel (2005) found no significant difference between the performance of Logistic regression and random forests and note that random forests are far more 'expensive' than logistic regression when it comes down to computing time. Based on these results from prior research, logistic regression can be seen as an appropriate method for the current study.

In a logistic regression model, one tries to predict the occurrence of an event (in this case defection or retention), as well as identify the factors that affect this event. To predict whether or not the event will occur, the probability of the event taking place is calculated (Janssens et al. 2008). The following formula is used to develop the model:

$$\text{Probability (Y)} = \frac{e^z}{1+e^z}$$

Where $Z = \beta_0 + \sum_i \beta_i X_i$

Y:	Event of interest
β_0:	Constant
β_i:	Estimated coefficient based on the data
X_i:	Independent variable
e:	Base of natural logarithm (≈2,718)

When the values of the independent variables are inserted into the model, the values of the parameters are estimated by using the maximum-likelihood estimation. This estimation chooses the parameters that make the observed values of Y most likely to have occurred (Field, 2009).

With the computed variables, the formula using all variables in the model will become:

$$\text{Probability (defection)} = \frac{e^z}{1+e^z}$$

Where $Z = \beta_0 + \beta_1 PlayTime + \beta_2 AverageSessionLength + \beta_3 DaysPlayed + \beta_4 ShortSessionAmount + \beta_5 Guilded + \beta_6 LevelsGained - \beta_7 AverageLevel + \beta_8 Endgame + \beta_9 Traveling + \varepsilon$

Interpretation of the influence of each variable is done by examining the coefficients of the variables. However, the Beta values are not the direct influence of the variable. The influence of a unit increase per variable is interpreted by calculating the change in 'log odds' and 'odds' due to the unit change in a variable (Janssens et al., 2008). The estimated model will calculate the value of 'Z', which is the logit of the odds of defection.

The log odds can be defined as

$$Log\ odds = Log \frac{Probability(event)}{Probability(no\ event)}$$

The value of 'β_i' in the expression of 'Z' indicates the change in log odds by a one unit change in the variable. For better interpretability, the odds can be calculated, which are defined as

$$Odds = \frac{Probability(event)}{Probability(no\ event)} = e^{\beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n} = e^{\beta_0}\, e^{\beta_1 X_1} \ldots e^{\beta_n X_n}$$

In this case, e^{β_n} indicates the factor by which the odds change when variable X_n changes by a unit. The odds depict the ratio of the studied event happening by the studied event not happening. Negative Beta-values and the accompanied decreased odds thus indicate that the studied event happening has a lower probability of happening.
Compared to Linear Regression, Logistic Regression follows fewer assumptions. Assumptions to be taken into consideration when using Logistic Regression are:

- The dependent variable is measured on a dichotomous scale. In other words, the dependent variable must classify observations into either of two groups. In this case, observations are classified as either 'Defected' or 'Not defected'.
- Outliers should be treated with caution. Although some sources mention there should be no outliers at all, some outliers might have more meaning than non-outliers. Therefore, outliers should be checked before removal. When an outlier has a high influence on half or more than half of the parameters in the model, I classify the outlier as an influential outlier (Janssens et al., 2008) and it will be removed from the dataset.
- There may not be high intercorrelations among the independent variables. A high intercorrelation indicates multicollinearity. Various definitions of 'High correlation' exist. Acceptable cut-off points can be 0,4 (Van den Poel & Larivière, 2004), 0,6 (Janssens et et al., 2008) or 0,9 (Field, 2009). Van den Poel and Larivière (2004) mention that the appropriate cut-off point can vary among studies. Therefore, other diagnostics can be produced, such as the variance inflation factor (VIF) (Field, 2009).
- There is a linear relationship between continuous independent variables and the logit of the outcome variable.

These assumptions will be checked before running the analysis in the next section.

4.3.2 Evaluation Criteria

To check the performance of the estimated models, several indicators of the performance can be considered. An often used criterion is the '-2LL' (-2 times the natural logarithm of the likelihood of the observations, given the estimated parameters) (Janssens et al., 2008 p. 200). Low values of the -2 Loglikelihood correspond with a high likelihood of the observation, indicating a high quality model. Linked to the -2LL is the Model Chi-Square, which indicates the difference of -2LL of the estimated model and the 'null' model, in which no parameters are added. Higher values of this Chi-Square indicate a greater improvement when using the estimated parameters. One problem of using the -2LL is the fact that is does not account for the number of parameters used. To tackle this problem, the Bayesian Information Criteria (BIC) can be calculated (Kass & Raftery, 1995). A formal notation of the BIC is the following:

$$BIC = -2 * \ln(L) + k * \ln(N)$$

Where L: The likelihood of the model
K: The amount of parameters (including the constant)
N: The amount of observations

By using this criterion, one can check whether a model truly improved by adding parameters. If the difference in BIC is smaller than 3, the difference can most likely be explained by the addition of a parameter. Therefore, in order to accept an additional parameter, the difference in BIC should be larger than 3 compared to the original model. Additional criteria include Cox & Snell and Nagelkerke R square. Interpretation of these criteria as similar to that of the R square in linear regression: the value indicates which part of the variance in the dependent variable is explained by variance in the included independent variables. Higher values indicate a higher performance of the model. A value of 0,5 can be seen as the lower bound of good scores (Janssens et al., 2008), although lower values can also be acceptable (Field, 2009). Finally, the classification table indicates the amount of observations that are classified correctly. When consulting this criterion, the classification table of the null model should always be checked first, as this indicates to what degree the estimated model outperforms a model which classifies all observation to the largest group (e.g. classify each observation as a retained character).

Table 8
Overview of model evaluation criteria

Criterion	Preferred values	Comments
-2 Loglikelihood	Lower is better	Does not account for number of parameters
Model Chi-Square	Higher is better	Merely shows improvement from null model
Bayesian Information Criteria	Lower is better	Accounts for parameters, improved models should decrease BIC by at least 3
Cox & Snell R square	Higher is better	Cannot reach maximum value of 1
Nagelkerke R square	Higher is better	Does reach maximum of 1
Classification Table	Higher is better	Must be compared to null model for interpretation

5. Results

5.1 Checking Assumptions

5.1.1 Linearity of the Logit

Continuous variables should be linearly related to the dependent variable (Field, 2009). To test for this linearity, each continuous variable should be entered into the model as an interaction with its natural logarithm. All variables, as well as interactions with their natural logarithms are then entered into the model. The interactions should then be checked for significance. A significant interaction indicates that the original variable does not pass the assumption of linearity of the logit (Field, 2009). After running this test, it seems Traveling does not pass the assumption of linearity, as the interaction with its logarithm is significant (see Table 9). All other variables pass the test. The natural logarithm of Traveling is computed to use in the analyses.

5.1.2 Multicollinearity

Since there are varying opinions about acceptable value of correlation between two variables, I will follow the criterion as stated by Janssens et al. (2008); correlation higher than 0,6 could become problematic. To check the correlations between variables, I ran a bivariate correlation analysis (Janssens et al., 2008 p. 161). The resulting table showed two correlations higher than 0,6: PlayTime and DaysPlayed, as well as AverageSessionLength and ShortSessionAmount (see table 9).

Field (2009) however states that this collinearity measurement does not necessarily apply to logistic regression. He suggests checking the tolerance and VIF values instead. Janssens et al. (2008) add the Condition Index as an additional measurement. To generate these values, a linear regression using the same independent and dependent variables must be run, while adding the collinearity diagnostics as the result of interest.

Table 9
Linearity and Collinearity test results

	Linearity	**Collinearity**		**Correlations*** **									
Parameters	P-Value	Tol.	VIF		1.	2.	3.	4.	5.	6.	7.	8.	9.
1. PlayTime	,79	,256**	3,908	1.								[a]	
2. Ses. Len.	,318	,311**	3,219	2.							[b]		
3. Guilded	,492	,855	1,170	3.									
4. Leveling	,459	,523	1,913	4.									
5. Av. Lev.	,201	,470	2,127	5.									[c]
6. Traveling	,028*	,855	1,169	6.									
7. Sho. Ses.	,976	,370**	2,704	7.		-,752[b]							
8. Days Pl.	,484	,349**	2,864	8.	,711[a]								
9. Endgame	,576	,435**	2,300	9.					,688[c]				

* P-value of interaction with logit <0,05: Traveling is not linearly related to dependent variable
** Tolerance values are lower than 0,5: indicating general presence of multicollinearity
*** Only significant correlations (>0,6) are mentioned

The Condition Index shows a maximum value of 17,13. According to Janssens and colleagues, an index of 30 or higher indicates a strong presence of multicollinearity. Next, the Tolerance value – which indicates the independence of one predictor variable to other predictor variables (0 meaning low independence) – and the variance inflation factors – which indicates to what degree the effect of one predictor variable is 'inflated' by other predictor variables – are consulted. Field (2009) applies a tolerance value of 0,1 as an indicator of serious multicollinearity, while Janssens et al. (2008) apply a value of 0,5 for a general presence of multicollinearity and 0,3 for serious multicollinearity. Field (2009) also applies a VIF value of 10 as an indicator of serious multicollinearity. In my model, PlayTime, AverageSessionLength, ShortSessionAmount and DaysPlayed have tolerance values below

0,5 (PlayTime is also below 0,3), but none of them show a VIF value above 4 (see table 9). These tests suggest there might be a multicollinearity problem with the data. However, not all tests do. It is therefore unclear whether there really is a multicollinearity problem. Variables with high correlation will be entered into the models both separately as well as combined. Based on the models' predictive performance, the better model will afterwards be selected.

5.1.3 Outliers

Identification of outliers can be done after a model is estimated, as well determining whether or not an outlier is influential. Before interpreting the coefficients and strength of the model, outliers will be investigated and further action will be determined afterwards. To decide whether outliers should be removed, 'DFBeta' plots are created for each variable in each model. These plots indicate to which degree the coefficients of the parameters in the model change due to an eventual removal of the outlier. When an outlier shows extreme values of changes in the coefficients for two or more parameters in the estimated model (or one if there is only one parameter), I classify an outlier as influential, after which the outlier is removed from the dataset. Afterwards, the model is estimated again for further analysis.

5.2 Models

In section 3 several variable categories were proposed. Each of these categories will first be separately added into a model and afterwards, all categories will be combined into one model. Variables are added to the model according to the 'enter' method, in which all selected variables are added to the model simultaneously. Because the first models check the significance of the variable categories separately, using a stepwise method – which checks the additional value of every selected variable before adding it to the model – is not needed. If variables show a low level of additional predictive power, they are still explored with the enter method, while the stepwise method would not allow them into the model. Detailed SPSS output can be found in the Appendix.

5.2.1 Product Usage Habits

The first category depicts product usage habits. The available variables in this category are PlayTime, AverageSessionLength, ShortSessionAmount and DaysPlayed. Given these four variables, the multicollinearity problem discussed above could be at hand. Therefore, every possible combination of the variable is run, and the model with the lowest Bayesian Information Criteria value is selected for further analysis, given the difference in BIC is greater than 3. A model using more parameters is more likely to have a higher BIC. When the difference in such a case is lower than 3, the difference is most likely caused by merely the higher amount of parameters (Kass & Raftery, 1995). A model using Play Time, Days Played and Amount of Short Sessions generates the lowest BIC (757,74). The second lowest BIC is generated by a model using Days Played and Short Session Amount (758,95). The difference in BIC is smaller than 3, so the model using the most parameters is selected. Therefore, the model using Play Time, Days Played and Short Session Amount is selected for further analysis.

In mathematical form, this model will obtain the following expression:

$$Z = \beta_0 + \beta_1 PlayTime + \beta_2 ShortSessionAmount + \beta_3 DaysPlayed + \varepsilon$$

After running this regression, 14 outliers were identified. Based on the influence these outliers have on separate variables, it seems observations 156, 195, 507 and 746 are influential outliers. These observation numbers correspond with characters 7864, 16473, 55609 and 72085. They are extreme outliers for Play Time and Short Session Amount based on the plots of the DFBetas for these variables. Therefore, they are excluded from the model and the model is run again.

The Omnibus Tests indicate the influence of adding the three variables to the model. By adding them to the model, the loglikelihood of the model decreases with 272,470 (lower values indicate a better model). Cox & Snell R square and Nagelkerke R square also indicate the model's performance, and are 0,285 and 0,408 respectively, which is a moderate score. The classification table is an additional indicator of the model's predictive power.

From the table, it can be seen that there are (492+84=) 576 retained characters in the dataset, of which the model classifies 492 correctly as retained characters. There are also (94+141=) 235 defectors in the data, of which the model classifies 141 correctly as defectors. Overall, the model classifies 78,1% of the observations correctly, which seems like a decent score. However, to see whether this truly is a good score, the classification table for the null model (in which no parameters are used), which classifies every character as a retained one, must be checked. Without any predictors, the model classifies 70,7% of the observations correctly. This indicates the decent quality of the model that only incorporates habit features.

In this model, Play time (positive) has a significant effect on the likelihood of a gamer's intention to defect, while the amount of days played per month has a significant negative effect. The amount of short sessions does not have a significant effect on the likelihood of defection.

5.2.2 Social Factor

The second category depicts social variables. The only variable in this category is Guilded. Obviously, no multicollinearity problems are at hand, and Guilded has a linear effect on the dependent variable.

In mathematical form, this model will obtain the following expression:

$$Z = \beta_0 + \beta_1 Guilded + \varepsilon$$

When only using the time spent in a guild as a predictor, no outliers are found.

By adding Guilded to the null model, the loglikelihood is decreased by 29,323, while both Cox & Snell and Nagelkerke R square are lower than in the login features model (0,035 and 0,050), indicating a low quality of the model. The classification table is exactly the same for both the null model and the model with a single predictor; all observations are classified as retained, making up for a correct prediction of 70,7%. In this model, being in a Guild has a significant negative effect on defection intentions.

5.2.3 Rewards, Product Mastery and Immersion

The third category depicts variables that describe the pursuit of extrinsic rewards, product mastery and immersion of a character. Variables in this category include LevelsGained, AverageLevel, Traveling and Endgame. These factors are combined into one model instead of separate models, because the variables conducted are examined together in online gaming literature (Suznjevic, 2011; Yee, 2007; Choi & Kim, 2004). It became clear that Traveling is not linearly related to the dependent variable, so the natural logarithm of this variable is added to the model.

In mathematical form, this model obtains the following expression:

$$Z = \beta_0 + \beta_1 LevelsGained + \beta_2 AverageLevels + \beta_3 Endgame + \beta_4 LnTraveling + \varepsilon$$

When only analyzing the rewards, mastery and immersion variables, Endgame and AverageLevel become correlated, as their correlation coefficient exceeds 0,6. Therefore, this analysis is also run with these two variables separately, to check whether this multicollinearity is a problem. The model incorporating both variables has the lowest BIC, so multicollinearity is not a problem with these variables. After running the regression, four outliers are identified.

Among these outliers, observation numbers 648 and 719 have a strong influence on multiple variables and are therefore excluded from the model. Deleting these outliers improves the model, as the BIC decreases from 932,47 to 919,01.

Adding these variables to the model decreases the loglikelihood by 95,782 compared to the null model. Cox & Snell R square and Nagelkerke R square are 0,111 and 0,159 respectively, which is higher than the model with only a communication variable.

Compared to the null model, the model which includes the immersion variables classifies 70,2% of the observations correctly. Compared to the null model, this is an even lower score.

In this model, Levels Gained, Endgame and Average Level have a significant effect on the intention of defection. Gaining levels and Average Level have a negative effect on the intention, while being endgame has a positive effect on the likelihood of defection.

5.2.4 All Variables Model

To check the combined predictive power of the variables, all variables of the separate models are combined into one full model. As Average session length and Traveling did not pass all assumptions of the model, they were not included into the full model. In mathematical form, this model will obtain the following expression:

$$Z = \beta_0 + \beta_1 PlayTime + \beta_2 DaysPlayed + \beta_3 ShortSessionAmount + \beta_4 Guilded + \beta_5 LevelsGained + \beta_6 AverageLevel + \beta_7 Endgame + \beta_8 LnTraveling + \varepsilon$$

In this model, 14 outliers are identified. Based on the DFBeta plots, two outliers can be seen as influential, as they strongly influence at least four variables. Observation numbers 156 and 507 are removed from the dataset and the model in run again. Removing these outliers improves the model, as the BIC decreases from 784,07 to 768,76.
By adding the variables to the model, the model is improved compared to the null model. The loglikelihood decreases by 272,841. The BIC becomes 768,76 and Cox & Snell and Nagelkerke R square are 0,285 and 0,407 respectively. The model correctly classifies 77,9% of the observations, which is a slight decrease compared to the habit features model.
Most variables lose their significant effect on the likelihood of defection when all variables are combined. Days played and Guilded have a significant negative effect on the likelihood of defection and Play Time has a significant positive effect on the likelihood of defection. Short Session Amount, Levels Gained, Average Level, Endgame and LnTraveling all lose their significant effect or retain their insignificant effect.

5.2.5 Play Time Test Model

In all the previous models, both Days Played and Play Time have a significant effect on the likelihood of defection. While both variables are seen as product usage habit features, the variables have opposing effects as Play Time increases the likelihood of defection, while Days Played decreases it. It was hypothesized that habits decrease the likelihood of defection, so the effect is Play Time is strange. It could be due to the relatively high correlation between Play Time and Days Played. Therefore, a model is run using the significant parameters from the All Variables Model, without using Days Played. This leaves Play Time and Guilded. The mathematical expression for this model becomes

$$Z = \beta_0 + \beta_1 PlayTime + \beta_2 Guilded + \varepsilon$$

In this model, eight outliers are found, of which two are classified as influential as they strongly affect both parameters. Observation numbers 507 and 719 are removed from the dataset and the model is run again. Removing these outliers improved the model, as the BIC decreases from 878,65 to 853,99. Compared to the null model, the -2loglikelihood decreases by 147,40. Cox & Snell R square and Nagelkerke R square are 0,166 and 0,237 respectively. The model classifies 73,7% of the observations correctly. Both parameters show a significant effect on the likelihood of defection and indeed, PlayTime does now have a negative effect on the likelihood. Guilded retains its negative effect.

5.2.6 Full Model

From the previous models it became clear that most variables have, to some degree, a significant effect on the likelihood of defection. However, when put together, a lot of variables lose their significant effect, while habits features remain significant. One possible explanation could be that the habit parameters mediate the other parameters. When observed separately, the habit variables have a significant effect, as well as all the other variables (except for Short Session Amount and Traveling). The habit factors also have a significant effect in the All Variables model. To check for this indirect effect, one more model will be estimated, which excludes the habit parameters because they might mediate the effects. This model will thus test for the full effect of all the variables. The variables that are entered in this model are Guilded, Average Level, Levels Gained, Endgame and LnTraveling, giving the following mathematical expression

$$Z = \beta_0 + \beta_1 Guilded + \beta_2 AverageLevel + \beta_3 LevelsGained + \beta_4 Endgame + \beta_5 Traveling + \varepsilon$$

In this model, four outliers are identified, of which one outlier is classified as influential as it strongly influences at least three variables. Observation number 648 is removed from the dataset and the model is run again. The removal of the outlier slightly improves the model, as the BIC decreases from 930,41 to 925,10. Compared to the null model, the -2loglikelihood decreases by 98,863. Cox & Snell R square and Nagelkerke R square become 0,114 and 0,163 respectively. The model classifies 71,5% of the observations correctly. Guilded, Levels Gained, Average Level and Endgame have a significant effect again, while LnTraveling still does not have a significant effect. Endgame has a positive effect on the likelihood of defection while the other variables have a negative effect.

5.2.7 Mediation Test

To statistically test for the expected mediating effect, a Sobel test is performed (MacKinnon & Dwyer, 1993). One can expect a mediating effect when an independent variable significantly affects the expected mediator, when the mediator has a significant effect on the dependent variable, when the independent variable has a significant effect on the dependent variable in absence of the mediator and when the effect of the independent variable is lost when the expected mediator is added to the model (Preacher & Leonardelli, 2010). Since Guilded does not lose its significant effect when either Play Time of Days Played is added, this effect is not mediated. Levels Gained, Average Level and Endgame do lose their effect, so a mediating effect is expected for these variables. To test for this, a regression must be run with the mediator as dependent variable and one of the independent variables that are mediated as predictor. This is done for each of the Reward and Mastery factors, using both Play Time and Days Played as possible mediators. The test calculates a z-test, with the null hypotheses being that the mediating effect is equal to zero. Table 10 lists all the test statistics and results.

Table 10 Sobel Test results

	Play Time				
	Coef. of association	Std. error	Coef. of PT on Defection	Std. Error	Mediating P-value
Levels Gained	3,314***	0,192	-,058***	,009	,000***
Average Level	,529***	,058	-,048***	,007	,001***
Endgame	19,028***	2,713	-,049***	,007	,007***
	Days Played				
	Coef of association	Std. Error	Coef. of DT on Defection	Std. Error	Mediating P-Value
Levels Gained	,611***	,048	-,262***	,026	,000***
Average Level	,140***	,013	-,240***	,023	,000***
Endgame	5,437***	,625	-,241***	,023	,000***

***Significant at the 1% level

6. Discussion

6.1 Summary of Findings

For an overview of all the models described above, as well as an easy comparison of their evaluation criteria, consider table 11.

Table 11
Parameter coefficients and evaluation of estimated models

	Hypo-theses	Habits	Social Factor	Rewards, Mastery & Immersion	All Variables Model	PlayTime Test Model	Full Model
Variables		Coefficients					
Constant		.846	-.306	-.778	.806	.075	-.495
Play Time	H1 (+)	.018***			.015**	-.062***	
Short Sessions	H1 (+)	.435			.371		
Days Played	H1 (+)	-.308***			-.291***		
Guilded	H2 (+)		-0.906***		-.350*	-.452***	-.525***
Average Level	H3 (+)			-.012**	-.001		-.010*
Levels Gained	H4 (+)			-,171***	.034		-.146***
Endgame	H4 (?)			.853***	.101		.708***
LnTraveling	H5 (+)			-0,082	-.069		-,094
Evaluation Criteria							
BIC		730,67	970,29	919,01	768,76	853,99	925,10
-2LL		703,88	956,89	885,51	708,45	833,89	884,89
C.& S. R^2		0,285	0,035	0,111	0,285	0,166	0,114
Nagelk. R^2		0,408	0,05	0,159	0,407	0,237	0,163
Accuracy		78.1	70.7	70.2	77.9	73.7	71.5

*Significant at the 10% level
**Significant at the 5% level
***Significant at the 1% level

When the variable categories are used in separate models, all of the parameters –except for short session amount and traveling appear to have a significant effect on the likelihood of defection. The significant habit parameters make the highest contribution to the model, as can be seen by the relatively low BIC and relatively high R squares. Average Session Length was not included because it caused multicollinearity. The communication, reward and mastery parameters all have significant effects in their separate models, but based on the BIC, R squares and classification accuracy, these parameters do not have strong predictive power on their own. In the model that incorporates all parameters, most of the significant effects observed in the separate models are lost. The amount of short sessions and traveling retain their insignificant effect, while all the reward and mastery parameters lose their significant effect. Based on the poor performance of the separate model of these parameters, this is not surprising. The Sobel test indicated that both habit variables mediate the effect of rewards and mastery. The communication parameter remains significant. Even though it has little predictive power on its own, being in a guild actually decreases the likelihood of defection when it is combined with other predictors.

The model that only incorporates habit features seems to be the best model based on the Bayesian Information Criteria. To test whether these models are able to generalize over a larger population, I will use the parameter estimates of this model, the All Variables model and the full model for my forecasting sample. This way, the external validity of the strongest and most complete models is tested, as well as the external validity of the reward and mastery variables.

6.2 Model Testing with Forecasting Sample

Using the significant parameters from the full model, the mathematical expression of the prediction whether or not a character defected becomes

$$Probability(defection) = \frac{e^z}{1+e^z}$$

$$Z = 0{,}806 + 0{,}015 * PlayTime - 0{,}291 * DaysPlayed - 0{,}350 * Guilded + \varepsilon$$

A character is assumed to have defected when the probability of defection is greater than 0,5. Using this criterion, the model correctly assigns 75,8% of the observations in the forecasting sample, while in the calibration sample 79,3% was classified correctly. Compared to the null model, the model thus seems to have a general predictive power.

When using the significant parameters from the habit features model, the mathematical expression of the prediction becomes

$$Probability(defection) = \frac{e^z}{1+e^z}$$

$$Z = 0{,}846 + 0{,}018 PlayTime - 0{,}308 DaysPlayed + \varepsilon$$

Using the same cut value, this model now classifies 77,4% of the observations correctly, compared to 78,1% in the calibration sample. This means that for the forecasting sample, both the BIC and the classification accuracy of the habit features model are better. When using the social factor and the reward and mastery variables, the mathematical expression becomes

$$Probability(defection) = \frac{e^z}{1+e^z}$$

$$Z = -0{,}495 - 0{,}525 * Guilded - 0{,}010 * AverageLevel - 0{,}146 * LevelsGained + 0{,}708 * Endgame + \varepsilon$$

The model now classifies all observations as retained characters, making the classification accuracy 59,7%. This is the same as the null model for the forecasting sample. For the calibration sample, this model also showed a minor change compared to the null model (71,5% versus 70,7%).

Because the classification accuracies are about the same for the calibration sample and the forecasting sample, it can be concluded that the models have predictive power beyond the calibration sample. This shows that the models have a good external validity. The classification accuracies of the three mentioned models are summarized in table 12.

Table 12

Classification accuracy of the models using the forecasting sample

Classification table[a]

			Predicted		
			Decision to Defect (1) or Retain (0)		Percentage correct
	Observed		0	1	
All Variables	Decision to Defect (1) or Retain (0)	0	35	2	94,5
		1	13	12	48,0
	Overall Percentage				**75,8**
Habit Features	Decision to Defect (1) or Retain (0)	0	32	5	86,5
		1	9	16	64,0
	Overal Percentage				**77,4**
Reward and Mastery	Decision to Defect (1) or Retain (0)	0	37	0	100,0
		1	25	0	0,0
	Overal Percentage				**59,7**

a. The cut value is ,500

6.3 Interpretation of the Significant Coefficients

When the two habit parameters are examined separately, both parameters have a significant negative effect. The correlation between the two might bias the estimated coefficients. Days played seems to have the strongest direct effect, as the coefficient is much larger than the coefficient for Play Time when the coefficients from the All Variables and the PlayTime test model are considered: -0,338 versus -0,062 respectively. Given that the amount of days played ranges from 1 to 31 and the amount of hours from 0 to 265, play time does have a stronger potential effect. Based on the separate results, it can be said that both habit parameters decrease the likelihood of defection, all else being equal.

The social factor remained its significant negative effect throughout every model. When the coefficient from the strong All Variables model is considered, the effect of being in a guild during all the play time corresponds with a coefficient of -0,350, giving it the strongest direct effect of the three parameters. Therefore, it can be said that socializing within the product usage decreases the likelihood of defection, other factors being equal.

Without habit parameters, the extrinsic reward and mastery parameters retain their significant effect. Only endgame has a positive effect, which means the lack of prospected rewards increases the likelihood of defection. When considering the full model, Levels gained, Average level and Endgame have coefficients of -0,146, -0,010 and 0,708 respectively. Each level gained thus decreases the likelihood of defection. This implies that the strive for attaining rewards makes it less likely for consumers to defect. Along with this reward seeking, the consumer masters the product, also decreasing the likelihood of defection. However, upon the arrival of the maximal level, the likelihood of defection increases a lot. It seems that the prospect of no more rewards in the future do not cancel out the utility of the obtained reward at the highest level. Based on these results, the pursuit of extrinsic rewards and product mastery decrease the likelihood of defection, while the prospect of no more rewards increases the likelihood of defection, all else being equal. Offering a continuous reward system thus corresponds with lower likelihoods of defection. However, these effects were only observed when taken separately from the habit parameters. The Sobel test indicates that the habit parameters mediate the effect of product mastery and extrinsic rewards. These two factors thus seem to influence the likelihood of defection by forming the product usage habits. This effect is also observed by looking at the relatively low performance of the models that do not incorporate product usage habit parameters.

6.4 Comparison of Findings with Prior Literature

It is clear that both the amount of days played per month and the amount of play time per month are the best predictors of defection. Both parameters depict the habit of product usage. Song et al. (2004) describe that a higher amount of daily returns decreases the likelihood of defection, while Tarng et al. (2008) describe that a higher amount of play time also decreases the likelihood of defection. This is in line with my own findings. Wood and Neal (2007) describe that product usage habits increase the affection to the product, therefore it is expected that habit factors will decrease the likelihood of defection. With both habit parameters decreasing the likelihood of defection, the findings of Wood and Neal (2007) are confirmed. Not only do habits increase the affection to the product, consumers showing a habit for the usage of the product are also less likely to defect from using the product in the near future.

Social factors are not broadly described in existing literature. Chen and Lei (2006) describe that communication with other users increases the affection to the game and can thus decrease the likelihood of defection. Social factors within entertainment products are not found in product usage literature. In its separate model, as well as in the full and the combined model, Guilded has a significant negative effect. It can thus be concluded that being in a guild (which is the best metric of inter-user communication [Debeauvais et al., 2011]) decreases the likelihood of defection. This is in line with Chen and Lei (2006) and contributes to literature on product usage. Based on my results, it can be said that there is a social factor that positively affects product usage, while making a defection from the product in the near future less likely.

The parameters that depict the rewards of the game and product mastery have a significant effect in their separate model, but this effect is lost in the full model. Whether rewards and product mastery can affect retention thus remains dubious. In the separate model, all parameters have such an effect; they indicate rewards and mastery decrease the likelihood of defection. Being endgame is among these parameters, having a positive effect. This indicates that the large reward that is received at the end of the game is not rewarding enough to keep enjoying the game. Yee (2007), Choi and Kim (2004) and Tarng et al. (2008) all describe the rewarding effect gaining levels has on users. Based on the results, this indicates that the pursuit of rewards gives consumers more pleasure than the actual obtaining of rewards. Nevskaya and Albuquerque (2012) and Teo et al. (1999) describe the positive effect product mastery has on product usage utility. My findings are in line with all these studies, as my results indicate that product usage mastery and the pursuit of rewards decrease the likelihood of defection. However, since the effects are not observed in combination with other factors, the findings are not robust. This could be explained by the mediating effect of product usage habits. However, there is no literature yet supporting this finding.

Immersion with the product can increase the affection to the product and thus decrease the likelihood of defection (Douglas and Hargadon, 2012). Choi and Kim (2004) and Yee (2007) describe that immersion with the game increase the affection to the game, thus decreasing the likelihood of defection. With the used dataset, the only parameter to depict immersion is traveling. However, traveling did not show a significant effect in any of the estimated models. Based on my analyses, I cannot conclude that immersion with the product decreases defection. As there are many other variables that could depict immersion (Suznjevic et al., 2011), it could well be that these other forms of immersion predict defection. To test this, other variables are needed.

7. Conclusion and Limitations

7.1 Conclusion

In saturating markets, companies find more and more use in Customer Relationship Management. By retaining customers instead of competing for new ones, companies can save 80% of the costs to serve a customer on average (Fornell & Wernerfelt, 1988). By using customer churn prediction models, companies try to increase the customer retention within the company (Coussement & Van den Poel, 2008). Within entertainment product categories, research has identified several factors that might influence product usage: usage habits, product mastery, immersion with the product and extrinsic rewards of consumption (Nevskaya & Albuquerque, 2012; Douglas & Hargadon, 2000). In this study, a fifth factor is identified: socializing. The effects of these factors on actual customer churn were untested; this study offers a first application of the effect of each factor on customer defection. The results show that customers who form habits for product usage less likely to defect in the near future compared to consumers without the habit. Furthermore, customers who socialize with other users of the product are more likely to continue using the product in the near future. Consumers that pursue the rewards that that product offers are less likely to defect. However, it seems the pursuit of the reward gives more pleasure than the actual obtaining of the reward, as the prospect of no future rewards actually increases the likelihood of defection. Consumers who get more experienced in using the product become less likely to defect from using the product in the near future. However, Nevskaya & Albuquerque (2012) note that an increased product complexity due to higher product mastery might demotivate consumers. Because of the nature of the game on which the dataset is based (World of Warcraft) in which a consumer chooses whether or not do complete more complex tasks, this effect could not be tested in this study. The data for this study were not broad enough to test the effect of consumer immersion with the product. Douglas and Hargadon (2000) describe that immersion could increase the affection with the product. The effect of immersion on actual consumer defection remains untested. An overview of the hypotheses and the used variables, as well as the significance of their effects is shown in table 13.

Table 13
Summary of results

Hypothesis	Studied factor	Expected sign	Hypothesis accepted?
Forming habit decreases defection	Monthly Play Time	-	Yes, in all models
	Days played per month	-	
Socializing decreases defection	Time in Guild	-	Yes, in all models
Pursuing rewards decreases defection	Levels Gained	-	Yes, in models without habits
	Endgame	+ / -	
Mastering the product decreases defection	Average Level	-	Yes, in models without habits
Product Immersion decreases defection	Traveling Time	-	No

7.2 Managerial Implications

Managers facing saturating markets face the challenge of identifying customers who are likely to defect from their product and undertaking remedial action to prevent the identified consumers from actual defecting. As this study can be applied to entertainment product categories, managers of firms within these categories can base their decisions, as well as the allocation of the budget for remedial action, on the results of this study.

The strongest predictors of defecting customers were product usage habits and socializing with other consumers. A high amount of monthly usage time and a high amount of days per month using the product positively affect customer retention. Therefore, managers should apply features to their product that give consumers an incentive to return to the product on a regular basis. Within online gaming, one such feature that is often used is the availability of in-game pets that need to be fed regularly, or in-game items that need regular maintenance (Nevskaya and Albuquerque, 2012). Offering rewards can also increase customer retention. By continuously offering consumers rewards in the future can keep consumers motivated to play. The effect is mediated by habit forming however. One implication of this can be that consumers use the product more because of the prospected rewards. Therefore, offering rewards based on the daily activities suggested could be a very effective procedure to increase customer retention.

When consumers get experienced in using the product, they enjoy the product more. This could be due to the fact that consumers become familiar with more complex product features (Nevskaya and Albuquerque, 2012), or because consumers are able to get more tasks done in the same time (Teo et al., 1999). This study could not identify whether consumers enjoy a more complex product or a more efficient usage of the product after they master the product. Firms should keep these two possibilities in mind, by offering both more complex features to experienced consumer, while they also keep offering the less complex features that consumers are able to use efficiently.

Finally, socializing with other consumers turned out to be one of the strongest predictors of retention. Firms should offer the possibility of interacting with other consumer whenever possible. Not only should consumers have the platforms needed for interaction, they should also be incentivized to interact. By offering rewarding tasks that require collaboration, consumers will be less likely to defect in the near future.

7.3 Limitations

7.3.1 Used Methods

In this thesis, logistic regression was used as the sole method for predicting churning customers. Although this form of regression is considered to be a reliable method with a relatively high performance and robust results (Coussement & Van den Poel, 2008, Neslin et al., 2004), several techniques can outperform or complement logistic regression. One of the disadvantages of logistic regression is the fact that the parameters are modeled in a linear way. This linearity may not always be true. By applying Generalized Additive Models (GAM), this restriction of logistic regression is relaxed (Coussement et al., 2009). By applying GAM, new structures in the data may be uncovered which would be overseen when using logistic regression. However, applying GAM to my study would require a statistics package that is not (yet) available to me and would require a lot of additional learning and time. Given these disadvantages, logistic regression was an appropriate method for this study. In future research, other techniques could be applied or added to the current research.

7.3.2 Sample Size and Time Frame

Although my sample size meets the rule-of-thumb requirements of regression analysis (5-10 times the number of parameters used), some additions to the sample might be beneficial. With the amount of data I was able to transcribe, I am able to create data over 3 months per character. However, the third month was likely to bias the data, leaving 2 observed months per character. A larger time frame could improve the estimates of the model, as well as improve the used parameters by allowing for the use of lagged terms (e.g. last month's play time). This lagged information might allow for earlier detection of potential defectors, allowing managers more time to construct prevention measures. However, to be able to create these variables I would have to transcribe a lot more data, which causes a workload beyond the scope of this thesis. Given more time (and perhaps a budget), a larger amount of historical data per character could be created in eventual further research.

7.3.3 Other Parameters

Although the World of Warcraft Avatar History dataset offers a novel freely available dataset, some factors of interest are not available from the dataset. It seems there are demographic factors influencing a person's affection to online games (Debeauvais et al., 2011). These include age, marital status, family size and others. To collect these data, one would have to individually track the studied players over a sufficient amount of time, which is an inefficient and probably impossible task for a master's thesis study. Besides that, these demographic data are not available to game designers and are therefore unlikely to be used in commercial defection detection models.

Another factor that seems to influence the likelihood of defection is the length of the relationship with the product or firm. As with most forms of entertainment, the longer one consumes it the less entertaining it gets. Therefore, consumers who have been with the product or firm for a longer time might show less affection to it and are thus more likely to defect. These data are probably available to firms, but due to privacy and perhaps business-confidentiality, I am not able to obtain these data.

Finally, more parameters that depict immersion with the product are needed. The used dataset had one parameter that could depict immersion (traveling), but this variable did not have a significant effect in any model. Future research could incorporate other variables that depict immersion.

7.3.4 Retention Increasing Procedures

Because of the quantitative nature of my data, it is hard to suggest actions to increase customer retention. Research suggests that game designers can keep retention rate high by constantly introducing new features to their game that follow customers' playing behavior (Day, 2001). My data do not suggest specific playing habits. Furthermore, the proposed actions for remedial procedures are not robust as they are not tested. As the data for this study are secondary, I was not able to alter several aspects of the product. Nevskaya and Albuquerque (2012) altered aspects of the studied product (e.g. they increased the time it takes to obtain the next reward) and found that changing mechanisms of the product could indeed change customer affection to the product. Future research should look into product changing.

7.3.5 Externalities

Although defection prediction models are beneficial for game designers, there is another side to the story. Online gaming has proved to be a highly addictive form of entertainment. Tarng and colleagues (2008) studied game hours of World of Warcraft players, and noticed that many players are playing the game during hours that should not be available to gaming. They noticed that teens were playing during hours that are usually spent at school, while adults are playing during traditional business hours. Tarng, Chen and Huang (2008) find that as the weekend draws closer, World of Warcraft gamers' playtimes increase. One possible explanation according to them is that gamers feel a growing urge to play the game as the weekend draws closer. But it does not end there. After the weekend ends, the playtime does not immediately drop significantly. This can be due to the fact that the game has such a high attraction, gamers find it hard to concentrate on their work and even play during working hours. There is no proof that these players indeed skipped school or were playing during their daytime job, but the findings are still alarming. This leaves food for thought about the ethics behind defection prevention procedures in the online gaming industry: isn't it a good thing that players are able to break with their addiction? Although this is not a limitation of this study, a broader look into the negative externalities (e.g. addiction) would be an interesting topic in, for example, consumer psychology literature.

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Appendix

World of Warcraft Screenshots

This Screenshot shows the overworld in World of Warcraft. In the left bottom of the screen the chat channel can be seen; green texts depict interaction within a guild, yellow texts depict notifications that apply to the player, purple texts depict the trade channel that is observable by anyone within the same fraction, orange texts depict interaction within the temporary party.

This screenshot shows the player's character, who is about to battle a boss monster to finish a quest.

SPSS Output

Null Model

Classification Table[a,b]

Observed			Predicted: Decision to Defect (1) or Retain (0): 0	1	Percentage Correct
Step 0	Decision to Defect (1) or Retain (0)	0	576	0	100,0
		1	239	0	,0
	Overall Percentage				70,7

a. Constant is included in the model.

b. The cut value is ,500

Habits Model

Casewise List[b]

Case	Selected Status[a]	Observed: Decision to Defect (1) or Retain (0)	Predicted	Predicted Group	Temporary Variable: Resid	ZResid
61	S	1**	,018	0	,982	7,483
156	S	1**	,029	0	,971	5,742
177	S	1**	,094	0	,906	3,108
195	S	1**	,038	0	,962	5,022
219	S	1**	,105	0	,895	2,922
260	S	1**	,078	0	,922	3,449
320	S	1**	,073	0	,927	3,556
401	S	1**	,108	0	,892	2,876
459	S	1**	,084	0	,916	3,304
507	S	1**	,026	0	,974	6,124
596	S	1**	,021	0	,979	6,821
719	S	1**	,016	0	,984	7,810
733	S	1**	,090	0	,910	3,182
746	S	1**	,090	0	,910	3,186

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2,000 are listed.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	272,470	3	,000
	Block	272,470	3	,000
	Model	272,470	3	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	703,880[a]	,285	,408

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Classification Table

Observed			Predicted		
			Decision to Defect (1) or Retain (0)		Percentage Correct
			0	1	
Step 1	Decision to Defect (1) or Retain (0)	0	492	84	85,4
		1	94	141	60,0
	Overall Percentage				78,1

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	DaysPlayed	-,308	,031	99,787	1	,000	,735
	ShortSessionAmount	,435	,346	1,581	1	,209	1,546
	PlayTimeHour	,018	,006	7,701	1	,006	1,018
	Constant	,846	,213	15,703	1	,000	2,329

a. Variable(s) entered on step 1: DaysPlayed, ShortSessionAmount, PlayTimeHour.

Social Factor Model

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	29,323	1	,000
	Block	29,323	1	,000
	Model	29,323	1	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	956,888[a]	,035	,050

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than ,001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Guilded	-,906	,167	29,407	1	,000	,404
	Constant	-,306	,127	5,784	1	,016	,736

a. Variable(s) entered on step 1: Guilded.

Rewards, Product Mastery and Immersion Model

Casewise List[b]

		Observed			Temporary Variable	
Case	Selected Status[a]	Decision to Defect (1) or Retain (0)	Predicted	Predicted Group	Resid	ZResid
648	S	1**	,060	0	,940	3,943
719	S	1**	,036	0	,964	5,209
746	S	1**	,028	0	,972	5,895
792	S	1**	,064	0	,936	3,840

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2,000 are listed.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	95,782	4	,000
	Block	95,782	4	,000
	Model	95,782	4	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	885,511[a]	,111	,159

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Classification Table[a]

Observed			Predicted: Decision to Defect (1) or Retain (0): 0	1	Percentage Correct
Step 1	Decision to Defect (1) or Retain (0)	0	531	45	92,2
		1	197	40	16,9
	Overall Percentage				70,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	LevelsGained	-,171	,033	26,268	1	,000	,843
	AverageLevel	-,012	,005	5,269	1	,022	,988
	Endgame(1)	,853	,264	10,477	1	,001	2,347
	LnTraveling	-,082	,064	1,637	1	,201	,921
	Constant	-,778	,415	3,509	1	,061	,460

a. Variable(s) entered on step 1: LevelsGained, AverageLevel, Endgame, LnTraveling.

All Variables Model

Casewise List[b]

Case	Selected Status[a]	Observed: Decision to Defect (1) or Retain (0)	Predicted	Predicted Group	Temporary Variable: Resid	ZResid
61	S	1**	,014	0	,986	8,320

156	S	1**	,038	0	,962	5,049
177	S	1**	,088	0	,912	3,211
195	S	1**	,031	0	,969	5,614
219	S	1**	,125	0	,875	2,649
260	S	1**	,063	0	,937	3,864
320	S	1**	,058	0	,942	4,040
401	S	1**	,101	0	,899	2,979
459	S	1**	,063	0	,937	3,843
507	S	1**	,020	0	,980	6,973
596	S	1**	,023	0	,977	6,557
719	S	1**	,027	0	,973	6,013
733	S	1**	,130	0	,870	2,582
746	S	1**	,100	0	,900	3,000

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2,000 are listed.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	272,841	8	,000
	Block	272,841	8	,000
	Model	272,841	8	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	708,451[a]	,285	,407

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Classification Table[a]

Observed			Predicted: Decision to Defect (1) or Retain (0) 0	Predicted: Decision to Defect (1) or Retain (0) 1	Percentage Correct
Step 1	Decision to Defect (1) or Retain (0)	0	497	79	86,3
		1	101	136	57,4
	Overall Percentage				77,9

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	PlayTimeHour	,015	,007	3,949	1	,047	1,015
	Guilded	-,350	,200	3,061	1	,080	,704
	LevelsGained	,034	,036	,901	1	,342	1,035
	AverageLevel	-,001	,006	,026	1	,872	,999
	DaysPlayed	-,291	,030	93,014	1	,000	,747
	Endgame(1)	,101	,302	,112	1	,738	1,106
	LnTraveling	-,069	,072	,907	1	,341	,933
	ShortSessionAmount	,371	,379	,959	1	,327	1,449
	Constant	,806	,509	2,511	1	,113	2,240

a. Variable(s) entered on step 1: PlayTimeHour, Guilded, LevelsGained, AverageLevel, DaysPlayed, Endgame, LnTraveling, ShortSessionAmount.

PlayTime Test model

Casewise List[b]

Case	Selected Status[a]	Observed: Decision to Defect (1) or Retain (0)	Predicted	Predicted Group	Temporary Variable: Resid	Temporary Variable: ZResid
61	S	1**	,121	0	,879	2,693
260	S	1**	,087	0	,913	3,232
320	S	1**	,050	0	,950	4,346
507	S	1**	,001	0	,999	29,476
596	S	1**	,046	0	,954	4,566
719	S	1**	,014	0	,986	8,457
746	S	1**	,014	0	,986	8,349
792	S	1**	,062	0	,938	3,879

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2,000 are listed.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	147,400	2	,000
	Block	147,400	2	,000
	Model	147,400	2	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	833,892[a]	,166	,237

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Classification Table[a]

	Observed		Predicted: Decision to Defect (1) or Retain (0): 0	Predicted: Decision to Defect (1) or Retain (0): 1	Predicted: Percentage Correct
Step 1	Decision to Defect (1) or Retain (0)	0	536	40	93,1
		1	174	63	26,6
	Overall Percentage				73,7

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	PlayTimeHour	-,062	,009	48,706	1	,000	,940
	Guilded	-,452	,177	6,550	1	,010	,636
	Constant	,075	,138	,297	1	,585	1,078

a. Variable(s) entered on step 1: PlayTimeHour, Guilded.

Full Model

Casewise List[b]

Case	Selected Status[a]	Observed: Decision to Defect (1) or Retain (0)	Predicted	Predicted Group	Temporary Variable: Resid	Temporary Variable: ZResid
648	S	1**	,081	0	,919	3,379
719	S	1**	,054	0	,946	4,205
746	S	1**	,026	0	,974	6,164
792	S	1**	,055	0	,945	4,143

a. S = Selected, U = Unselected cases, and ** = Misclassified cases.

b. Cases with studentized residuals greater than 2,000 are listed.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	98,863	5	,000
	Block	98,863	5	,000
	Model	98,863	5	,000

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	884,892[a]	,114	,163

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Classification Table[a]

Observed			Predicted: Decision to Defect (1) or Retain (0): 0	Predicted: Decision to Defect (1) or Retain (0): 1	Predicted: Percentage Correct
Step 1	Decision to Defect (1) or Retain (0)	0	531	45	92,2
		1	187	51	21,4
	Overall Percentage				71,5

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Guilded	-,525	,183	8,252	1	,004	,592
	LevelsGained	-,146	,031	22,223	1	,000	,864
	AverageLevel	-,010	,005	3,477	1	,062	,990
	LnTraveling	-,094	,065	2,141	1	,143	,910
	Endgame(1)	,708	,266	7,077	1	,008	2,030
	Constant	-,495	,429	1,332	1	,248	,610

a. Variable(s) entered on step 1: Guilded, LevelsGained, AverageLevel, LnTraveling, Endgame.

Mediating Test

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	12,823	1,231		10,418	,000
	Levels Gained	3,314	,192	,517	17,243	,000

a. Dependent Variable: PlayTimeHour

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	LevelsGained	,036	,032	1,290	1	,256	1,037
	PlayTimeHour	-,058	,009	39,887	1	,000	,944
	Constant	-,261	,098	7,096	1	,008	,770

a. Variable(s) entered on step 1: LevelsGained, PlayTimeHour.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-3,482	3,065		-1,136	,256
	Average Level	,529	,058	,304	9,101	,000

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-3,482	3,065		-1,136	,256
	Average Level	,529	,058	,304	9,101	,000

a. Dependent Variable: PlayTimeHour

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	16,099	1,517		10,610	,000
	Endgame	19,028	2,713	,239	7,014	,000

a. Dependent Variable: PlayTimeHour

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	PlayTimeHour	-,049	,007	45,938	1	,000	,952
	Endgame	-,543	,199	7,451	1	,006	,581
	Constant	-,136	,105	1,690	1	,194	,873

a. Variable(s) entered on step 1: PlayTimeHour, Endgame.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8,523	,307		27,739	,000
	Levels Gained	,611	,048	,408	12,737	,000

a. Dependent Variable: Days Played

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	DaysPlayed	-,262	,026	105,130	1	,000	,770
	LevelsGained	,053	,029	3,406	1	,065	1,055
	Constant	,848	,147	33,336	1	,000	2,335

a. Variable(s) entered on step 1: DaysPlayed, LevelsGained.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,494	,707		4,941	,000
	Average Level	,140	,013	,343	10,399	,000

a. Dependent Variable: Days Played

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	DaysPlayed	-,240	,023	105,798	1	,000	,787
	AverageLevel	-,007	,004	2,715	1	,099	,993
	Constant	1,115	,223	25,020	1	,000	3,048

a. Variable(s) entered on step 1: DaysPlayed, AverageLevel.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8,523	,350		24,376	,000
	Endgame	5,437	,625	,292	8,698	,000

a. Dependent Variable: Days Played

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	DaysPlayed	-,241	,023	107,674	1	,000	,786
	Endgame(1)	,342	,218	2,450	1	,118	1,407
	Constant	,556	,233	5,704	1	,017	1,745

a. Variable(s) entered on step 1: DaysPlayed, Endgame.