PREDICTION OF PARTIAL CHURNERS AND BEHAVIOURAL LOYAL CUSTOMERS THROUGH BEHAVIOURAL HISTORICAL CUSTOMER DATA

PUBLIC, NON CONFIDENTIAL VERSION

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To simply the reading, in some cases, words or sentences have been replaced by ***

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Management summary

Importance of a churn analysis

A lot of companies experience that their products become commodities and that it is more difficult to solely differentiate on price and product quality. This increased the competition in those kind of industries and companies have a harder time to offer an added value that makes customers want to switch between suppliers. The cost of acquiring new customers exceeds, therefore, in most cases the cost of preventing customers from leaving. Besides, B2B companies have often long-term relationships with their customers. So, a small decrease in churners can have a substantial influence on the long-term profit. Preventing customers from leaving is therefore a necessity for companies. Often, companies implement a shotgun strategy by targeting all customers with an incentive to stay. Although it is easy to implement, it is a waste of valuable resources because the company also sent incentives to customers who are already loyal. This is one of the reasons that churn analyses are becoming more popular among academics and companies.

The goal of churn analysis is to detect the customers that have the highest probability of leaving, by means of a predictive model that is based on the behaviour of previous churners. It is the first step in preventing customers from churning. The second step is to identify the reason for churning and the third step is to target them with an incentive to stay. This ensures a higher efficiency and allocation of resources because the company is only focusing on the customers that have the tendency to leave.

Churn analysis at *

This study conducted a churn analysis at *** by using logistic regression. The focus was on customers with the highest purchase behaviour of the *** market that bought *** in 2014 and 2015. A difficulty of the *** market is that the company does not have contracts with their customers. The complexity of a churn analysis lies then in the fact that it is not sure when a customer ended the relationship. In this case, it is more appropriate to focus on partial defection of a customer in the next period (prediction period) instead of the prediction of a permanent defection. That is, when the customer terminates the contract.

This study took the same approach as previous partial churn studies by operationalizing a partial churner through a calibration and prediction period – figure 3. The calibration period is used to measure the customer behaviour while the prediction period is used for the classification of partial churners. More specifically, a customer is classified, in this study, as a partial churner when he decreased its purchases with more than 25% and when he fell below a frequency threshold. This threshold was the total average of all customers purchases in the calibration period. The data set consisted eventually of 112 customers of which 21 were churners.

To data, this study was the first churn analysis and data mining project at ***. The current data system is mainly build for the registration of data that can improve the processes of customer support, marketing and sales, instead for the purpose of predictive analyses. So, the underlying objective of this study was not to get a churn model that directly could be implemented into the daily operations but rather to lay the groundwork for future churn analyses. This study therefore suggested a list of variables (churn predictors), through literature and interviews with employees of ***, independent of the data available at ***. This gave direct implications for *** on what data they should collect for churn analysis. The variables that could not be tested in this study, are recommended for future analyses.

Customer behaviour that differentiate churners from behavioural loyal (repeat purchasing) customers

The objective of a churn analysis is to identify the typical customer behaviour of previous churners, with the purpose of developing a model, that can predict future churners beforehand. However, to identify this churn behaviour, it is first important to understand the drivers that influence the level of behavioural loyalty (repeat purchasing). Behavioural loyalty means a customer that continues doing business with the supplier. The literature review in this study showed that the most important driver of repeat purchasing is the strength of the relationship between a customer and firm. Factors that moderate the relation between strength of the relationship-repeat purchases are situational factors and customer characteristics.

This study focused on customer satisfaction to describe the strength of the relationship and demographic as a way to explain the different characteristics between customers. Situational factors were excluded due to the small time period of the data set of this study. Customer behaviour that explains the level of customer satisfaction (and subsequently, strength of the relationship) is related to the buying behaviour and complaining behaviour. In other words, customers that are not satisfied with the company will generally have a different complaining and buying behaviour than customers that are satisfied. A list of variables, that could measure this customer behaviour and demographic attributes, is suggested through interviews and literature. To lay groundwork for future churn analyses, this was done independent of the data available at ***.

Methodology & results

The churn analysis was conducted through logistic regression with 14 variables, suggested through literature and interviews, that could be extracted from the database. The tested variables were related to RFM and consist of the buying behaviour of the customer. RFM stands for the recency between purchases, frequency of purchases and the monetary spending of a customer. Complaint behaviour and demographic variables could not be included in the analysis due to the quality of the data system. This should be tested in follow-up studies. In total, 10 of the 14 variables showed predictive power in the univariate analysis. These consist of the recency and frequency variables. The monetary variables had no predictive power.

After an extensive model selection, a multivariable model with the 'frequency of purchases in the last 6 months' and 'the amount of days since last purchase' was the most predictive combination that could differentiate churners from behavioural customers. This model could identify 11 of the 21 churners and improved the base model (a model without predictors) with 6,2%. However, the model should not be generalized and implemented because the linearity of the logit was violated. Moreover, it is worth mentioning that only two variables could be included in the model due to the rule of thumb of logistic regression. This rule states that one variable can be added for every 10 events (churners). It is therefore recommended to retest this model in a larger data set. It also advisable to test the model in combination with, at first, the other variables that showed predictive power and second, the variables that could not be tested due to the lack of data.

Recommendations & conclusions

The churn analysis in this study has led to a few recommendations that is advisable for *** to consider in order to be effective and efficient in predictive analyses. First of all, *** should retest the variables (of the model), and the variables that have not been tested, in a larger data set. The variables and model in this study are tested on a small data set of 112 customers and generalizing it is therefore not advisable. Especially since the linearity of the logit of the model was violated. Besides, a dataset with more churners could include more predictors. This could further improve the predictability of the model.

Second, the main conclusion of this study is that the data system at *** is not build for predictive statistical analyses. It is recommended that ***, therefore, makes some adjustments in their data system before they embark on a follow-up study. This implies ***. Besides, it is advisable to assess whether statistical analyses, as churn analyses, should be done in-house or whether is better to outsource it to another company. Namely, these analyses depend on a lot of arbitrary and complex decisions and proper statistical knowledge and experience is therefore required.

At last, because the quality of the data system and the required knowledge for predictive analyses, it is not recommended to begin directly with predictive (churn) analysis. *** should follow up the recommendations above. In the meantime, the company can begin with monitoring churn by means of the RFM variables. This gives the organization more time to organize their organization for the purpose of predictive (churn) analyses. Monitoring churn analysis is cheaper and more simplistic than predictive churn analysis. The only difference is that predictive churn analysis is a leading indicator while monitoring churn analysis is a lagging indicator. In other words, with predictive churn analyses, you want to predict the probability that the customer will churn while with monitoring churn analyses, you measure their current churn status. Therefore, it is advisable to use a more conservative criteria that determines if a customer is a partial churner or not. If the customer falls below/above that criteria, it is classified as a partial churner. Monitoring the changes in the RFM of a customer is valuable because a customer will not leave all of a sudden. Instead, the customer will gradually change its business from one supplier to another. So, monitoring a significant change in a customer's RFM behaviour can be a sign of churn. The company should then target those customers with an incentive to stay.

Table of Contents

1.0 Introduction

1.1 Outline of this chapter

This study is conducted at *** (from now on, ***) and is commissioned by the Customer Experience Manager of the ***. The sections of the introduction are divided as follows. The description of situation and complication consists of information about the external and internal situation of *** that explains the importance of this topic. The direction of this study is chosen, in conjunction with ***, after a comprehensive company analysis described in Appendix 1. This is based on literature and diverse interviews with employees of ***. The remaining parts of the introduction consist of a deepening of the most important concepts of this study, the research goal, research question and the structure of this study. Background information about the company *** can be found in Appendix 2.

1.2 Description of situation and complication at ***

There are a lot of external developments that have an effect on the current competitive landscape, on how companies behave and how they are doing business. Nowadays, customers conduct a large amount of research themselves before even contacting the supplier (Kamaladevi, 2009; Adamson, et al., 2012). This has ensured that customers are better informed than they used to be and that they make their most important buying decisions earlier in the buying funnel (Lecinski, 2011). As an example, consider how customers make their buying decision without talking to the sales person. These customers are doing their own research on quality, price and type of products. At the time they are in the shop, they have made their buying decision and are difficult to influence. This development is mainly due to the easiness of getting and sharing information through the internet and the continuing development of the technology to share - i.a. computers, smartphones, tablets - and the channels to share - social media and other platforms (Lecinski, 2011). As a result, customers are more sophisticated about the suppliers products and are therefore increasingly demanding (Smith et al., 2014; Hollyoake, 2009). Second, besides the increased customer knowledge, companies are experiencing that products become commodities and markets are getting saturated – especially in the maturity phase of the product cycle (Liu & et al., 2011; Schmitt, 2003). These factors have ensured that it is more difficult for companies to create competitive advantage by differentiating on price and product quality. Hence, a lot of companies are looking for ways to get better insights in the needs of the customers and try to create the best customers experience as possible.

*** has anticipated on the external developments by ***. Second, the company has introduced a Customer Experience Management (CXM) function in August 2015 – see Appendix 3. The rationale behind Customer Experience Management is that customer value is created in the whole customer journey and not only in the core product or service (Verhoef et al., 2009; BT White paper, 2006; Hollyoake, 2009). One of the core tasks of the Customer Experience manager at *** is to increase the satisfaction and loyalty of current customers. To create such a customer satisfaction and engagement, *** needs to understand the customer needs and the value that is delivered to the customer. At the moment, *** measures the satisfaction and loyalty through surveys and interviews where a customer is asked to reflect its experience in a cognitive way (Journée & Weber, 2014). A disadvantage of such measurements is that the results could be biased. For instance, a very positive or negative experience just before the survey could have an influence on the outcome.

*** has recognized the limitations of subjective measurements, like surveys and interviews, for loyalty and wants to begin with analysing customer (dis)loyalty through a more objective measurement. Namely, historical customer data. The importance of collecting and processing large amounts of data and translating it into knowledge is also described in literature. Cooper et al. (2000) state that it is a core competency for successful companies. The process of utilizing raw data is known as knowledge discovery in data bases and data mining. Most customer data is often captured in the company's CRM systems. These can consist of all data that is gathered through a company after an interaction with the customer. One of the major criticisms about CRM systems is that companies invested a lot of money without getting valuable customer information in return. In most cases, the problem is not the lack of data, but the redundancy of unnecessary data. Therefore, it is extremely valuable for companies to convert this data into valuable information. Another advantage of using customer data instead of subjective methods, like interviews and surveys, is that it consists of the actual behaviour of customers. So, it is more objective and the participant cannot affect the results of the measurement (Bryman & Bell, 2011). At the moment, *** has gathered a lot of data in their data warehouse that could consists of valuable customer information. However, this data has not been utilized to full extent.

The focus of this study is on developing a model that can predict what customers abrupt the relationship with *** (churners) by using historical customer data. The aim is to identify behavioural characteristics that are particular for a customer who tends to leave the company. Because this is the first time that such an analysis is done at ***, it is likely that the data system is not perfectly suitable for data mining projects. Therefore, the underlying objective is not to develop a model that can directly be implemented at ***. Rather, its objective is to identify important variables and to lay the groundwork for future data mining projects in the field of churn analysis at ***. This topic is chosen, in conjunction with ***, after the comprehensive external and internal analysis – Appendix 1. The subsequent sections describe a deepening of the concept churn analysis and the concept knowledge discovery through data mining. These concepts are described inseparable from each other in literature and form a good base for the sequel of the study.

1.3 Basic concepts

1.3.1 Churn analysis

It is well-known that it is less expensive for a company to retain customers than to attract new customers (Berson, et al., 2000; Tsai & Lu, 2009; Dick & Basu, 1994). Furthermore, a small decrease in churners can have a major positive effect on the profit.[1] This applies in particular to business-to-business (from now on, B2B) where customers spend in general more money (Rauyruen et al., 2007; Jahromi et al., 2014).

However, it has become more difficult to retain the increasingly demanding customers due to the saturated markets, products that become commodities and the knowledge that customers have about the products. It is even more difficult to retain customers for companies that have no contract with the customer. As a consequence, customers can switch between suppliers without noticing. In those businesses, companies apply often a ‘shotgun strategy’ to prevent customers from leaving (Jahromi et al., 2014). The company send incentives to all customers, in the hope that they will remain loyal. Although this strategy is easy to implement, it is highly inefficient because it is wasting valuable recourses to customers who are already loyal (Jahromi et al., 2014). For this reason, churn analysis has gained increasingly attention by many academics and practitioners (Van den Poel & Lariviére, 2004; Chen et al.,2015; Buckinx & Van den Poel, 2005; Mozer et al. 2000).

A churner is a customer that has the “the tendency to defect or cease business with a company” (Kamakura et al., 2005, p. 286). In contrast, a customer that continues doing business with the supplier is behavioural loyal (Bandyopadhyay, 2007). Predicting customer churn is “the process of calculating the probability of future churning behaviour for customers in the database, using a predictive model, based on prior behaviour” of churners (Jahromi et al., 2014, p.1259). In other words, with a churn analysis you try to identify the typical customer behaviour of previous churners, with the purpose of developing a model, that can predict future churners beforehand.

Most studies on customer churn have focused on the B2C sectors retail, backing and telecommunications (Chen et al., 2015). These studies are mostly conducted in contractual settings where it is easier to identify a churner. The extant literature of customer churn in B2B remains relative novel (Jahromi et al., 2014; Chen et al., 2015). This has mainly to do with the non-contractual setting and the fact that (big) data has not been embraced as it has been in B2C (Jahromi et al., 2014). As a consequence, it is more complex to get the necessary data from a B2B company and to operationalize a churner in a business

[1] Buckinx and Van den Poel (2005) described an example that indicates the importance of reducing customers who are leaving the company. They showed that a 1 percent decrease compared to a customer defection rate of 25 percent can increase profits by 102,923 euro over five years per 1000 customers. Considering, an average amount of spending of 2000 euro a year and a 5 percent discount rate.

where there is no contract between the customer and the supplier. In other words, when can we conclude that the customer really stopped doing business with the supplier (churn)?

To summarize, the premise of a churn analysis is that companies should pay attention to the customers behaviour – figure 1 (Klepac, 2014). More specifically, is the behaviour of a leaving customer different than for a loyal customer? The objective of a churn analysis is then to predict the customers who have the greatest probability of churning. A company should then use the analysis to determine why a customer is leaving and to conduct a strategy to prevent those churners from leaving. This ensures a more efficient allocation of valuable resources.

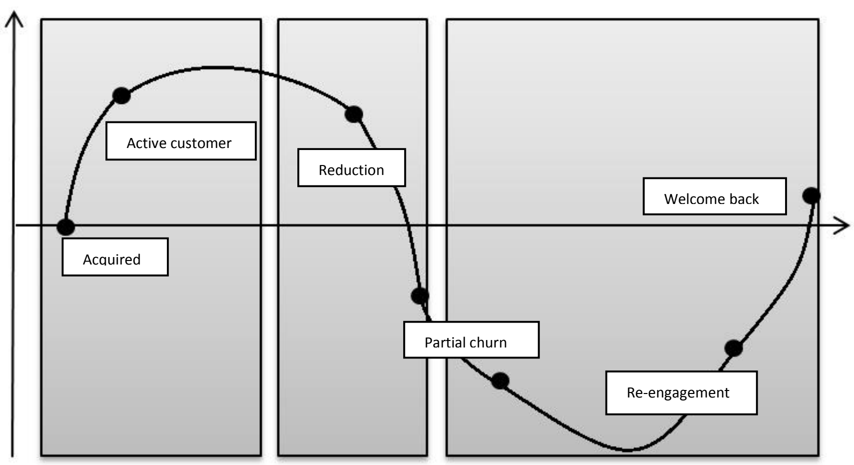


FIGURE 1: ADAPTED FROM "DEVELOPING CHURN MODELS USING DATA MINING TECHNIQUES AND SOCIAL NETWORK ANALYSIS (P.9), BY G. KLEPAC, 2014, IGI GLOBAL, COPYRIGHT 2014 BY IGI GLOBAL.

1.3.2 Knowledge discovery through data mining

The internet and the development of different technologies and systems have made it easier for companies to rapidly gather a high volume of data. However, this data is only useful when it has made the transition to information and subsequently to knowledge. Nowadays, companies are more aware of this potential source of information (Ngai et al., 2009; Berson et al., 2000). It is also noticed by academics that the traditional data analytic and query techniques extract often superficial information from the databases, while this data often consists of much more valuable information (Ngai et al., 2009). Hence, there is an increasing need from companies to process this data in an effective and efficient way with the purpose to utilize this deeply hidden information. The utilization of data for the discovery of information and knowledge has many definitions – data archaeology, data pattern processing, information discovery, information harvesting, knowledge extraction - but is often known as knowledge discovery in databases and data mining (Fayyad et al., 1996).

Data mining can be defined as the “application of specific algorithms for extracting patterns from data“ (Fayyad et al., 1996, p.39). The most common data mining techniques consist of decision tree, logistic regression and neural networks (Ngai et al., 2009). Knowledge discovery in databases can be seen as the overall process of utilizing data wherein data mining is a sub phase. In general, a knowledge discovery in databases project consists of the following phases: business problem, data understanding, data preparation, data mining, interpretation results and the implementation of the results (Cabena et al., 1998; Cos et al., 2012; Fayyad et al., 1996; Miller & Han, 2009). Appendix 4 shows an overview of the phases described in literature. In some literature, data mining is used interchangeable with the definition of knowledge discovery in databases. In these cases, data mining is also seen as the overall process of utilizing data (Watson, 2000; Edelstein, 2000). However, this study sees data mining as a single step – application of a specific algorithm - of knowledge discovery in data bases projects.

The phases of this study will consist of the business problem phase – described in the introduction, literature review, data preparation, data mining and the interpretation of the results. This can serve as a guideline for this study. It is remarkable, from an academic perspective, that the phases proposed in literature did not include a clear theoretical phase. A section that describe the prior literature about the specific business problem is more efficient. For this study, previous literature about churn analysis can increase the likelihood of successful identification of churners. Moreover, the step which consists of the ‘implementation of the results’ falls outside this study. This step should be done by *** after the study.

1.4 Research objective:

Develop a model that consists of variables, that can be extracted from *** databases, which predict whether a customer will remain behavioural loyal or churn.

1.5 Research question:

What customer characteristics or behaviour, extracted from *** existing data warehouse(s), can differentiate behavioural loyal customers from churners?

1.5.1 Sub questions

Theoretical section:

1. What is behavioural loyalty and how can it be operationalized in a non-contractual B2B organization?
2. What antecedents of behavioural loyalty can differentiate churners from behavioural loyal customers?

Deduction:

3. How can these antecedents be operationalized, into variables, through literature?

Induction:

4. How can these antecedents be operationalized, into variables, through the experiences of employees of ***?

Practical section:

5. To what extent are the variables predictors for customer behavioural loyalty and churn for *** customers?

1.6 Structure of this report

The direction of this study is chosen after a comprehensive analysis of the current internal and external situation in the area of Customer Experience Management of ***. The structure of narrowing down from a broad, diverse list of ‘problems’ to one problem situation is common for business problem solving and has been taken over from the regulative cycle by Van Strien (1997). It gives a complete picture of the internal and external situation and how it is related to each other. This report is structured as follows. The first phase, set of problems, can be found in Appendix 1. The second phase, problem choice, is explained in the description of situation and complication. The remaining phases consist of the literature review, the identification of churn predictors through a deductive and inductive approach, testing these predictors and the interpretation of the results. The structure of this report is illustrated in figure 2.

The literature review describe the first two sub questions. The first sub question consists of the concept (behavioural) loyalty and how churn can be defined and operationalized in a non-contractual business. The second question will explain the most important antecedents of behavioural loyalty. The focus is on antecedents that can be measured in customer data and can differentiate churners from behavioural loyal customers.

The identification of predicting variables for behavioural loyalists and churners are twofold. First of all, the deduction approach is more top-down and starts with literature for the operationalization of predicting variables. Second, the induction part is more bottom-top and consists of experiences *** employees. These employees could give novel input about customer behaviour that is different for churners and behavioural loyalists in a B2B sector. This is valuable, especially, because most extant literature tested variables in a B2C context with a contractual setting.

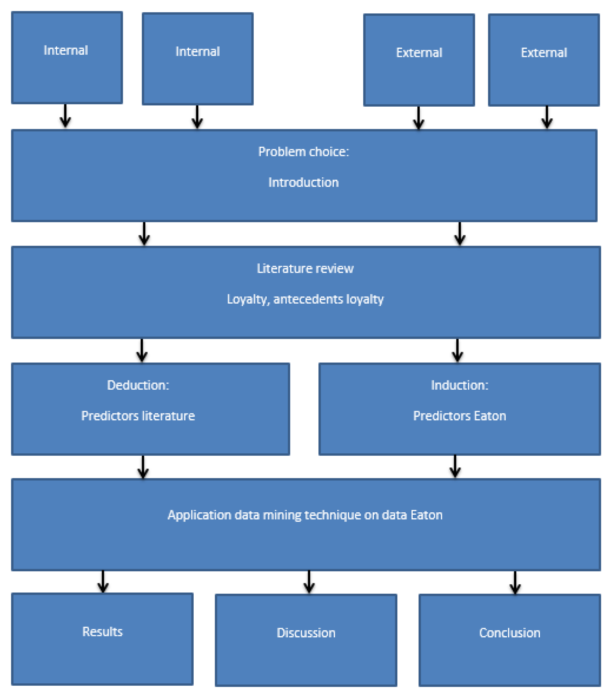


FIGURE 2: STRUCTURE OF THIS REPORT

The methodology part consists of the: operationalization of a partial churner for this study, data mining technique, data selection, data preparation and a selection of the variables that could be extracted from *** database. The outcomes of the analysis are evaluated in the chapters results, discussion and conclusion.

At last, a difficulty with the data of *** is that it is gathered through different data systems. ***. Hence, the quality of the data is not known. Thus, in consultation with *** is decided that the identification of predicting variables (deduction and induction chapters), that could differentiate churners from behavioural loyal customers, will be written beforehand and independently of the data available. This creates an ideal overview of data that *** should gather for the purpose of churn analysis. A disadvantage is that there is a possibility that some indicators from literature can't be tested due to the absence of data.

2.0 Literature review

2.1 Outline of this chapter

The first section explains the strategy for the search of literature in this study. The second section (first sub question) begins with a general explanation of the importance of the concept customer loyalty, the types of loyalty and how previous studies defined and operationalized non-behavioural loyalty (churn) in a B2B company with a non-contractual setting. In a contractual setting, it is easy to identify a customer who is leaving the company. In this case, a customer terminates the contract and goes to a competitor. Identifying a churner in a B2B organization, with a non-contractual setting, is arbitrary and complex because it is unclear when a customer is actually churned. The third section (second sub question) describes the antecedents of customer behavioural loyalty that can be measured in customer data and can differentiate churners from behavioural loyal customers. Subsequently, the antecedents that are most applicable to this study are described in more detail.

2.2 Search strategy literature

The databases that will be used for finding literature consist of Scopus and Google Scholar. The initial search for literature is based on the keywords "customer loyalty", "customer churn" and "churn analysis". The other sections have a more targeted approach where above keywords are used in combination with "types of", "operationalization of", "partial", "B2B", "data mining" or "behavioural". The first step is to select relevant articles with the most citations. To get the most recent literature, the focus is on literature from the year 2000 until now. Only the articles with a minimum citations of 10 will be selected. However, the minimum citations does not apply for articles of the last two years. The second step is to find articles through the snowball method. The snowball method gives the opportunity to you use references or citations from a highly cited article. In this case, articles will also be used that fall outside the demarcation of the sixteen years.

2.3 Customer loyalty

The concept of customer loyalty remains very popular among academics and practitioners because it is seen as an important way to create competitive advantage. Recent studies are still using very old literature as a baseline to describe loyalty (Oliver, 1999; Dick & Basu, 1994). Instead of criticizing the dominant literature, they focused more on the effects and ways to reach customer loyalty (Sureshchandar et al., 2002; Rauyruen et al., 2007; De Canniere et al., 2009; Liu, Guo, & Lee, 2011). Well-known outcomes of customer loyalty are increased revenue and a reduction of the customer acquisition costs (Shankar et al., 2004). However, saturated markets and increasingly sophisticated customers make it more difficult for companies to keep them loyal (Kamaladevi, 2009; Adamson, et al., 2012; Smith et al., 2014; Hollyoake, 2009). Identifying churners beforehand could be therefore a valuable asset for a company. This ensures that they do not have to target all customers but only have to focus on the customers with the highest likelihood of churn.

2.3.1 Types of loyalty

The popularity of loyalty is of all times. Although, when two people talk about loyalty it is easy to create confusion. This is caused by the different components and types that loyalty consist of. In general, with the concept customer loyalty is often meant composite loyalty (Day, 1969; Jacoby & Chestnut, 1978; Jacoby & Kyner, 1973), consisting of attitudinal and behavioural loyalty (Dick & Basu, 1994; Bandyopadhyay, 2007). With behavioural loyalty is meant a customer who continuously buys a product at the same company while with attitudinal loyalty is meant a customer that is an advocate and recommends the company to friends or partners. The level of attitudinal and behavioural loyalty is different per customer. As a consequence, the varying degrees of loyalty leads to four different kinds of outcomes – see table 1. Namely, no loyalty, spurious loyalty, latent loyalty or true loyalty (Dick & Basu, 1994).

First of all, true loyalty is the most admirable situation consisting of both a high attitudinal as a high behavioural loyalty (Dick & Basu, 1994). These kind of customers are an advocate of the company and are not sensitive to switching incentives from competitors. For instance, a change in price will not have an effect on the customer to switch between suppliers. In the worst case, the customer makes an adjustment in the quantity of the order.

Second, latent loyalty consists of customers that have a high attitudinal level and a low behavioural level of loyalty (Dick & Basu, 1994). Although the customers are a true advocate of the company, they are restraint by situational factors. For instance, money restraints or distribution channels make it difficult to acquire the product. Moreover, it could also be that customers are highly satisfied with the supplier, but that they don’t need the products because of the low demands of their own customers. It is important for a company to recognize this type of customers and to subsequently, develop ways to remove or minimalize the barriers which hold them back to purchase.

Third, spurious loyalty consists of a low attitudinal loyalty and a high behavioural loyalty (Dick & Basu, 1994). It is also known as ‘phantom’ loyalty. This category includes customers that show high levels of repeat purchases while they are not really committed to the supplier. These customers are restrained by barriers to switch. For instance, due to monetary constraints, habit, convenience or a lack of alternative suppliers (Dick & Basu, 1994). A customer that is spurious loyal will likely churn when a competitor offers an appealing incentive to switch.

The last category consists of no loyalty. As the name suggest, this refers to customers who are no advocate of the company and have low levels of repeat purchases (Dick & Basu, 1994). Often, the potential of these customers are limited and it is very difficult to change them into true loyal customers. As a consequence, these customers are churning when a switching incentive is offered by a competitor.

Another view is described through the Apostle model by Jones & Sasser (1995). This is almost similar as described above, although now it is classified as loyalists, mercenaries, defectors and hostages – see table 1. Furthermore, this model is operationalized by satisfaction and loyalty, while the aforementioned is operationalized by behavioural and attitudinal loyalty. It is important for a company to understand in which category their customers belong to one of the discussed models above.

To conclude, this study will focus on behavioural loyalty rather than attitudinal loyalty. This is in line with Haghkhah et al., (2013) who suggest that the focus on behavioural loyalty is better when interpreting patterns for repeat purchases. As a repetition, behavioural loyalty can be defined as a customer who continuously buys a product at the same company. The opposite of a behavioural loyal customer is a churner. Churn can be defined as "the tendency of customers to defect or cease business with a company" (Kamakura et al., 2005, p. 286). From now on, with the concept loyalty is meant behavioural loyalty unless specified otherwise. At last, the different types of loyalty can give the reader a better understanding of the whole loyalty concept. However, the objective of this study is not to identify why a customer is churning but to identify the behaviour of churning customer.

		Advocate of the company	
		Strong	*Weak*
Repeat purchase	*Strong*	True loyalty	Spurious loyalty
	Weak	Latent loyalty	No loyalty

		Satisfaction	
		High	*Low*
Loyalty	*High*	Loyalist/Apostle	Hostage
	Low	Mercenary	Defector/Terrorist

TABLE 1: TYPES OF LOYALTY

2.3.2 Partial customer non-activity in a non-contractual business

The definition and operationalization of a customer who is going to churn (behavioural disloyalty) in a non-contractual setting is a complex task. This section will therefore give an explanation about how this is done in current literature. It provides a better understanding of churn analysis and the sequel of this study. Although, it is worth mentioning that the operationalization of churn for this study is described in the methodology chapter (section 5.2 and 5.3) while this section provides only an overview of extant literature.

The crux of churn in a non-contractual setting is that the absence of a contract between a supplier and a customer makes it difficult to identify the exact time when a customer is leaving the company permanently. This is probably the reason that most academic literature has focused on sectors with a contractual setting, such as the finance, telecom or the insurance sector (Jahromi et al., 2014). In a contractual setting, a customer who is going to churn has terminated the contract. In this case it is clear when the customer stopped doing business with the company.

The exact time of termination of the customer relationship in a non-contractual setting is more arbitrary. Therefore, extant literature about the prediction of churn in non-contractual settings has focused on the partial defection of a customer in the next period instead of the prediction of a permanent decision (Buckinx & Van den Poel, 2005; Jahromi et al., 2014). In this case, the focus is on customers who bought no or significantly less products than previous period. These customers are partial churners because they are deviating from their normal buying pattern (Buckinx & Van den Poel, 2005). The focus on partial churners could also be more valuable for a company than total churn because there is still an opportunity to retain those customers. In other words, a partial churner in a non-contractual setting is defined as a customer who is "being active (calibration period) in the first period while being inactive (prediction period) in the second period" - See figure 3 (Tamaddoni Jahromi et al., 2014, p. 1260). To get a better understanding, the calibration period in churn analysis is then used to measure the behaviour (independent variables) that differentiate churners from behavioural loyal customers.

The inactive of a customer in a non-contractual setting is often operationalized through a certain threshold. So, the customer is seen as a partial churner when the indicator is below or higher than the determined threshold in the prediction period. Tamaddoni Jahromi et al. (2014) and Chen et al. (2015) operationalized a non-active customer when the customer had at least one purchase in the calibration period and no purchase in the prediction period. They based the non-activity of a customer on the frequency of purchases. Slightly different, Buckinx & Van den Poel (2005) focused on the customers who had a frequency of purchases and a standard deviation of the inter-purchase time above average in the calibration period. Subsequently, if these selected customers fell below these averages in the prediction period, they were identified as a non-active customer. A disadvantage of a (frequency) threshold is that a customer with minor changes could be determined as a churner while a customer with major changes in their buying behaviour, and not fall below the threshold, is determined as a loyalist (Glady et al., 2009). Migueis et al. (2012) solved this disadvantage by operationalizing a partial defector based on percentage changes in customers spending from one period to another. In this case, a customer was classified as a churner if he spent less than 40% in the next period. Although, these authors focused on new customers with similar spending through the succession of first products' categories purchased (Migueis et al.,2012).

To conclude, a calibration and a prediction period have to be used when defining and operationalizing partial churn in a non-contractual business. The calibration period serves then for the measurement of the (predicting) variables and the prediction period is used to define a partial churner. The operationalization of partial customer churn and a further explanation of the prediction and calibration period for this study can be found in the methodology chapter.

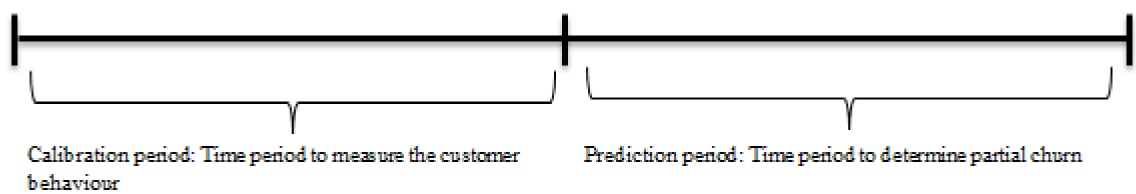


FIGURE 3: PARTIAL CHURN BY MEANS OF A PREDICTION PERIOD

2.4 Antecedents of behavioural loyalty

The purpose of this study is to identify what customer data comprises behavioural characteristics that differentiate churners from behavioural loyal customers. Most studies of customer churn have focused on the B2C sectors retail, backing and telecommunications (Chen et al., 2015). Variables that had an effect on churn in these articles were related to the customer usage, buying behaviour and customer characteristics based on demographic or geographic variables (Van den Poel & Lariviére, 2004; Chen et al.,2015; Buckinx & Van den Poel, 2005; Mozer et al. 2000). Although, the relation between these type of variables is not clearly explained in literature. The focus in most churn studies was mainly on the statistical analysis rather than an explanation of the variables. This study will therefore contribute to previous literature by providing a better theoretical explanation between the drivers of behavioural loyalty and the type of variables described in previous churn studies. This will give a better understanding about the relation between the variables and what these type of variables really explain.

To begin with, composite customer loyalty is influenced by "the strength of the relationship between a customer's relative attitude and repeat purchases" (Dick & Basu, 1994, p.99). This lead to the four types of loyalty that is described in chapter 2.3.1. The focus of this study is on customers who remain a high repeat patronage. Previous chapter showed that a high repeat patronage (behavioural loyalty) can be created with both a high and a low attitudinal loyalty. This implies that the customer does not have to be an advocate of the company to have a behavioural loyal relationship. To get a good grip on what determines the strength of a behavioural relationship, the first paragraph will explain the antecedents of relationship quality. According to Palmatier et al. (2006, p.138) "relationship quality is the "overall assessment of the strength of a relationship". Moreover, it is stated that high levels of relationship quality results in a high purchasing behaviour (de Canniére et al., 2008). The sequel paragraphs will explain antecedents that moderate the strength of a relationship. In general, this can be divided into the individual characteristics of a customer and situational factors (Ball et al., 2004; Dick & Basu, 1994).

Strength of the relationship between a customer and firm

The strength of the relationship can best be described through the relationship quality antecedents. These are often seen as the most influential antecedents of loyalty. There are a lot of antecedents that are described as a part of relationship quality. These concepts are highly related but have a different meaning (Palmatier et al., 2006). The most common concepts are trust, satisfaction, commitment and sometimes service quality (Rauyruen et al, 2009; Palmatier et al., 2006). There is no unambiguous agreement among academics which antecedent comprises "the key aspects of a relationship that most affect outcomes" (Palmatier et al., 2006, p.139). The focus of this study is on antecedents that affect the outcome repeat purchases (behavioural loyalty). Researchers that investigated whether the individual antecedents of relationship quality have an effect on attitudinal and/or behavioural loyalty are Rauyruen et al. (2009). It turned out that satisfaction and service quality were the only antecedents of relationship quality that have a significant effect on behavioural loyalty. Rauyruen et al. (2009, p.8) state that "while both the attitudinal and behavioural components are important in achieving composite loyalty there are different paths to achieving each component", suggesting that customer satisfaction/service quality are better drivers of behavioural loyalty. The importance of these drivers of behavioural loyalty is also recognized by other authors (Shankar, Erramilli, & Lam, 2004; Walsh et al., 2006; Eriksson & Vaghult, 2000) and will therefore be the focus of this study. Customer satisfaction and service quality have received a lot of academic attention, although the operationalization of the concepts remains ambiguous and uncertain. Therefore, this study adopt the view of the highly cited article of Sureshchandar (2002) who sees customer satisfaction as a multidimensional construct that should be operationalized along the same factors and variables as service quality is operationalized. So, an increase in customer satisfaction will likely lead into an increase in service quality. The next paragraphs will explain the antecedents that moderate the relation between the strength of the relationship (customer satisfaction) and a customer's repeat purchases. These moderators fall into situational and customer characteristics.

Situational factors

Situational factors are events that ensure an abruption or a barrier to switch in a relationship between a customer and supplier (Dick & Basu, 1994). This could be caused by several temporary conditions that have an effect on whether customer buy or not. For instance, stock-outs of products, switching costs, incentives from competitors or by macro environment developments (Dick & Basu, 1994; Ball et al., 2004; Blut et al., 2015). This could be legal changes, economic changes or technological changes (Ball et al, 2004). All these factors mediate the relation between the relationship quality and a customer's repeat purchasing behaviour (Dick & Basu, 1994). These conditions are often measured through surveys where a customer is asked to evaluate their perception of the situational factors. However, situational factors are not popular in churn analyses. The reason is that situational factors are often difficult to measure in data. Authors who included situational factors in their churn study are Van den Poel & Lariviére (2004). They measured the effect that mergers/acquisitions and the prosperity at a certain moment have on churn. These authors used a data set of 77 years. Measuring the effect of situational factors will be difficult when a short time period is used. This is also recognized by Mozer et al. (2000) that excluded macro environment in their churn analysis due to the short time period used in their study.

Customer characteristics

Customer characteristics describe the differences between customers based on their attributes (Ball et al., 2004). It could give an explanation why customers have a different purchase behaviour. These attributes moderate the relation between relationship quality and a customer's purchasing behaviour (Buckinx & Van den Poel, 2005). The attributes of customer characteristics are mostly applicable to B2C where the customer is an individual person. In this case, the focus is on characteristics that can differentiate the personality and the societal factors – norms and values, culture beliefs – of customers. These are often described through the demographic attributes of a customer (Dick & Basu, 1994; Buckinx & Van den Poel, 2005). This category is widely adopted in the churn literature (Van den Poel & Lariviére, 2004; Mozer et al. 2000; Buckinx & Van den Poel, 2005). The popularity of demographic is thanks to the easiness of measuring and the fact that demographic variables are often correlated with the product/service usage, customer demands and their preferences (Kotler, 2003). In B2B, where the customer is seen as an entity, it is more difficult to describe their disparate characteristics. In general, it is stated that B2B relationships are more rational than B2C relationships (Hollyoake, 2009). This is due to the fact that a B2B customer is often acting on behalf of their customers. Most B2B studies use therefore more standard demographic attributes as a way to segment customers (Kotler, 2004; Chen et al., 2015).

Antecedents of this study

The relationship between the antecedents of this study is visualized in figure 4. This study will focus on customer satisfaction as a concept to describe the strength of the relationship of behavioural customers. Previous paragraph described that the other antecedents that determine the strength of a relationship had no significant effect on behavioural loyalty. Moreover, it is more difficult to capture concepts as trust and commitment in observational data while the behaviour of a (dis)satisfied customer is easier to capture. Second, demographic attributes of a customer will be used to describe the factors that moderate the relation between the strength of a customer's relationship and repeat purchases (behavioural loyalty). Demographic variables have been proven to be a good moderating predictor for churn (Buckinx & Van den Poel, 2005). And at last, situational factors will be excluded from this study because the difficulty of measuring it in a data set with a small time period. Although, it remains interesting for the prediction of churn when a longer time set is used. For instance, it would be interesting to see if certain legal, economic or environmental changes have an effect on the actual switching behaviour of customers. Although, for the reliability of the results, a data set with a long time period is essential.

To conclude, the antecedents identified in this chapter show directly the relationship with the type of variables in previous studies about churn analyses. Namely, the customer buying behaviour and usage of a product/service are outcomes of the strength of the relationship (customer satisfaction) between a customer and supplier. This is moderated by the customer characteristics (demographic attributes) and situational factors. This can work as a framework for future churn studies that want to identify customer behaviour that can differentiate churners from behavioural loyal customers. In other words, what customer behaviour shows the strength of the relationship between a customer and firm and what factors moderate the relation between the strength of the customer relationship and repeat purchases. The next sections will describe a more detailed explanation of the chosen antecedents.

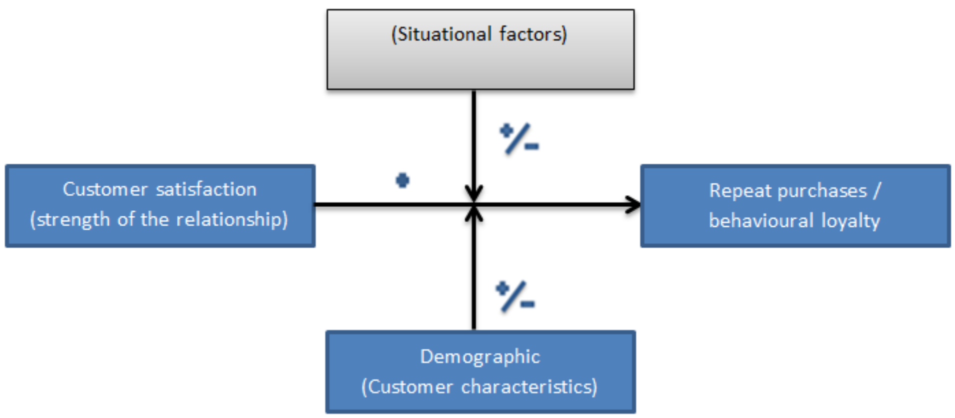


FIGURE 4: RELATIONSHP ANTECEDENTS

2.4.1 Customer satisfaction

This section tries to give a better understanding of the concept customer satisfaction. Previous chapter showed that customer satisfaction can explain the strength of the relationship between a customer and a supplier. The first part of this chapter will explain the general effect of customer satisfaction on behavioural loyalty. The remaining paragraphs will explain the definition, interpretation, antecedents and how a customer express the strength of the relationship by means of customer satisfaction. At last, an explanation on how to operationalize customer satisfaction for churn analyses will be purposed for this study.

First of all, there is an overall agreement that customer satisfaction leads to both behavioural loyalty as well as attitudinal loyalty (Rauyruen, 2009). Moreover, previous studies have revealed that a positive customer satisfaction negatively affect churn (Walsh et al., 2006; Eriksson & Vaghult, 2000). For instance, Eriksson & Vaghult (2000) showed that satisfied customers are more likely to stay at the same firm. They found a positive correlation between relationship satisfaction and their repeat purchases.

Although, despite the popularity of the concept satisfaction, there is still no univocal definition. One definition that is widely accepted by authors (Eggert & Ulaga, 2002; Rauruen, 2009), that describe B2B relationships, is from Chumpitaz and Paparoidiamis (2004). They define customer satisfaction as "an overall evaluation of the total purchase, use and relationships experience with a product or service over time, as expressed by members of the buying decision centre" (p. 238). Customer satisfaction can be intrepreted in two different ways. Namely, as a transaction specific satisfaction or a cumulative customer satisfaction. Transaction specific satisfaction can be defined as the evaluation of an individual specific purchase occasion, while the cumulative customer satisfaction can be defined as the overall evaluation of the relationship or brand between a customer and firm to date (Gil Saura & Frasquet, 2009). Levik-Olsen & Johnson (2003) suggest that cumulative satisfaction is more appropriate in making predictions of customer behaviour. Therefore, this study will focus on cumulative customer satisfaction.

Whether a customer is satisfied or not depends on many factors. For instance, the degree of satisfaction of a customer can be influenced by the functional quality, technical quality, expectations, price, image of the firm or a customer desires (Gandhi & Sing Kang, 2011). These factors can best be explained through the most dominant antecedents of customer satisfaction, namely, disconfirmation (expectation-performance), affact and customer equity (Szymanski & Henard, 2001) - these are explained in more detail in Appendix 5. On the other hand, only a few studies have investigated the outcomes of customer satisfaction. Szymanski & Henard (2001) suggest in their meta-analysis that a customer is expressing its (dis)satisfaction through repeat purchasing, complaining behaviour and word of mouth. As a repetition, extant churn literature focused on variables that explained the strength of a relationship between a customer and supplier. These studies focused mainly on the purchasing behaviour and the customer usage of a product or service to differenitate churners from behavioural loyal customers (Van den Poel & Lariviére, 2004; Chen et al.,2015; Buckinx & Van den Poel, 2005; Mozer et al. 2000). Therefore, it seems also logical to focus on outcomes of customer satisfaction rather than the focus on antecedents. Namely, the perception of an expectation and performance is different for each customer and could be influenced by a lot of factors, while the outcomes customer satisfaction are more homogeneous. Thus, the focus on how a customer express its satisfaction makes it easier to identify behavioural patterns that are typical for churners.

To conclude, the objective of this study is to identify behavioural attributes that can differentiate churners from behavioural loyal customers. In other words, what behaviour is typical for churners? Previous chapter described that the strength of the relationship have an affect on repeat purchases. This study will therefore focus on complaint behaviour and buying behaviour, as categories to operationalize variables, because this explains the strength of the relationship between a customer and supplier. Namely, these are the outcomes of a (dis)satisfied customer and therefore, customers who are going to churn will probably have different complaint and buying attributes than (behavioural) loyal customers. Word of mouth will not be applicable to this study due to the absence of this type of customer data in data systems. Chapters 3 and 4 will operationalize predicting variables that can be measured in customer data and that explains the behavioural characteristics of customers by means of complaint and buying behaviour.

2.4.2 Demographic

Previous chapter described that demographic attributes moderate the relation between strength of the relationship, between a customer and supplier, and repeat purchases (Buckinx & Van den Poel, 2005). The popularity of demographic as a way to segment customers is mainly thanks to the correlation that it has with product/service usage, customer demands and customer preferences (Kotler, 2003). Besides, demographic variables are often easy to measure. It is therefore not surprising that the antecedent demographic is adopted by many authors as a category for variables in churn analyses. More specifically, Buckinx & Van den Poel (2005) described that demographic is one of the most popular category for variables in churn analyses.

In general, demographic variables are mostly applicable to the B2C market. Variables that can segment customers are, among others, household, age, gender, education, religion and geographical data (Kotler, 2003; Buckinx & Van den Poel, 2005). Most variables are, however, not relevant for B2B. This is due to the fact that a business customer is seen as an entity, where a B2C customer is often an individual. Demographic variables that are used in B2B markets to segment customers consist of industry, company size and location (Kotler, 2003). It is most likely that customers with a different industry, company size and location have a different behaviour and thus a disparate level of behavioural loyalty. Therefore, these attributes will be used as demarcation for the operationalization of the variables by means of a deductive and an inductive approach described in chapter 3 and chapter 4.

3.0 Deductive approach; Predictors and operationalization

3.1 Outline of this chapter

This chapter uses a deductive approach to identify customer behaviour that could be different for churners and behavioural loyal customers. More specifically, extant literature on how a customer express its degree of customer satisfaction will be used to identify if the behaviour of a dissatisfied customer is different than for a satisfied customer. This behaviour will be further explained through the moderators of the demographic attributes.

It should be said that the operationalization of variables is written independently from the data available at ***. A difficulty with the data at *** is that it is currently gathered through different data systems. As a consequence, it is possible that the systems gather not the same data or in the same format. Thus, in consultation with *** is decided that the identification of predicting variables will be written independently of the data available. This creates an ideal overview of data that *** should gather for the purpose of churn analyses. A disadvantage is that there is a possibility that some variables from literature can't be tested due to the absence of data. Hence, the definitive list of variables used in this study can be found in the methodology chapter while this chapter only suggests variables in an ideal situation where all data is available.

The chapter will begin with a general explanation about buying behaviour, complaining behaviour and the moderating demographic attributes. These will be divided into sub-categories and at last, operationalization's for variables – that can differentiate churners from behavioural loyal customers - will be suggested for this study. It is worth mentioning that the suggested variables, in the deductive and inductive chapters, are based on the prediction of partial churn that is operationalized through a frequency threshold. The operationalization of partial churn for this study is described in more detail in the methodology section.

3.2 Customer satisfaction

3.2.1 Type of product(s)

A company who wants to do a churn analysis should determine which products to include for analysis. Namely, a customer who buys a convenient product has a totally different behaviour and preference than someone who buys an expensive or customized product. Therefore, it is suggested that the variables of customer satisfaction - repeat purchasing and complaint behaviour - should be adjusted to the determined product (category) used for the churn analysis. Grouping the customers behaviour based on product characteristics is recognized by Chang & Tsai (2011).

3.2.2 Purchasing behaviour

As previously mentioned, repeat purchasing is one of the ways how a customer is expressing its satisfaction and strength of the relationship with the supplier. However, a customer who is dissatisfied in a non-contractual setting is not going to switch all of a sudden (Buckinx & Van den Poel, 2005). The customer is probably switching some of his products gradually from one supplier to another supplier. In this case, a customer becomes a partial churner. If the supplier does not recognize this partial churner, the chances are that the customer is defecting totally. This also explains that a significant change in buying behaviour of a customer could imply that the strength of the relationship is weakened and that the customer is going to churn.

So, it can be stated that changes in the buying behaviour are a predictor of a customer's future repeat purchasing. This is also seen in literature, where the inclusion of buying behaviour attributes for the prediction of churners are used by several authors (Miguéis et al., 2012; Jahromi et al., 2014; Buckinx & Van den Poel, 2005; Chen et al., 2015). The most common attributes of buying behaviour are recency, frequency and monetary (RFM). Another suggested attribute that can influence the company's profitability is the total length of a relationship (LOR) with a company. LOR moderates the buying behaviour of a customer (Buckinx & Van den Poel, 2005; Chen et al., 2015; Miguéis et al., 2012).

To summarize, the above sub-categories will be explained and operationalized into variables in the following sections. This is an ideal list of variables based on extant literature. The definitive selection of predictors can be found in the methodology chapter because it is unclear whether the variables can be extracted from current data warehouse(s).

Operationalization variables

Recency / Inter-purchase time

Recency is considered to be the most powerful predictor for identifying churners compared to the other variables of RFM (Miguéis et al., 2012). It describes how recently a customer did business with the company (Chen et al., 2015). It is proposed that the more recent a customer buys products from the supplier, the lower the probability that the customer is going to churn in the subsequent period. In other words, a customer that is changing its purchasing behaviour significantly, by enlarging the number of days between purchases, will have a greater likelihood of churn. This study suggests four recency variables that explain the purchasing behaviour based on the amount of days since the last transaction and the inter-purchase time (IPT). The inter-purchase time is the time between two purchases. The variables are based on literature by Buckinx & Van den Poel (2005), Jahromi et al. (2014), van den Poel, Lariviére (2004) and Chen et al. (2015).

First of all, three inter-purchase-time variables are suggested. The inter-purchase time is sometimes mentioned in literature as the latency between purchases. The first suggested variable is for the whole calibration period, the second one is for a more recent time period and the third one explains the standard deviation between the IPT. The last variable explains the amount of days since the last transaction. These variables could indicate attributes that are different for churners and behavioural loyal customers.

The $_p$ in the variable stands for the type of product or product categories that are taken into account. The focus should be on product groups that have similar buying behaviour characteristics. The variables are operationalized as follows.

1. $The\ average\ number\ of\ days\ between\ transactions\ \ (for\ product_p)$
2. $The\ average\ number\ of\ days\ between\ transactions\ in\ the\ last_t\ (for\ product_p)$
3. $The\ standard\ deviation\ of\ the\ inter - purchase\ time$
4. $Number\ of\ days\ since\ the\ last\ transaction\ (for\ product_p)$

Frequency of purchases

The second category of RFM is frequency. The extant literature of churn analysis has shown that the more often a customer is purchasing, the less likely the customer is going to churn in the subsequent period (Miguéis et al., 2012). Hence, a customer's frequency of purchases is seen as a good predictor for their future behaviour (Buckingx & Van den Poel, 2005; Jahromi et al., 2014; Chen et al., 2015).

Frequency is often measured through the number of purchases or transactions. In this study, a purchase is defined as a single product bought while a transaction is an order that could consists of more purchases. This study will use both concepts to measure the behavioural category frequency.

The first two variables are focusing on the amount of transactions. This is the original frequency measurement. It is stated that the more often a customer is buying, the less likely the customer is going to churn in the following period. The first variable is based on the whole period while the second variable is based on a more recent period (Buckinx & van den Poel, 2005). For instance, a customer could have a high frequency in the total calibration period while their buying behaviour totally changed in the last months/weeks. [2]

Variables seven and eight are focusing on the amount of products bought in the period before churn. This could be an indication that the customer is moving its business from one supplier to another. Moreover, a customer who buys more products is more dependent on the vendor. As a result, such a customer will probably have a lower tendency to leave than a customer who buys only a few products. The transaction and purchase variables are based on the literature by Jahromi et al., (2014), Van den Poel & Lariviére (2004), Chen et al. (2015) and Mozer et al (2000).

The last variable that is suggested is based on a monetary variable of Jahromi et al. (2014). It consists of the relative change between two periods. The logical is that a customer who is spending less money in the second (more recent) period, compared to the first period, will likely have a higher probability of churn - see figure 5. This is based on the reasoning that a customer who is going to churn will gradually move its business from one supplier to another.

The $_t$ in the variable stands for the time period. This could be weeks, months, a year or another time period. The $_p$ in the variable stands for the type of product or product categories that are taken into account. The focus should be on product groups that have similar buying behaviour characteristics.

5. $Number\ of\ transactions_p$
6. $Number\ of\ transactions_p\ last_t$
7. $Number\ of\ purchases_p$
8. $Number\ of\ purchases_p\ in\ the\ last_t$
9. $Relative\ change\ in\ total\ frequency\ (for\ product_p)\ of\ a\ customer\ in\ the\ second\ half\ of\ the\ calibration\ period\ (f_2) compared\ to\ the\ first\ half\ of\ the\ calibration\ period\ (f_2)$

   $\Delta f = f_2 - f_1$

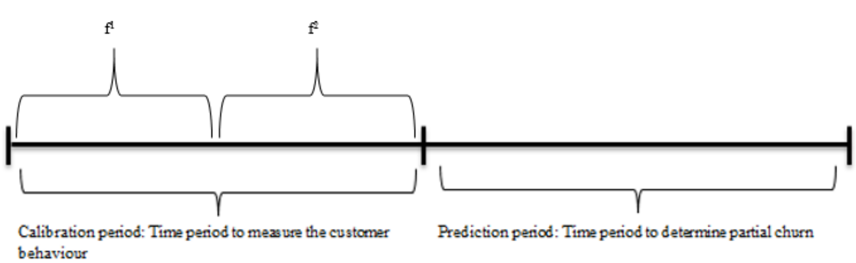


FIGURE 5: RELATIVE CHANGE OF A CUSTOMER PURCHASES

Monetary

[2] The length of the time period depends on the kind of business and its frequency of transactions. As an example, a customer from a supermarket has a higher frequency than most B2B companies and can therefore use a shorter time period.

The last transactional behaviour of RFM consists of the spending pattern of a customer. This can be defined as the amount of euros/dollars spent by a customer at a company. Previous studies found that the monetary spending of a customer can differentiate churners from behavioural loyal customers (Buckinx & Van den Poel, 2005; Miguéis et al.,2012). In other words, a customer who is changing their buying behaviour significantly by means of cutting back on spending could be a signal for churning. As previously stated, a customer will not churn all of a sudden but rather move their business gradually to a competitor. With this reasoning, a customer that is already churning will have a lower spending pattern than a behavioural loyal customer.

This study suggests three monetary variables. The monetary predictors are often seen as the least powerful variables compared to the recency and frequency predictors. Although, it is still advised to use monetary in conjunction with the other buying behaviours (Miguéis et al.,2012). The first suggested variable is the most operationalized one in literature (Buckinx & van den Poel, 2005; Miguéis et al., 2012; Chen et al., 2015). The second variable focuses more on a recent time period. And at last, the third variable explains the relative change in spending. This variable has been taken over from Jahromi et al., (2014). Although they found that this variable had less impact, than their tested recency and frequency variables, it remains interesting because it takes a recency factor into account. So, a customer who is spending less in the second (more recent) period will likely have a higher probability of churn - see figure 6.

The $_p$ in the variable stands for the type of product or product categories that are taken into account. Note, the $_t$ in the variable stands for the time period. The focus should be on product groups that have similar buying behaviour characteristics.

10. $Total\ monetary\ amount\ of\ spending\ (for\ product_p)$
11. $Monetary\ amount\ of\ spending\ in\ the\ last_t\ (for\ product_p)$
12. $Relative\ change\ in\ total\ spending\ \left(for\ product_p\right)\ of\ a\ customer\ in\ the\ second\ half\ of$ $the\ calibration\ period\ (m_2) compared\ to\ the\ first\ half\ of\ the\ calibration\ period\ (m_2)$
    $\Delta m\ = m_2\ -\ m_1$

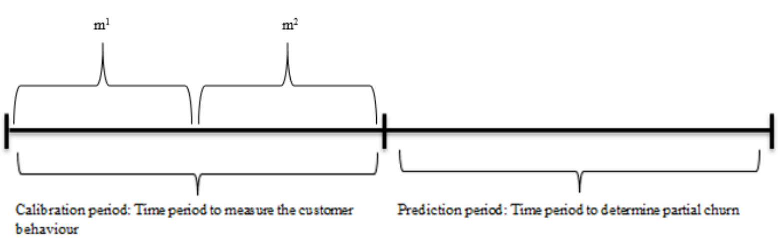


FIGURE 6: RELATIVE CHANGE OF A CUSTOMER SPENDING PATTERN

Length of relationship:

The length of the relationship (LoR) between a customer and supplier is positively correlated with the future stability of the relationship (Buckinx & van den Poel, 2005). It is stated that LoR is moderates the buying behaviour of a customer (Buckinx & Van den Poel, 2005). In other words, a customer with a longer relationship with the supplier will less likely churn in the subsequent period than a customer with a shorter relationship.

The inclusion of this predictor is popular in the churn literature (Mozer et al., 2000; Buckinx & Van den Poel, 2005; Burez & Van den Poel, 2008; Buckinx et al., 2007; Chen et al. 2015), although the predictive performance of this variable is contrary and varies between industries. For instance, Buckinx et al. (2007) found that LoR has a minimal effect on churn while the LoR has in another article of Buckinx and Van den Poel (2005) a clear predictability. Same positive results were found by Chen et al. (2015) and Burez & Van den Poel (2008). Therefore, this study suggests that the length of the relationship can be a predictor that differentiate churners from behavioural loyal customers. The operationalization has been taken over from the study by Buckinx & Van den Poel (2005). The only difference is that the focus is on years instead of days because B2B relationships are, in general, long. The suggested operationalization of the length of the relationship is as follows:

13. $Amount\ of\ years\ since\ the\ first\ transaction\ until\ the\ end\ of\ the\ calibration\ period$

3.2.3 Complaining behaviour

The literature review explained that the strength of the relationship between a customer and supplier can be identified through the behaviour of a customer. The previous paragraph described how the purchasing behaviour of a customer says something about the relationship. Another way is through the complaint behaviour of a customer. Namely, customers express their level of dissatisfaction through complaining. Although a dissatisfied customer has the option to leave the company, it will probably express their displeasure to the company first. Customer complaints can vary widely, however, most complaints are about: the core product/service, employees, a failure of an earlier complaint or inconvenient changes in the customers contract (Keaveney, 1995).

A few authors have included complaint behaviour variables for churn analyses (Hadden et al.,2006; Coussement et al., 2009; Ahn et al., 2006). The results are, however, mixed. There are some disadvantages, of using complaints as a predictor for churn analyses, that can explain these ambiguous results. First of all, it is likely that a lot of 'micro' complaints are not captured in customer data. For instance, a customer could express their dissatisfaction to an employee of the suppliers firm. It could be that the dissatisfaction is solved at the same moment and, therefore, that it is not registered as a complaint. However, the complaint could still have an effect on the strength of the relationship. Second, it is also likely that the importance of the complaints differ. A company with only two critical complaints can churn while a customer with 20 complaints about small issues can remain loyal. For this reason, this study propose that the importance rather than the frequency of a complaint will be critical for the identification of churners. Therefore, the type of customer complaint should be taken into account. Moreover, the sub categories will be split into initial customer complaints and complaints which are not solved at the first time.

Operationalization variables

Initial customer complaints

As previously stated, a customer is expressing its dissatisfaction through complaining. Previous churn analyses, that included variables of complaint behaviour, operationalized the concept through the amount of complaints and the duration of problem solving (Hadden et al., 2006; Mozer et al., 2000). An ideal situation, however, is that the type of complaint is classified differently. For instance, have customers with delivery complaints a higher likelihood of churn than customers with product complaints? This could solve the problem with complaint predictors for churn analyses that is mentioned above. Although, the applicability of such a classification depends highly on the data available. Therefore, the following variables are a suggestion. The selection of variables for this study is described in the methodology chapter.

The $_c$ stands for the type of complaint. The $_p$ in the variable stands for the type of product or product categories that are taken into account. The focus should be on those with similar characteristics.

14. $Number\ of complaints_c\ (for\ product_p)$
15. $Average\ number\ of\ days\ before\ the\ complaints_c\ were\ handled\ (for\ product_p)$

Recovery of customer complaints

As mentioned above, this study proposes that the importance of the customer complaint is more critical for churn behaviour than the frequency of complaints. Solving customer complaints appropriately can increase the satisfaction and loyalty of a customer. However, if a company fails to solve the initial problem, it can expect a higher dissatisfaction of the customer (Jones & Sasser, 1995). Therefore, the following variable and its operationalization is suggested. This variable has not been described in previous churn literature.

The $_t$ stands for the type of complaint. The $_p$ in the variable stands for the type of product or product categories that are taken into account. The focus should be on those with similar characteristics.

16. $Number\ of\ failed\ recovery\ of\ complaints_c\ \ (for\ product_p)$

3.3 Demographic

3.3.1 Moderators

Previous chapter described behavioural variables, related to purchase and complaint behaviour, that suggest something about the strength of a relationship between a customer and supplier. However, there are factors that moderate the strength of the customer relationship-repeat purchases link. The literature review described that this partly could be explained through customer characteristics and situational factors. This study will focus on demographic attributes to explain the customer characteristics that moderate the satisfaction-repeat purchase link.

Demographic attributes are a popular category for variables in churn analyses (Mozer et al., 2000; Buckinx & Van den Poel, 2005; Van den Poel; Lariviere, 2004; Chen et al., 2015). Although they have mostly been studied in a B2C context. For instance, a demographic attribute that has a moderating role in B2C markets is household (Buckinx et al., 2004). It is stated that large households are less prone to deals than small households. So, the strength of the relationship for small households is less strong than for large households.

However, for B2B, there are less demographic attributes. This is due to the fact that the B2B customer is an entity instead of an individual person. The three demographic attributes which are described in the literature review are company size, industry and geographical location. These attributes will be explained according to current literature and operationalized into variables. It is worth mentioning that only geographical location is tested in extant B2B churn studies (Chen et al., 2015), while the other operationalized variables – to the best of our knowledge - have not been described and tested in churn studies. Therefore, this study will make a contribution to the extant literature. The predictability of these variables are interesting because a customer's behaviour is often correlated with demographic attributes of a customer (Kotler, 2003)

Operationalization variables

Geographic

Geographical variables are popular attributes that can differentiate churners from behavioural loyal customers that is both used in B2C (Buckinx & Van den Poel, 2005; Mozer et al., 2000) and in B2B churn analyses (Chen et al., 2013). These variables can explain the differences between customers behaviour based on where they are located. Previous studies have shown that geographical variables, with the focus on region, are not powerful predictors for churn (Buckinx & Van den Poel, 2005; Chen et al., 2013). However, it remains interesting to add this variable because it could be different per sector. Moreover, it is most likely that there are greater differences in the customer behaviour based on what country the company is located. This could be due to cultural differences and the regulation in a certain country. The following moderating variables are suggested.

17. $The\ region\ of\ the\ customer$
18. $The\ country\ of\ the\ customer$

Industry

The industry is a demographic attribute that can segment B2B customers. For instance, a company who make rubber-tires could sell to manufactures of aircrafts, farm tractors or cars (Kotler, 2003). These different type of customers could have a disparate level of satisfaction even though the delivered performance was the same. As a result, it could be that customers churn faster from a certain industry. The following variable is suggested. It is worth mentioning that the utilization of the variable depends on the level of analysis. For instance when there is a cross analysis between industries or if only one industry is taken into consideration.

19. $The\ industry\ of\ the\ customer$

Company size

Kotler (2003) suggests that large and small sized companies have a different purchasing behaviour. Moreover, the laws and regulations that a company has to meet is also different for small and large entities (Kamer van Koophandel, 2016). For this reasons, the company size of a customer will probably influence the strength of the relationship. This is also stated by Samanta (2014), who found that a large company has more benefit by a long term relationship while a small company is more prone to competitive actions in fragile economic conditions. Therefore, the following variable is suggested.

The $_l$ stands for the company size. The company sizes are based on the subdivision of the European Commission (Kamer van Koophandel, 2016). It is subdivided into: Micro businesses (0-10 employees), small company's (10-50 employees), medium-sized businesses (50-250 employees) and large businesses (>250 employees).

20. $Company\ size_l\ of\ the\ customer$

4.0 Inductive approach; Predictors and operationalization

4.1 Outline of this chapter

The previous chapter identified customer behaviour that could be different for a churning and behavioural loyal customer, based on extant literature. Subsequently, variables were operationalized and suggested for churn analyses. This chapter, the induction part, is more bottom-top and consists of the experiences of employees of ***. These employees could give novel input about customer characteristics that differentiate churners from behavioural loyal customers. An inductive approach could be valuable for this thesis because churn analyses is mostly done in B2C business. Therefore, there could be variables that are more applicable to B2B and the sector wherein *** operates. Another advantage of interviews is that the questioned employees have more knowledge about their own data.

The input is described through six semi-unstructured interviews with employees of *** that have experiences with pricing, marketing, data and case management – see Appendix 6. Semi-structured interviews allow an open conversation through more general questions where the researcher has the possibility to act on the response of the interviewee (Bryman & Bell, 2011).

For this study, the interviewees were asked two simple questions. The first question was related to what behaviour a customer of *** is expressing when he is (dis)satisfied. The second question referred to what demographic attributes could segment the behaviour of *** customers. In other words, what demographic attributes can explain differences between customers at ***?

The outcomes of these interviews corresponded to the outcomes of the inductive approach. According to the respondents, a customer express its (dis)satisfaction via their purchasing behaviour, word of mouth and complaint behaviour. The demographic attributes that are described in the deductive part were also covered by the respondents. Although, the interviews have also resulted in some variables that were not mentioned in previous chapters. These variables are related to the complaining behaviour and the demographic attribute industry. The categories and suggested variables are described below according to the interviews. The category purchasing behaviour and demographic attributes were mentioned by the respondents but have not led to new variables.

4.2 Customer satisfaction

6.2.1 Complaining behaviour

The respondents agreed that complaining is a way of how a customer is expressing its dissatisfaction. A customer with more complaints will probably have a higher likelihood of churn than a customer with less complaints. However, one respondent agreed with the reasoning of the deductive chapter that the importance of a complaint is more critical than the amount of complaints. This respondent stated “complaints are not always an indication of a leaving customer. A customer with only a few complaints could leave while a customer with a lot of complaints stays loyal”. This respondent agreed that the type of complaints should be taken into account when measuring the complaining behaviour of a customer. Variables that were suggested by the respondents for complaining behaviour were amount of complaints (by type), the initial time of problem solving and the customer defective parts per million. Although, the time of problem solving is currently not measured by *** and is already suggested in the deductive chapter. The customer defective parts per million is described below.

Operationalized variables

Customer defective parts per million (DDPM)

*** is measuring the operational excellence of their company through the defective parts per million (DPPM). This metric is suggested for churn analyses, by a respondent, as a way to identify the problems experienced by customers. The DDPM is measuring the number of defective parts experienced by a customer to the number of units shipped to external customers. The lower the number, the better the performance of ***. One respondent stated “it gives an indication about our performance and the perception of the customers”. A disadvantage with this indicator is that it is measured by division rather than the individual customer. As a consequence, it can only be used for cross analyses between divisions.

21. $The\ external\ customer\ DDPM\ \frac{1\,000\,000 * external\ customer\ field\ defects}{Units\ shipped\ (external)}$

4.3 Demographic

4.3.1 Moderators

The demographic attributes that were described in the literature review for B2B were ‘industry’, ‘company size’ and ‘location’. In general, the respondents agreed that these are the only attributes that could segment B2B companies. However, a few respondents described that a B2B customers should not always be seen as an entity because it also interact with individual people. One respondent stated “there are a lot of factors that could describe the behaviour of a customer. Is the decision maker a man or a woman, what is its age, religion etc.” According to this reasoning, the B2C demographic attributes are also applicable to a B2B company. This study recognize that these are important factors. However, for the purpose of churn analysis, this unit of analysis is too broad. Namely, it is not possible to include every individual characteristic of an employee within the customer firm. On the other hand, a variable that could be valuable which was suggested by a respondent, and is not described in the deductive chapter, is related to the demographic attribute ‘industry’. This is described below.

Operationalized variables

Industry

The demographic attribute ‘industry’ is mentioned by most respondents as a relevant variable for segmenting customers. Although, some respondents suggested that a customer should not only be segmented by industry but also by customer. One respondent stated “a company has often different types of customers in the same industry. For instance, a wholesaler, panel builder or a retailer. These customers could have distinctive demands and behaviours.” As a consequence, the level of disconfirmation between the type of customers in a specific industry could also differ. The following variable is suggested. It is worth mentioning that the utilization of the variable depends on the level of analysis. For instance, when there is a cross analysis between customers or if only one type of customer is taken into consideration. The $_x$ stands for the type of industry.

22. $The\ type\ of\ customer\ in\ industry_x$

5.0 Methodology

5.1 Outline of this chapter

This chapter will give the reader a good understanding of the steps taken in this study prior to the analysis. This could make it easier to replicate or to improve future churn analyses at ***. This study will focus on the most behavioural loyal customers in a repetitive market. These are customers who had a total amount of purchases above the average of all customers in 2014. The reason for the focus on the most behavioural loyal customers and the operationalization for partial churn at *** is explained below. The other sections in this chapter describe the data mining technique, data selection, data preparation, the predicting variables and the data mining technique for this study.

5.2 Selection of most behavioural loyal customers

The analysis is conducted at ***. ***. This study focuses on a repetitive business because this ensures that the customers are buying regularly. So, this makes it easier to detect if a customer abrupt its normal purchasing behaviour. The segment that is chosen for analysis is the *** market. This market is chosen after a consultation with ***. The market consists of ***. The product portfolio of the *** market consists mainly of convenience products.

While most studies in churn analyses have focused on the whole customer base (Van den Poel and Lariviere, 2004; Mozer et al., 2000), Buckinx & Van den Poel (2005) excluded customers from their analysis because some are not worth the effort and money when developing long-term relationships. They stated that the most behavioural loyal customers are the ones that ensure a high and constant stream of profits. The focus on the most behavioural loyal customers is important, especially, when you consider the fact that this small percentage of the customer base, accounts often for a large part of the profit. A clear example of a supermarket can underpin the statement of focusing on the most behavioural loyal customers (Buckinx & Van den Poel, 2005). This supermarket found out, through a churn analysis, that there customers were leaving because of the absence of fast tills (for customers who buy less than 10 products). After the investment in extra tills and personnel, they recognized that their defection was decreasing. However, so was their profit. It turned out that the investments did not served the most profitable customers, who have more products in their basket. It had only an effect on the customers with less than 10 products. Thus, the supermarket served the needs of the less profitable customers instead of the needs of the, most profitable, customers that have more effect on the profit. This study adopt this reasoning and will focus only on the most behavioural loyal customers for the churn analysis.

Some studies used frequency of transactions to determine a behavioural loyal customer (Glady et al., 2009). Migueis et al.). The frequency of transactions indicates that the customer is buying regularly. In this study, a customer will be determined as behavioural loyal by its number of purchases (Buckinx & van den Poel (2005). This is also described by Saura et al. (2009) and Bennet et al. (2002) that states that the total purchases of a customer can be used to measure behavioural loyalty. One of the reasons to not include a transaction indicator is that this study is focusing on a repetitive business where customers already buying regularly.[3] Moreover, the number of purchases ensures that customers are selected who are valuable for the company in the sense that they provide a lot of business. The frequency of transactions shows that they are buying regularly but a customer who buys regularly does not have to be a profitable customer. To give an example, a customer can buy one product with every transaction while another customer buys 20 products with less transactions.[4] Another reason to focus on the number of purchases is that a B2B customer is not leaving all of a sudden. The customer is probably gradually moving its business (products) from one supplier to another (Buckinx & Van den Poel, 2005). Thus, a significant change in purchases give an implication of their level of behavioural loyalty and their tendency to leave while less transactions could also mean that the customer is buying the same amount of products but only in less transactions. Therefore, it is better to focus on the number of purchases when to determine of a customer is behavioural loyal or not. To define the group of behavioural loyal customers, the following transactional attribute is used. This criteria is based on the article of Buckinx & Van den Poel (2005).

1. *Amount of products bought by a customer falls above the total average of all customers.*

5.3 Operationalization partial churners

Buckinx & Van den Poel (2005) have shown in their literature review that almost all studies of churn analyses described a churner through total defection. Total defection means that a customer completely stops doing business with that company. As a result, a company can determine the exact point in time, that a customer ends the relationship. This makes it easier and more reliable to detect and analyse churners. These studies were conducted in telecommunication, banking and mobile industries.

However, it is more complex and arbitrary to define a churner in a B2B business with a non-contractual setting like ***. The complexity lies in the fact that it is not clear when a customer ended a relationship. Therefore, extant literature about the prediction of churn in non-contractual setting has focused on partial defection of a customer in the next period instead of the prediction of a permanent decision. Partial defection or churn means that a customer is changing its transactional behaviour significantly compared to the previous period (Buckinx & Van den Poel, 2005). As previously described, a voluntary churner in B2B will probably not leave all of a sudden but will move its business gradually to another supplier. Identifying

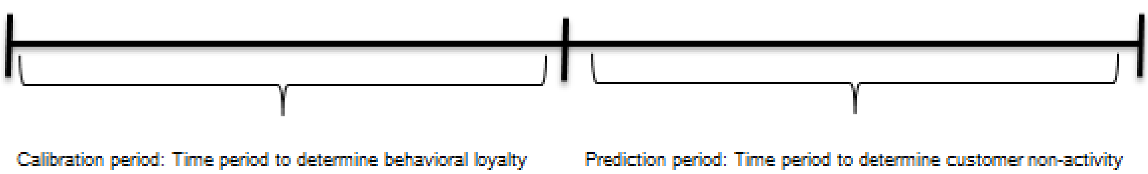
[3] It is advisable to include a transaction treshold when the focus is on a less repetitive market.

[4] This also underpins the previous example of the supermaket. A customer with more interactions could be more expensive for a company. So, the company can better focus on the customers who buying more products in a period (and buying more products at once) than solely focusing on customers who buying more often in a period.

partial churners is therefore important otherwise it could lead to total defection. Because *** is operating in a non-contractual business-to-business context, this study uses also the concept of a partial churner.

Churn analysis that measures partial churn is often operationalized through a period that is divided in two. This study uses a period of two years that consist of a calibration and a prediction period.[5][6] So, a partial churner is a customer that significantly changed its buying behaviour in the prediction period compared to the calibration period – see figure 7. More specifically, the criteria from previous paragraph that is used to define the behavioural loyal customers, is used again, but this time over the next period. In this case, a second criteria is added because this ensures that a churner is someone that changed its buying behaviour significantly. To the best of the our knowledge, this combination has not been used before in previous churn studies. The operationalization of a churner has been verified by ***. The following criteria is used to define a partial churner.

1. *Amount of products bought by a customer in the prediction period falls below the total average of all customers that is measured in the calibration period.*
2. *Amount of products bought by a customer in the prediction period is 25% less than the amount of purchases of that customer in the calibration period.*



This study classifies the customer as a partial churner if both criteria are fulfilled, because they changed their normal purchasing pattern significantly. If one of these criteria is not fulfilled, it is classified as a customer who remains behavioural loyal.

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[5] The calibration period is the time where the predicting (independent) variables are measured. In other words, this is the period prior to customer churn. The prediction period is only used to determine if a customer has done significantly less business with the company (partial churner). This period will not be used anymore after the classification of partial churners and behavioural loyal customers.

[6] Tamaddoni Jahromi et al. (2014) suggest that the duration of the two time periods can be defined arbitrarily as long as it is useful and in line with the business objectives. For instance, a company with a high repetitive business can use a smaller time set with data than a company with a low repetitive business.

Table 2 shows an example of five hypothetical customers to explain the selection of the most behavioural loyal customers and the operationalization of a partial churner. The total amount of products bought of all customers in the calibration period in this example is 73. The customers who fall below this average are not included in this study. The remaining customers are classified as a partial churner when they spend less than 25% in the prediction period and fall below the predetermined threshold. This is also recognized by Buckinx & Van den Poel (2005) who states that "the customer deviates from his established transactional pattern" (p. 256). So, a customer is classified as a partial churner or as a customer who maintains its high purchasing behaviour (behavioural loyalist). However, because the arbitrary operationalization of a churner, it is essential to identify the customers who did not fulfilled both conditions. Especially, the customers who bought significantly less than the second criteria, but did not fall below the average of the calibration period. The classification of the partial churners in the data set of this study is described at chapter 5.5

	Calibration period	Prediction period	Classification
Threshold:	The average amount of purchases of all customers: 73 products	The average amount of purchases of all customers: >73 Change in purchases: <-25%	
Customer 1	142	142 (-0,71%)	Behavioural loyal
Customer 2	252	252 (3,08%)	Behavioural loyal
Customer 3	75	**30 (-150%)**	Partial churn
Customer 4	40	-	Not included
Customer 5	10	-	Not included

TABLE 2: EXAMPLE SELECTION BEHAVIOURAL LOYAL CUSTOMERS AND OPERATIONALIZATION PARTIAL CHURN

5.4 Data

5.4.1 Data acquisition

The data used for this study is collected through a consolidated data system. This system integrate the data from different systems into one format. However, this system is relative new and not all individual data systems have been integrated. ***. As a consequence, not all variables that are suggested in the deductive and inductive chapters can be tested in the churn analysis of this study.

5.4.2 Data selection & preparation

The data selection and preparation phase takes most time during a churn analysis or a data mining project. Normally 10-30 percent of the time in a data mining project is spent in the business problem, data mining and evaluation phase. The rest of the time involves the selection and preparation of the data. Because this study involved a comprehensive literature review, this time span is not accurate. Besides, although a minimum time is spent on the business problem phase, it remains a fundamental step because it ensures that the project does not result in producing the right answers to the wrong questions (Watson, 2000). The following paragraphs explain how the data of this study is selected and prepared for data mining.

First of all, this study focuses on a customer base that is highly stable in the sense of their purchasing behaviour. The reason to choose a stable repetitive market is because this ensures that the customers are buying regularly. Second, the analysis is done in a B2B organization where customers do not have a contract. As a result, it is not possible to determine the exact point in time that a customer ends the relationship. A churner is therefore operationalized through its decreasing purchasing behaviour compared to the previous period. If this study would focus on a market or product group with a high fluctuation in purchases (unstable market), it would make it more difficult to really identify churners. Namely, a decrease in the purchasing behaviour of a customer does not mean that he is ending the relationship. Contrary, in a stable market, it is more reliable to suggest that a customer that deviate from their normal buying pattern is churning.

***

5.5 Final data set and classification partial churners at ***

This study will use a data set of two years consisting of the year 2014 and 2015 of the product group *** for the churn analysis at *** . A comprehensive analysis showed that this was the most stable and repetitive product group of the *** market. The year 2014 will be used as the period to measure the customer behaviour of the selected customers (calibration period) and 2015 will be used as the period to determine if that customer is a churner or not (prediction period) – figure 8.

The initial data set of the select product group consisted of *** customers. The focus of this study was on customers that are most behavioural loyal in the sense that they had a high purchase behaviour in this repetitive market. The focus on purchases to determine behavioural loyalty is also described by Saura et al. (2009) and Bennet et al. (2002). These authors stated that the total purchases of a customer can be used to measure behavioural loyalty. The reason for focusing on this type of customers and the operationalization is explained in the beginning of this chapter (section 5.2). The threshold that determines if a customer is behavioural loyal is when the customer has a higher amount of purchases than the total average of all customers in 2014.

For this study, the average amount of purchases of all customers was *** products in 2014 (*** products per month). All customers that had an amount of purchases in 2014 below this average, are excluded. As a consequence, 112 customers are selected for analysis. These (behavioural loyal) customers had a total average of *** purchases a month. Because the focus was on a repetitive and stable market, all customers purchased regularly at ***.

The year 2015 was used to classify partial churners. Churners are customers who changed their buying behaviour significantly compared to the previous period and fall below a certain threshold. As a repetition, customers are classified as a partial churner when they fell below the threshold (*** purchases) in 2015 and with a decrease of 25% compared to their amount of purchases of previous period. This is described in section 5.3. As a result, 21 of the 112 customers satisfy these criteria and are classified as partial churners. The other 91 customers are classified as customers who maintain their purchasing behaviour.

5.6 Data mining techniques

5.6.1 Data mining functions and techniques

The choice of a data mining technique is closely related to the objectives of the business regarding the data mining projects. The goal of a data mining project can vary but consists, in general, of the identification of new customers, attraction of customers, retaining customers or to increase the sales of extant customers (Ngai et al., 2009). Every objective has different functions and data mining techniques. A function can contain more than one technique. According to Ngai et al. (2009), the most used techniques for data mining consist of association rule, decision tree, genetic algorithm, neural networks, K-Nearest neighbor and linear/logistic regression. These functions with corresponding techniques are described in table 3. This is adopted from the literature by Ngai (2009).

Data mining functions	Purpose	Data mining techniques
Association	Investigation of relationships between items	Association rules
Classification	Predicting future behavior through classifying database records	Logistic regression Neural networks Decision tree Genetic algorithm K-Nearest neighbor
Clustering	Segmentation of a population with heterogeneous characteristics	Association rules K-Nearest neighbor Neural network Genetic algorithm
Forecasting	Forecast the value of the future based on patterns from database records	Neural networks
Regression	Predicting a dependent variable through independent variable(s).	Linear/logistic regression
Sequence discovery	Investigation of patterns over time	Association rules
Visualization	Presentation of data	Graphs and see net

TABLE 3: OVERVIEW DATA MINING FUNCTIONS AND TECHNIQUES

The data mining functions that are appropriate for churn analyses are classification and regression (Ngai, 2009). The most popular techniques for churn analyses are logistic regression, neural networks and decision trees (Klepac, 2014). These data mining techniques have its strengths and weaknesses – see table 4. Although, logistic regression is the most used technique for churn analysis and is recommended for companies who starting with data mining (Neslin et al., 2004). The popularity is mainly attributable to the easiness of the methods and its quick and robust results in comparison to other classification techniques (Buckinx & Van den Poel, 2004; Neslin et al., 2004). Moreover, the logistic regression technique has been associated with good results in the prediction of churners (Buckinx & van den Poel, 2005; Klepac, 2014). Therefore, this thesis will use logistic regression. The following section will explain this data mining technique in more detail.

Data mining method	Strengths	Weaknesses
Decision tree	• Simple technique • Reliable results • Concrete results	• Difficulties with the extraction of rules for classification • The stability of their steady the optimal solution
Neural network	• Prediction is precise	• Difficulties arise with performing the construction • Lack of transparency
Regression	• The application of the performing model is easy • Robust results • Rich literature about the use of the technique	• Fails to express behavioural hidden patterns in data

TABLE 4: STRENGTHS AND WEAKNESSESS DATA MINING METODS

5.6.2 Logistic regression

Regression analysis is a technique for predicting outcomes based on independent variables. The most common regression analysis is linear regression. In this case, the dependent variable is a continuous variable. Although there are also research questions where the dependent variable of interest is categorical. For instance, what is the probability that a certain decease will cause death? Or a better example, what is the probability that a certain customer behaviour will cause churn? In other words, it gives the opportunity to predict which of the two groups a person is belonging based on certain historical data (Field, 2015). This regression technique is called logistic regression and is extremely popular as a data mining technique for churn analysis (Buckinx & Van den Poel, 2004; Ngai et al., 2009). As with ordinary linear regression, it can be used for the prediction of one variable (binary) or multiple dependent variables – multinomial (or polychotomous) logistic regression (field, 2015).

The formula of linear regression is

$$P(Y) = \mathrm{b}_0 + \mathrm{b}_1\mathrm{X}_{1i} + \mathrm{b}_2\mathrm{X}_{2i} + e_i$$

The formula of logistic regression is

$$P(Y) = \frac{1}{1 + e - (\mathrm{b}_0 + \mathrm{b}_1\mathrm{X}_{1i} + \mathrm{b}_2\mathrm{X}_{2i})}$$

P(Y) is the probability that Y (dependent variable) will occur, e is the base of natural logarithms, b_0 Is a constant, $\mathrm{X}_{1\mathrm{i}}$ is the predicting (independent) variable and the weight of the predictor is b_1. This study has only one dependent variable. So, the dependent variable is churn (the value 1) or not-churn/behavioural loyal (the value 0). The value that comes out of this equation falls between zero and one. A value that is closely to zero, means that a customer stays behavioural loyal. A value that is closely to one means that the customer has a high likelihood of churn in the next period.

5.7 Behavioural predictors churn analysis ***

The extensive literature review has led to two categories that are suggested for churn analysis. The first category is customer satisfaction. This consists of sub categories that explain the outcome of the strength of the relationship between a customer and firm. The second category are the demographic attributes of a customer. These consist of attributes that moderate the relationship between customer satisfaction and its repeat purchasing behaviour.

The aim of the deduction (literature) and induction (practical experiences) chapters was to operationalize customer behaviour and characteristics into measurable variables that, fall into the above mentioned categories and, could predict churn. This approach is chosen because this study is the first data mining project to date at ***. So, it provides an ideal set of variables that *** should be gather for churn analyses purposes. However, a limitation of this approach is that the current state of the data (system) quality was not known. As a consequence, variables cannot be tested due to the lack or quality of data.

Table 5 explains the selected predictors for churn analysis. These consist of variables that explain the buying behaviour of a customer. RFM variables are popular in churn literature and have proven to be predictive. This study uses different time periods of the variables because a more recent time period could be more predictive for churn. ***

Table 6 explains the excluded predictors of this study. The reason for excluding this variables is due to ***

Category		Variable type	Variable name	Description
Satisfaction				
	Buying behaviour	Frequency	Freq_trans_total	Number of transactions in the calibration period
			Freq_trans_last6	Number of transactions in the calibration period in the last 6 months
			Freq_trans_last2	Number of transactions in the calibration period in the last 2 months
			Freq_pur_total	Number of purchases (products bought) in the calibration period
			Freq_pur_last6	Number of purchases (products bought) in the calibration period in the last 6 months
			Freq_pur_last2	Number of purchases (products bought) in the calibration period in the last 2 months
			Freq_dif	Relative change in total frequency of a customer in the second half of the calibration period compared to the first half of the calibration period
		Recency	Rec_lastpur	Number of days since the last purchase
			Rec_IPT	The average number of days between transactions
			Rec_last6	The average number of days between transactions in the last 6 months
			Rec_std_IPT	The standard deviation of the inter-purchase time
		Monetary	Mon_total_2014	Total monetary amount of spending
			Mon_last6	Monetary amount of spending in the last 6 months
			Mon_dif	Relative change in total spending of a customer in the second half of the calibration period compared to the first half of the calibration period
Demographic				
	Moderator	Location (country of the customer		Variable is only used for descriptive statistics because the logistic regression model can only include two variables. (1 variable for every 10 churners)

TABLE 5: PREDICTORS USED IN THIS STUDY

Category		Variable type	Description	Reason for excluding
Satisfaction				
	Buying behaviour	Length of relationship (moderator)	Amount of years since the first purchase until the end of the calibration period	***
	Complaint behaviour	Initial customer complaints	Number of complaints	***
			Average number of days before the complaints were handled	***
			The external customer defective parts per million	***
		Recovery of customer complaints	Number of failed repairs of complaints	***
Demographic				
	Moderators	Location	The region of the customer	***
		Industry	The type of customer in industry	***
			Type of industry	***
		Company size	Company size of the customer	***

TABLE 6: PREDICTORS EXCLUDED IN THIS STUDY

6.0 Results

6.1 Outline of this chapter

The previous chapter described the selection of customers of this study. As a repetition, the focus is on the most behavioural loyal customers, in the sense that they had an amount of purchases above average, of the product group ***. These products are sold in the *** market. This has led to a sample of 112 customers. The prediction period is used to operationalize the churners. The customers that purchased less than *** products (overall average of 2014) in 2015, and had a decrease of more than 25% in purchases (compared with their own purchase of 2014) are classified as churners. As a consequence, the data set consists of 91 behavioural loyal customers and 21 churners. The predictors used for analysis consist of variables that explain the buying behaviour. These variables could be extracted from the current database of ***. Other data was not available due to a variety of reasons. As a consequence, 14 variables are used for analysis.

The demographic variable ‘country’ is only used for the descriptive statistics because, although the variable could be extracted from the data base, it cannot be included in the model. The reason is that the model of this study can only include 2 variables. This is caused by the small events of 21 churners. The rule of thumb is that one variable can be included for every ten events – churners (Hosmer et al., 2013). A moderator term should always include both main effects in the model. As a consequence, the model will then consists of at least three variables. Otherwise, the model is not valid. Therefore, country is excluded as a variable due to the limitation of two variables in the model.

This chapter will explain the results of logistic regression. It begins with a first glance on the descriptive statistics and correlations of the variables. Thereafter, there will be an explanation given on how the variables are chosen for the multivariable model. And at last, the best model will be explained in further detail.

6.2 Descriptive statistics

The descriptive statistics of the predicting variables are described in table 7. At first sight there seem to be differences in the buying behaviour prior to partial churn for behavioural loyal customers and partial churners. Most variables show the expected behaviour. First of all, the frequency variables show that churners bought less products and has less transactions prior to churning than the behavioural loyal customers. Second, the recency variables show that the amount of days between purchases for churners is higher than behavioural loyal customers. And at last, the monetary variables also show that churners spent less than the behavioural loyal customers. To get more insight in the descriptive statistics per country, a more detailed overview can be found in Appendix 8.

The two variables that show a different expected pattern is Freq_dif and mon_dif. These variables measured the relative difference in frequency and monetary between the first half year and the second half year of 2014 (calibration period). The table shows that behavioural loyal customers spent less money and bought less products in the second period compared to the first period than churners. Although this seems remarkable, it is actually caused by the way of operationalization. A lot of behavioural loyal customers have a much higher frequency of purchases and monetary spending than churners. Because the high frequency in purchases and monetary spending, there is also a higher difference between the two periods for most customers. This has led to the fact that behavioural loyal customers have a higher difference in percentage between the periods than churners. This variable is therefore not useful when there are large differences, in frequency of purchases and monetary spending, between customers. As a conclusion, it might be better to exclude this variable or to operationalize it differently in subsequent studies.

***

TABLE 7: DESCRIPTIVE STATISTICS

6.3 Pearson correlation

The Pearson correlations give a first indication of the presence of a relation between churn and the buying behaviour variables – table 8. This shows that there is a correlation at the 0.05 level (2-tailed) for Freq_trans_total, Freq_trans_last6, Freq_trans_last2, Freq_pur_total, Freq_pur_last2, Freq_pur_last6 and Rec_std_ipt. Moreover, a correlation at the 0.01 level (2-tailed) is found for Rec_lastpur, Rec_IPT and Rec_last6. Thus, a conservative conclusion is that there may be a predicting relationship between Recency, frequency variables and churn. Monetary variables show no correlation with churn. This is in line with extant literature that also found that the monetary variables have less predictive power (Migueis et al.,2012).

		Churn
Churn	Pearson Correlation	1
	Sig. (2-tailed)	
Freq_trans_total[a]	Pearson Correlation	**-,203***
	Sig. (2-tailed)	,031
Freq_trans_last6[a]	Pearson Correlation	**-,204***
	Sig. (2-tailed)	,031
Freq_trans_last2[a]	Pearson Correlation	**-,197***
	Sig. (2-tailed)	0,38
Freq_pur_total[a]	Pearson Correlation	**-,220***
	Sig. (2-tailed)	0,20
Freq_dif[a]	Pearson Correlation	-,029
	Sig. (2-tailed)	,763
Freq_pur_last2[a]	Pearson Correlation	**-,237***
	Sig. (2-tailed)	,010
Freq_pur_last6[a]	Pearson Correlation	**-,237***
	Sig. (2-tailed)	,012

		Churn
Churn	Pearson Correlation	1
	Sig. (2-tailed)	
Rec_IPT[a]	Pearson Correlation	**,261****
	Sig. (2-tailed)	,006
Rec_lastpur[a]	Pearson Correlation	**,264****
	Sig. (2-tailed)	,005
Rec_last6[a]	Pearson Correlation	**,291****
	Sig. (2-tailed)	,002
Rec_std_ipt[a]	Pearson Correlation	**,220***
	Sig. (2-tailed)	,020
Mon_total_2014[a]	Pearson Correlation	-,138
	Sig. (2-tailed)	,147
Mon_last6	Pearson Correlation	-,103
	Sig. (2-tailed)	,282
Mon_dif	Pearson Correlation	,054
	Sig. (2-tailed)	,569

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

a. The definitions of the abbreviations of variables can be found in table 5

TABEL 8: PEARSON CORRELATIONS

6.4 Selection of variables for logistic regression model

6.4.1 Methods in literature for the selection of variables

There are a lot methods to select variables for a regression model. Logistic regression can use the same methods as ordinary linear regression (Field, 2015). In general, the methods for the selection of variables of a model consist of hierarchical, forced entry and forward or backward stepwise methods. It is worth mentioning that stepwise methods for logistic regression are using different statistics compared to the ordinary linear regression (Field, 2015). The different methods will be explained shortly.

First of all, hierarchical is a method that select variables based on extant literature. The researcher decides the order of entering the variables into model based on the importance in literature (Field, 2015). Second, with the forced entry method, all variables are added simultaneously to the model. Variables that make no contribution to the model are then systematically removed (Field, 2015). The inclusion of variables for the forced entry method relies also on the importance of extant literature. And at last, with stepwise methods, variables are automatically added (forward) or subtracted (backward) from the model based on mathematical criteria. The stepwise methods are widely criticized because the researcher has no influence in the decision making process of the variables (Field, 2015). The main critic is that a stepwise method selects the fit of a variable based on the present variable(s) in the model. Nevertheless, when choosing a stepwise method, it is advisable to choose a backward method because it minimize suppressor effects (Field, 2015).

This study will use a forced entry method because, although the selected predictors are based on churn literature, it is unclear what variables are most important in the B2B sector wherein *** operates. The extant literature tested the variables mostly in the B2C market with a contractual setting. A hierarchical method is therefore not the best option. Especially, because the model can only consists of two variables due to the small data set with only 21 events (churners). As a repetition, the rule of thumb is that for every 10 events, a variable can be added to the model (Hosmer et al., 2013).

6.4.2 Selection of the best model through a forced entry method

This selection of variables for the multivariable model will begin with a univariate analysis of every variable. A univariate analysis helps to identify variables that could be interesting for the model. Only the variables will be selected, for the multivariable analysis, that have a (conservative) significance level at a p-value of 0.25 in the univariate analysis (Hosmer et al., 2013). This p-value is based on the Wald-statistic of logistic regression. The traditional significance level of 0.05 can fail in identifying variables that could be important. A disadvantage of the ordinary cut-off point is that it ignores variables that have a weak significance level in the univariate analysis, but become important predictors when it is considered in combination with other variables (Hosmer et al., 2013).

Normally, in the sequel process of the forced entry method, the variables are added simultaneously to the model. Thereafter, variables are removed from the model if they fall below the significance level of 0.1. The new model should then be compared to the previous model by assessing the likelihood ratio test. Moreover, the researcher should analyse if coefficients have changed enormously after removing a variable. This can indicate that this specific variable depended on the removed variable(s).

However, this study can only add two variables in the model due to the low events (21 churners) in the overall sample size. Hosmer et al. (2013) suggest, that the "appropriateness of the decision to begin the multivariable model with all possible variables depends on the overall sample size and the number in each outcome group related to the number of candidate variables". Adding all variables can cause a numerically unstable multivariable model which leads to complete separation. Complete separation means that the dependent variable can be predicted by one or a combination of variables. This is mainly caused by a model that includes too many variables with too few events. As a solution, Hosmer et al. (2013) suggest that a subset of variables should be selected based on the univariate analyses and this should be refined to what is scientifically relevant. For this study, all predictors are scientifically relevant because it is extracted from previous literature. Therefore, this study will test all possible models with variables that had a significance level below the p-value of 0.25 in the univariate analyses – see Appendix 7. In total, 45 models were conducted – see table 9.

Models	Variables[a]	Chi-square	2log likelihood	Cox & Snell R	Nagelkerke R	Classification table	
						Churners	Total
Model 10	Freq_purlast6 + Rec_lastpur	43,467	64,630	,322	,520	52,4%	87,5%
Model 39	Freq_pur_total + Freq_pur_last6	40,211	67,886	,302	,487	47,6%	85,7%
Model 9	Freq_pur_last6 + Rec_IPT	39,311	68,787	,296	,478	42,9%	86,6%
Model 40	Freq_pur_total + Freq_pur_last2	39,049	69,048	,294	,475	38,1%	83,9%
Model 11	Freq_pur_last6 + Rec_last6	38,805	69,293	,293	,473	42,9%	85,7%
Model 27	Freq_trans_last6 + Freq_pur_last2	38,355	69,742	,290	,468	38,1%	83,9%
Model 41	Freq_pur_last6 + Freq_pur_last2	38,348	69,75	,290	,468	47,6%	87,5%
Model 12	Freq_pur_last6 + Rec_std_IPT	38,340	69,757	,290	,468	47,6%	87,5%
Model 19	Freq_trans_total + Freq_pur_last6	38,191	69,907	,289	,467	52,4%	89,3%
Model 26	Freq_trans_last6 + Freq_pur_last6	38,015	70,08	,288	,465	52,4%	89,3%
Model 2	Freq_pur_total_2014 + Rec_lastpur	37,910	70,187	,287	,464	23,8%	80,4%
Model 33	Freq_trans_last2 + Freq_pur_last6	37,722	70,375	,286	,462	47,6%	88,4%
Model 3	Freq_pur_total_2014 + Rec_last6	36,311	71,786	,277	,447	28,6%	80,4%
Model 1	Freq_pur_total_2014 + Rec_IPT	35,725	72,373	,273	,441	28,6%	81,3%
Model 25	Freq_trans_last6 + Freq_pur_total	35,252	72,845	,270	,436	23,8%	79,5%
Model 4	Freq_pur_total_2014 + Rec_std_IPT	35,180	72,917	,270	,435	23,8%	78,6%
Model 18	Freq_trans_total + Freq_pur_total	34,514	73,584	,265	,428	19,0%	79,5%
Model 32	Freq_trans_last2 + Freq_pur_total	34,418	73,680	,265	,427	19,0%	79,5%
Model 44	Freq_trans_total + Freq_trans_last2	34,033	74,064	,262	,423	38,1%	79,5%
Model 7	Freq_pur_last2 + Rec_last6	31,854	76,243	,248	,400	28,6%	83,0%
Model 5	Freq_pur_last2 + Rec_IPT	31,437	76,661	,245	,395	28,6%	83,9%
Model 6	Freq_pur_last2 + Rec_lastpur	30,401	77,697	,238	,384	14,3%	81,3%
Model 20	Freq_trans_total + Freq_pur_last2	30,045	78,052	,235	,380	23,8%	83,0%
Model 8	Freq_pur_last2 + Rec_std_IPT	29,270	78,828	,230	,371	23,8%	83,0%
Model 34	Freq_trans_last2 + Freq_pur_last2	28,939	79,158	,228	,368	33,3%	83,9%
Model 28	Freq_trans_last6 + Rec_lastpur	13,700	94,397	,115	,186	14,3%	83,9%
Model 21	Freq_trans_total + Rec_lastpur	12,483	95,614	,105	,170	14,3%	83,9%
Model 35	Freq_trans_last2 + Rec_lastpur	12,354	95,743	,104	,169	14,3%	83,9%
Model 16	Rec_lastpur + Rec_last6	11,862	96,236	,100	,162	23,8%	85,7%
Model 30	Freq_trans_last6 + Rec_last6	10,701	97,396	,091	,147	14,3%	83,9%
Model 17	Rec_lastpur + Rec_IPT	10,650	97,447	,091	,147	9,5%	83,0%
Model 37	Freq_trans_last2 + Rec_last6	10,026	98,072	,086	,138	14,3%	83,9%
Model 23	Freq_trans_total + Rec_last6	9,915	98,182	,085	,137	14,3%	83,9%
Model 29	Freq_trans_last6 + Rec_IPT	9,944	98,153	,085	,137	4,8%	82,1%
Model 31	Freq_trans_last6 + Rec_std_IPT	9,652	98,445	,083	,133	4,8%	82,1%
Model 45	Freq_trans_last6 + Freq_trans_last2	9,644	98,454	,083	,133	0,0%	81,3%
Model 43	Freq_trans_total + Freq_trans_last6	9,361	98,737	,080	,130	0,0%	81,3%
Model 36	Freq_trans_last2 + Rec_IPT	9,073	99,024	,078	,126	9,5%	83,0%
Model 22	Freq_trans_total + Rec_IPT	8,945	99,153	,077	,124	4,8%	82,1%
Model 38	Freq_trans_last2 + Rec_std_IPT	8,473	99,624	,073	,118	4,8%	82,1%
Model 42	Rec_last6 + Rec_IPT	8,929	99,169	,077	,124	19,0%	83,9%
Model 14	Rec_std_IPT + Rec_last6	8,731	99,367	,075	,121	9,5%	83,0%
Model 24	Freq_trans_total + Rec_std_IPT	8,375	99,722	,072	,116	4,8%	82,1%
Model 15	Rec_std_IPT + Rec_last pur	7,847	100,25	,068	,109	14,3%	83,9%
Model 13	Rec_std_IPT + Rec_IPT	7,532	100,565	,065	,105	9,5%	83,0%

a. The definitions of the abbreviations of variables can be found in table 5

TABLE 9: MODEL FIT AND CLASSIFICATION ACCURACY MODELS

The different measurements in the table give explanation about the fit and the predicting accuracy of the models. First of all, there is some disagreement about a good evaluation of the R^2 in logistic regression. There are a variety measurements that give different answers. However, according to Field (2015) they are conceptually the same and could be interpreted in the same way as the R^2 in linear regression. It gives the researcher an understanding of the substantive significance of the model. First of all, The 2log-likelihood give an indication how much of the observations are explained. This measurement is based on the comparison between the actual value and the prediction of the dependent variable. The higher the value of the statistic, the more observations are unexplained (Field, 2015). The Cox & Snell R^2 and the Nagelkerke R^2 are a comparable measure of the R^2 of linear regression, but then for logistic regression. These measurements are based on the deviance of the base model and the new model. Nagelkerke adjusted the R^2 of Cox & Snell because this statistic could not reach the theoretical maximum of 1. In this case, the premise is that the larger the R^2 value, the better the model (Field, 2015).

Table 9 shows that Freq_pur_last6 is the best predictor of the frequency variables. Moreover, models that have a combination with frequency and recency variables have more predictive power than a model with solely recency variables. For this study, a combination with the variables Freq_pur_last6 and Rec_lastpur is the best model. This combination explains the most observations and has the highest Cox & Snell R^2 and Nagelkerke R^2. Furthermore, these predictors could also identify the most churners.

When looking closer to the variables of the model, it shows that Freq_pur_last6 has a significant Wald statistic while the variable Rec_lastpur is almost significant with a p-value of 0.071 – table 16. Because the Wald statistic has sometimes the tendency to underestimate the significance of a variable, it has been advised to analyse a model with and without a variable that is slightly above the 0.05 cut-off point (Field, 2015). So, to be sure that the model is stronger with both variables, an additional test is executed with and without this variable – see table 10 and 11. Although, the classification model shows better accuracy with only the variable Freq_pur_last6, the model shows a better fit with both variables. Therefore, this study will focus on the model that includes both Rec_lastpur and Freq_pur_last6. This model will be analysed in more detail in subsequent sections.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	37,284	1	,000
	Block	37,284	1	,000
	Model	37,294	1	,000

TABLE 10: MODEL WITHOUT REC_LASTPUR

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	6,182	1	,013
	Block	6,182	1	,013
	Model	43,467	2	,000

TABLE 11: MODEL WITH REC_LASTPUR

6.5 Interpretation of logistic regression model

6.5.1 Graphs

Before looking at the model, a visual overview of the predictors that are included in the model is displayed below. This could give an explanation whether there is an observational difference between the behavioural customers and churners.

Graph 10 shows the differences in Freq_pur_last6 of behavioural customers and the customers that are partial churners. It clearly shows that partial churners have a lower frequency of purchases in the last 6 months than loyal customers prior to churn. It is worth mentioning that this illustration is magnified. The outliers are therefore not seen on this illustration – see Appendix 8 for the original illustration.

Graph 11 explains the variable Rec_lastpur. It shows that the customers that have a high amount of days since the last purchase are churners. Although, this is the case for customers with an extremely high Rec_lastpur. In general, it seems that most churners not really have a different behaviour than the behavioural loyal customers. This variable shows the importance of doing a retest in a larger data set.

*** ***

FIGURE 10: VARIABLE REC_LASTPUR

FIGURE 11: VARIABLE FREQ_PUR_LAST6

6.5.2 Base model

The output of a logistic regression begins with a null-model – see table 12. This model explains the predictability without any predictors. Instead of identifying churners, the model tries to predict the most accurate model as possible. That is, categorizing most cases right. Because the behavioural loyal customers consist of 91 customers and the churners of 21 customers, the model predicts that all customers are behavioural loyal. This gives by chance namely the most correct answers. In other words, this base model for this study results in an overall correct classification of 81,3% where 100% predicted as behavioural loyal customers and 0% predicted as churners. However, the objective of a churn analysis is of course to identify as much churners as possible.

Classification Table[a,b]

Observed			Predicted		
			Churn		Percentage Correct
			Behavioural loyal	Churn	
Step 0	Churn	Behavioural loyal	91	0	100,0
		Churn	21	0	,0
	Overall Percentage				81,3

a. Constant is included in the model.

b. The cut value is ,500

TABLE 12: CLASSIFICATION TABLE BASE MODEL

6.5.3 Model and model fit

As previously discussed, there is some disagreement about the best assessment of the model fit (Field, 2015). The R^2 of logistic regression does not provide the same coefficient as produced with ordinary linear regression. It is merely an approximation. The Cox & Snell R^2 for the model is ,322 while the Nagelkerke R^2 is ,517 – see table 13. This means that according to Cox & Snell, 32,2% of the variation in the dependent variable is explained by the logistic model. For the figure of Nagelkerke, 52% is explained by the model.

An alternative to assess the model fit is by looking at the Hosmer and Lemeshow test - see table 14. Contrary to what is normal, the Hosmer and Lemeshow test statistic has to be greater than 0.05. This means that the null-hypothesis – that there is no difference between the observed and the predicted values of the model – should not be rejected (Field, 2015). The Hosmer and Lemeshow test of this study is ,977 which means that the prediction of the model does not significantly differ from the observed values. In other words, the model fits to the data. Although, the value of Hosmer and Lemeshow has to be evaluated with caution. Small sample sizes, like this study, could give a non-significant outcome, while it actually has no correct fit (Kramer & Zimmerman, 2007). It is therefore important to test the variables with a larger dataset.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	64,930[a]	,322	,520

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than ,001.

TABLE 13: FIT OF THE MODEL

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	2,120	8	,977

TABLE 14: FIT OF THE MODEL

6.5.4 Classification table

The classification table gives an explanation about the proportion that the model has classified correctly (Field, 2015). The base model – see table 15 – showed that a model without predictors had an overall percentage of 81,3 percent. In this case, all customers are identified as behavioural loyal customers. This study has the objective to identify the minority group (churners). The new model, including the two predictors, identified 11 churners correctly while 4 behavioural loyal customers were misclassified. The overall percentage of the classification table of the new model improved with 6,2% compared to the base model. So, the predictors can identify 11 churners based on the predictors frequency of purchases last 6 months and the amount of days since last purchase. In other words, customers who are going to churn have a lower frequency of purchases six months prior to churn than the customers who remain behavioural loyal. Second, it means that customers that have a higher amount of days since last purchase have a greater likelihood of churn.

Classification Table[a]

Observed			Predicted: Churn: Behavioural loyal	Predicted: Churn: Churn	Predicted: Percentage Correct
Step 1	Churn	Behavioural loyal	87	4	95,6
		Churn	10	11	52,4
	Overall Percentage				87,5

a. The cut value is ,500

TABLE 15: CLASSIFICATION TABLE OF MODEL 17

6.5.5 Variables in the equation

Table 16 shows if the predicting variables make a significant contribution to the model. This can be assessed through the Wald statistic (Field, 2015). The Wald statistic is calculated through the regression coefficient and its standard error. The significance of the Wald statistic can be interpreted through the Sig. column. The cut-off point for the Wald statistic is 0.05. For this data, the Freq_pur_last6 is significant, with a p-value of ,000, while the Rec_lastpur is almost significant with a p-value of ,071. Previous section – model selection - explained that the Wald statistic has the tendency to underestimate variables where the significance level is slightly above 0.05. In this cases, it is advised to compare the -2log likelihood values for models with and without this variable. This showed that the model with both variables explain more of the variation in the dependent variable than a model with only Freq_pur_last6.

The Exp(B) column represents the sensitivity of the variable. It explains to what extent the odds change due to a change in the unit of the predictor. More specifically, if the odds ratio is less than one, any increase of the predictor leads to a decrease in the odds of the outcome occurring (Field, 2015). Contrary, if the odds ratio is above one, any increase of the predictor leads to an increase in the odds of the outcome occurring (Field, 2015). For this study, when a customer bought one product more on average in the last 6 months, the customer is ,990 times likely not going to churn. Second, when a customer's last purchase is 20 days ago, the customer is 1.2 more likely to churn than someone who has a bought a product 19 days ago.

At last, with the confidence interval you can assess whether the aforementioned interpretation is reliable. It explains that it is for 95% sure that the exp(B) lies between the lower and upper bound of the confidence interval, if it is calculated in 100 different samples. The criteria is that the interval does not contain 1. This is true for the variable Freq_pur_last6 – see table 18. This gives confidence that the direction of the relationship is true in the population. This is even true for a confidence interval of 99%. However, for the variable Rec_lastpur, a confidence interval of 95% contains 1. This means that the population value could suggest that Rec_lastpur could increase the likelihood of churn but also could decrease the likelihood of churn. However, with a confidence interval of 90%, the lower and upper bound does not contain 1 – see table 17. It is therefore important to test the model with a larger dataset before generalizing the model too other samples.

Equation for the probability of a churner according to the model:

$$Probability\ of\ a\ chuner = \frac{1}{1 + e - (2{,}856 + -0{,}010 * \text{Freq\_pur\_last6} + \ ,182 * \text{Rec\_lastpur}\ )}$$

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Freq_pur_last6[b]	-,010	,003	12,521	1	,000	,990	,984	,995
	Rec_lastpur[c]	,182	,100	3,247	1	,072	1,200	,985	1,463
	Constant	*2,856*	*1,2106*	*5,611*	*1*	*,018*	*17,391*		

a. Variable(s) entered on step 1: Freq_pur_last6, Rec_lastpur.

b. Purchases in the last 6 months.

c. Number of days since last purchase.

TABLE 16: CONTRIBUTION OF THE VARIABLES TO THE MODEL

Variables in the Equation

		90% C.I.for EXP(B)	
		Lower	Upper
Step 1[a]	Freq_pur_last6	,985	,995
	Rec_lastpur	1,017	1,417

a. Variable(s) entered on step 1: Freq_pur_last6, Rec_lastpur.

TABLE 17: CONFIDENCE INTERVAL OF 90%

Variables in the Equation

		99% C.I.for EXP(B)	
		Lower	Upper
Step 1[a]	Freq_pur_last6	,982	,997
	Rec_lastpur	,925	1,556

a. Variable(s) entered on step 1: Freq_pur_last6, Rec_lastpur.

TABLE 18: CONFIDENCE INTERVAL OF 99%

6.5.6 Residuals

There are different ways to assess whether the data consists of outliers. First of all, the Catewise list identifies cases that did not have a good fit with the model – table 19 (Field, 2015). In the dataset of this study, case 67 and 98 falls into the category that did not fit to the general pattern. The standardized residuals has to be assessed to check whether the cases have an influence on the model. For the standardized residuals (ZResid), only 5% of the cases are allowed to lie outside ±1.96 and about 1% of the cases are allowed to lie outside ±2.58. This criteria is met according to the table below. Moreover, the Cook's distance and DFBeta values should be less than one. The residual statistics show that these values are met for the dataset of this study – see table 20. In other words, there are no influential cases that have an excessive effect on the model.

Casewise List[b]

Case	Selected Status[a]	Observed	Predicted	Predicted Group	Temporary Variable	
		Churn			Resid	ZResid
67	S	1**	,143	B	,857	2,445
98	S	1**	,027	B	,973	5,987

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

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

TABLE 19: STANDARDIZED RESIDIUALS

Residual statistics

	N	Minimum	Maximum
Analog of Cook's influence statistics	112	,00000	,67047
DFBETA for constant	112	-,64697	,27841
DFBETA for Freq_pur_last6	112	-,00209	,01073
DFBETA for Rec_lastpur	112	-,04066	,10848
Valid N (listwise)	112		

TABLE 20: COOK'S DISTANCE AND DFBETA VALUES

6.5.7 Multicollinearity

Multicollinearity test for the bias that is caused by collinearity (Field, 2015). Collinearity can have an effect on the parameters of the model. SPSS does not have a standard option to test this assumption of logistic regression. Therefore, it is advised to do a linear regression to check for the multicollinearity. At first, the tolerance and VIF values have to be evaluated – table 21. An indication of violation is when the tolerance values are less than 0.1 and VIF values are above 10. In this study, both values are below the threshold. Second, another criteria is by looking at large differences between the eigenvalues or the condition index. It gives an indication how accurate the regression parameters are. Although there are no strict rules that suggest when the differences between the values are too large, it seems not the case for this model. A third way to check for multicollinearity is by looking at the variance proportions – table 22. You may speak of collinearity when there is a low eigenvalue and when the variables have both high variance proportions. This indicate that there is dependency between the variables. The results of this study show that there is no collinearity between variables. In other words, the assumption of multicollinearity is not violated.

Coefficients[a]

Model		Collinearity statistics	
		Tolerance	VIF
1	Freq_pur_last6 [b]	,998	1,002
	Rec_lastpur[c]	,998	1,002

a. Dependent Variable: Churn

b. Purchases in the last 6 months.

c. Number of days since last purchase.

TABLE 21: TOLERANCE AND VIF STATISTICS

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Freq_pur_last6[b]	Rec_lastpur[c]
1	1	1,871	1,000	,12	,11	,10
	2	,783	1,546	,01	,24	,71
	3	,345	2,328	,87	,65	,19

a. Dependent Variable: Churn

b. Purchases in the last 6 months.

c. Number of days since last purchase.

TABLE 22: VARIANCE PROPORTIONS

6.5.8 Linearity of the logit

Another assumption of logistic regression is that the independent variables are linearly related to the log of the dependent variable. A measurement that is often used to test this assumption is the Box-Tidwell approach of Hosmer and Lemeshow (Field, 2015). This approach suggests to conduct a test with each independent variable and an interaction between the independent variable and the log of this variable – table 23. The assumption is violated when the interaction term is significant. For this study, the variable Rec_lastpur is not significant. This means that the assumption has been met. However, the variable Freq_pur_last6 is with ,003 smaller than ,05. This means that the assumption of linearity of the logit is violated for this variable. A violation of this assumption can lead to parameter estimates that are biased. Second, it could create a logit of the dependent variable that is not stable across the values of the independent value (Lomax & Hahs-Vaughn, 2013). It is acknowledged that this is a limitation of the model. Normally, an option is to transform the violated variables (Field, 2015). However, because the data set of this study is relative small, it is more advisable to retest the variables on a larger data set with more events.

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Freq_pur_last6[b]	-,043	,015	8,661	1	,003	,958
	Freq_pur_last6 by LN_Freq_pur_last6	,005	,002	7,088	1	,008	1,005
	Rec_lastpur[c]	-,903	,967	,872	1	,351	,405
	LN_rec_lastpur by Rec_lastpur	,345	,312	1,225	1	,268	1,412
	Constant	7,089	2,748	6,657	1	,010	1198,898

a. Variable(s) entered on step 1: Freq_pur_last6, Freq_pur_last6*LN_Freq_pur_last6, Rec_lastpur, LN_rec_lastpur * Rec_lastpur
b. Purchases in the last 6 months.
c. Number of days since last purchase.

TABLE 23: LINEARITY OF THE LOGIT

7.0 Discussion

7.1 Outline of this chapter

This chapter describes the practical implication, contribution to the extant literature and the limitations of this study. It is important to notice that the objective of this study was not to make a scientific contribution but rather to lay the groundwork for churn analysis purposes at ***.

7.2 Practical implication

This study is commissioned by *** and the results are therefore mostly applicable to their organization. To date, this churn analysis is the first data mining project at ***. Therefore, the objective of this study was not to get a model that directly could be implemented into the daily operations at *** but rather to lay the groundwork for future data mining projects. There are three practical implications which are valuable for *** and other B2B organizations.

The first implication that could be valuable for other organizations is the operationalization of partial churn that is suggested in this study. The definition of a churner in a business without a contract is complex and arbitrary. The complexity lies in the fact that it is not clear when a customer ended a relationship. Extant literature focused therefore on partial churn of a customer in the next period instead of the prediction of a permanent decision. This study used a combination of a threshold and percentage decrease to operationalize a partial churner. This combination has not been used, to the best of our knowledge, in other churn studies.

Second, the suggested variables, through the deductive (literature) and inductive (interviews) chapters, that have been tested and the ones that have not been tested could be valuable for *** and other companies that are interested in churn analyses. First of all, some variables that are suggested could not be tested due to the quality of the data at ***. These variables remain interesting and it is recommended to test it in subsequent studies. Second, the results of the variables that are tested in this study show that recency and frequency variables are good predictors of churn while monetary variables had no predicting value in this study. More specifically, a model with 'frequency of purchases of the last 6 months' and 'the amount of days since last purchase' was most predictive. This model could identify 11 of the 21 churners and improved the base model with 6,2%. However, this model should not be implemented due to the violation of the linearity of the logit. It is therefore recommended to retest the model, and the other variables, in a larger data set.

The third implication stems from the reason that some variables could not be tested in this study. The extant data system is not perfectly suited for data mining and especially churn analysis. This is caused by ***. It is recommended that *** should therefore make some adjustments in their data system before they embark on a follow-up study.

7.3 Research implication

This study makes a few contributions to the extant literature. First of all, the objective of a churn analysis is to predict the likelihood of a customer to churn. Previous churn studies described categories of churn predictors that were related to the customer usage, buying behaviour and customer characteristics based on demographic or geographic variables. Although, the relation between the categories and the antecedents of repeat purchasing is not clearly described in previous churn studies. The focus was mainly on the statistical techniques and analysis rather than an explanation of the relation between the type of variables. This study therefore contribute to previous literature by providing a better theoretical explanation between the drivers of behavioural loyalty (repeat purchases) and the type of variables described in previous churn studies. More specifically, this study suggests that buying behaviour, usage of products/services and complaining behaviour are outcomes of the strength of the relationship between a customer and firm. Customer characteristics moderate the relation between strength of a relationship and behavioural loyalty. This theoretical explanation gives a better understanding about the relation between the type of variables and what these type of variables really explain. Moreover, it can help researchers that embark on a churn analysis with identifying other customer behaviour that, explain the strength of the relationship and/or customer characteristics and therefore possibly, can differentiate churners from behavioural loyal customers.

Second, this study contribute to the extant literature by conducting a churn analysis at a B2B company in an *** sector with a non-contractual setting. First of all, there are almost no churn studies in a B2B context while no study has been done in this sector. Second, the operationalization of (partial) churn in a non-contractual setting has not been described in many churn studies. The complexity lies in the fact that it is not clear when a customer ended a relationship. Extant literature focused therefore on partial churn of a customer in the next period instead of the prediction of a permanent decision. This study used a combination of a threshold and percentage decrease to operationalize a partial churner. This combination has not been used, to the best of our knowledge, in other churn studies.

The third contribution to the literature is the confirmation of the predictability of the buying behaviour variables in this study that is conducted at a B2B company that operates in an *** sector. The results of the analysis show that recency and frequency variables are good predictors of churn. More specifically, the best model included the variables Rec_lastpur and Freq_pur_last6. The monetary variables had no predicting value in this study. This is partly consistent with the existing churn literature that suggests that monetary variables have less predictive power in identifying churners.

At last, this research makes a contribution to the literature by suggesting new variables that could differentiate churners from behavioural loyal customers. Because the absence of this data at ***, it could unfortunately not be tested. Although, these variables are underpinned through literature and experiences of employees of *** and remain therefore interesting for churn analyses.

7.4 Limitations

Although the underlying objective of this study was to lay groundwork for future churn analysis at ***, instead of providing a model that could directly be applied into the daily operations. It is important to consider a few limitations of the churn analysis in this study. This could improve the efficiency and effectivity of future churn analyses.

First of all, the data set of this study is relative small. As a consequence, not all variables could be included into the model. The rule of thumb for logistic regression is that one variable can be included for every 10 events. This study had only 21 events (churners) and could therefore only include two variables in the model. Moreover, the results of the model show that the linearity of the logit was violated. It is therefore not recommended to implement this model into the organization but to retest the variables into a new and larger dataset. This model should also be tested in combination with the other suggested variables. Especially since a lot of variables could not be tested due to the lack of data. This is caused by the data system that is not perfectly suited for churn analyses and data mining purposes. It is recommended that *** should therefore make some adjustments in their data system before they embark on a follow-up study.

At last, during the study the objective was to capture the behaviour and characteristics of a customer who is going to churn. With the exception of the mon_dif and Freq_dif variables, the operationalized variables in this study explain the customer behaviour at that specific moment, instead of the change in the customer behaviour in time. After the statistical analysis and interpretation of the results of this study, it became clear that variables that measure the changing behaviour could be more interesting. As explained in the literature review, a dissatisfied customer does not switch all of a sudden. The customer is rather moving its business gradually from one supplier to another. This will eventually lead to churn. Therefore, it is recommended that future churn studies focus more on variables that measure this changing customer behaviour. For instance, a suggested variable could be one that explain the changing behaviour of a customer through the amount of different products that a customer buys. In other words, a customer who, in course of time, is purchasing significant less different products will probably have a higher likelihood of churn. This could suggest that the customer is moving its business gradually from one supplier to another.

8.0 Conclusion

Churn analysis is a topic that is becoming increasingly popular. The primary goal of a churn analysis is to build a predictive model that can differentiate churners from behavioural loyal customers. It is the first step in preventing customers from churning. The second step is to identify the reason for churning and the third step is to target them with an incentive to stay. This ensures a higher efficiency and allocation of resources because the company is only focusing on the customers that have the tendency to leave.

This study conducted a churn analysis through logistic regression at ***. To date, this company had no experience with data mining and churn analysis. Therefore, the underlying objective of this study was not to get a model that directly could be implemented into the daily operations but rather to lay the groundwork for future data mining projects. The focus was on the most behavioural loyal customers of the *** market that bought products from the product group *** in 2014 and 2015. The data set consisted of 112 customers of which 21 were classified as partial churners.

The churn analysis was conducted with 14 variables, suggested through literature and interviews, that could be extracted from the database of ***. These variables consist of the buying behaviour of the customer. This behaviour is the outcome of the strength of a relationship between customer and supplier. 10 of the 14 variables showed predictive power in the univariate analysis. These were the recency and frequency variables. The monetary variables had no predictive power.

After an extensive model selection, a model with Freq_pur_last6 and Freq_lastpur was most predictive. This model could identify 11 of the 21 churners and improved the base model with 6,2%. In other words, the frequency of purchases in the last 6 months and the amount of days since last purchase was the best combination that could differentiate churners from behavioural customers. However, the model should not be generalized and implemented because the linearity of the logit was violated. Moreover, it is worth mentioning that only two variables could be included in the model due to the rule of thumb of logistic regression. This rule states that one variable can be added for every 10 events (churners). It is therefore recommended to retest this model in a larger data set. It also advisable to test the model in combination with, at first, the other variables that showed predictive power and second, the variables that could not be tested due to the lack of data. The latter leads to the main conclusion of this study.

The data system at *** is namely not build for predictive statistical analysis. It is recommended that *** should therefore make some adjustments in their data system before they embark on a follow-up study. This implies consolidating the data systems, automatically measuring the buying behaviour variables and start with registering the missing data. Besides, it is advisable to assess whether statistical analyses, as churn analyses, should be done in-house at *** or whether is better to outsource it to another company. Namely, these analyses depend on a lot of arbitrary and complex decisions and proper statistical knowledge and experience is therefore required.

To conclude, because the quality of the data system and the required knowledge for predictive analyses, it is not recommended to begin directly with predictive (churn) analysis. *** should follow up the recommendations above. In the meantime, *** can begin with monitoring churn by means of the RFM variables. This gives the organization more time to organize their organization for the purpose of predictive (churn) analyses. Monitoring churn analysis is cheaper and more simplistic than predictive churn analysis. The only difference is that predictive churn analysis is a leading indicator while monitoring churn analysis is a lagging indicator. In other words, with predictive churn analyses, you want to predict the probability that the customer will churn while with monitoring churn analyses, you measure their current churn status. Therefore, it is advisable to use a more conservative criteria that determines if a customer is a partial churner or not. If the customer falls below/above that criteria, it is classified as a partial churner. Monitoring the changes in the RFM of a customer is valuable because a customer will not leave all of a sudden. Instead, the customer will gradually change its business from one supplier to another. So, monitoring a significant change in a customer's RFM behaviour can be a sign of churn. The company should then target those customers with an incentive to stay.

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Appendix 1: Set of problems

Description of internal situation and complication

***

Description of external situation and complication

***

Description of situation and complication which emerged with the introduction of CXM

***

Appendix 2: Company information

***

Appendix 3: Concept clarification CXM

Customer experience management (CXM)

Customer Experience Management has received a lot of interest the last years by both practitioners and academics (Berry, Carbone, & Haeckel, 2002; Meyer & Schwager, 2007; Shaw & Ivens, 2004). The premise of CXM is that value is created in the whole customer journey and not only in the core product or service. Hence, every experience, touch point, that a customer has with a company has an influence on their future actions and buying behaviour (Verhoef et al., 2009). As a consequence, companies are recognizing that it is critical to understand where value is created and destroyed in the customer journey and what the customers action is after the experience. The main reason for companies to focus on creating a good CX is because this will eventually lead to more loyal customers. Additional effects of CEM consist of increasing employee satisfaction, market share, and new customer attraction (Journée & Weber, 2014).

Appendix 4: Phases knowledge discovery through data mining

The tables below show the phases that are described in the extant literature about knowledge discovery in databases and data mining. Table 25 shows the phases where data mining is seen as the whole process while table 26 shows the phases where data mining is seen as a sub phase.

Two Crows data mining process (Edelstein, 2000)	**CRISP-DM** (Watson, 2000)
Define Business Problem`	Business understanding
Build Marketing Database	Data understanding
Explore data	
Prepare Data for Modeling	Data preparation
Build model	Modeling
Evaluate Mode	Evaluation
Deploy model and results	Deployment

TABEL 25: LITERATURE WHERE DATA MINING IS SEEN AS A PROCESS

From Data Mining to Knowledge Discovery in Databases (Fayyad et al., 1996)	**Data mining methods for knowledge discovery** (Cos et al., 2012)	**Data mining & Knowledge discovery Process** (Cabana et al.,1998)	**The Six-Step Knowledge Discovery and Data Mining Process** (Cios & Kurgan, 2005)	**Adjusted KDD Process** Miller & Hann
Developing an understanding of the application domain, identification of the knowledge discovery goals	Understanding the domain in which the discovery will be carried out	Business objective determination	Understanding the problem domain	Data selection
Creating a target data set	Forming the data set, its cleaning and warehousing	Data preparation	Understanding the data	
Cleaning and preprocessing, removing noise			Preparation of the data	Data pre-processing
Data reduction and protection				
Matching the goals of the KDD process to a particular data mining method				Data enrichment
Exploratory analysis and hypothesis selection				
Data mining	*Data mining*	*Data mining*	*Data mining*	*Data mining*
Interpreting mined patterns	Post-processing of the discovered knowledge	Analysis of results	Evaluation of the discovered knowledge	Interpretation
Acting on the discovered knowledge	Putting the results of knowledge discovery into use	Knowledge assimilation	Using the discovered knowledge	Reporting

TABEL 26: LITERATURE WHERE DATA MINING IS SEEN AS A SUB PHASE OF THE KNOWLEDGE DISCOVERY IN DATABASES

Appendix 5: Antecedents satisfaction

Antecedents of satisfaction

Affect

It is stated that customer satisfaction consists not only of cognitive judgments, but also of affective responses. As defined by Saura & Frasquet (2009) the "cognitive component represents a mental process of evaluation of an experience in which a series of comparison variables intervene, the affective component is shown through certain feelings which are generated as a result of the evaluation" (p. 597). The affective component is different for B2B and B2C companies. In general, it is stated that B2B relationships are more rational than B2C relationships (Hollyoake, 2009). This is due to the fact that a B2B customer is often acting on behalf of their customers. As a result, B2B companies try to minimize the risk and focus more on consistency, risk and price instead of emotional factors (Hollyoake, 2009).

Disconfirmation

Disconfirmation is probably the most dominant and adopted antecedent in literature of customer satisfaction (Oliver, 1980; van Vuuren et al., 2012). For instance, Matilla & O'neill (2003) stated that disconfirmation is the most popular customer satisfaction theory while Szymanski & Henard (2001) revealed in their meta-analysis that the conceptualization of disconfirmation is highly related to customer satisfaction.

Disconfirmation can be explained as the difference between the performance and expectations. Namely, a customer assess their perception of a performance and compares it with their expectations. The variation between these two concepts is called disconfirmation. There are three types of disconfirmation. A positive disconfirmation (satisfaction), a negative disconfirmation (dissatisfaction) and zero disconfirmation (expectations were met).

This result in the following reasoning:
Expectations – Perception of a performance = Disconfirmation

The disconfirmation conceptualization states that customer satisfaction depends highly on the perception of the customer. As an example, customers who bought the same product and have received the same performance can have a different level of disconfirmation. This depends on the perception that they had about the expectation before the purchase and the actual performance. In this case, there is a level of disconfirmation. This can lead to, what is called, the assimilation-contrast effect (Oliver 2014). If there is a small discrepancy between the expectation and the perception of the performance, this will result in assimilation. In this case, the perceived performance will be adjusted to the expectation and the performance will be acceptable for the customer. Contrary, if there is a large discrepancy between the expectation and the perception of the performance, this will result in a contrast. This means that the perceived performance will be exaggerated positively or negative. The performance is then unacceptable for the customer. Moreover, Anderson & Sullivan found that a negative disconfirmation has a greater impact on customer satisfaction than a positive disconfirmation (Anderson & Sullivan, 1993).

Equity

The equity antecedent is another way how a customer can evaluate his or her level of satisfaction. It is seen as a direct influencer of customer satisfaction. This conceptualization consists of a customer judgment of the received input/output compared to the input/output received by other customers. Hence, the customer is using a benchmark to evaluate their perceived value (Szymanski & Henard, 2001). This can be written as the following calculation.

$$\frac{O_c}{I_c} \propto \frac{O_b}{I_b}$$

The O is the perception of the outcome or perceived value, the I is the perception of the input, the b is the benchmark and the c is the customer. Based on this calculation, a customer is satisfied when their equity ratio is proportionally greater than the equity ratio by the other customer (Szymanski and Henard, 2001).

Equity theory and Disconfirmation theory

The two concepts are distinct but are seen as complementary drivers on satisfaction (Oliver, 2014). Although the theories relate to each other by means of their comparison process and prior standards, they are conceptually different. Oliver (2014) suggest that the two theories differ on standard on comparisons, nature of comparisons, attribute and dimensions, stages in process and emotional response. For this study, both antecedents can help to understand how customer satisfaction is achieved. However, the focus of this study is on the outcomes of customer satisfaction. So, expressing churners and behavioural loyal customers their level of equity and disconfirmation in a different way? This more easy to measure than the focus on the multiple factors that create disconfirmation. This could be different for every customer.

Appendix 6: List of interviewees

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Appendix 7: Univariate analysis

Variables	B	SE	Wald	Sig.	Exp(B)
Freq_trans_total	-,002	,001	7,568	,006	,998
Constant	-,525	,321	2,671	,102	,592
Freq_trans_last2	-,002	,001	6,552	,010	,998
Constant	-,734	,297	6,129	,013	,480
Freq_trans_last6	-,002	,001	6,705	,010	,998
Constant	-,678	,303	4,989	,026	,508
Freq_pur_last2	-0,024	0,007	12,491	0,000	0,976
Constant	*1,23*	*0,66*	*3,469*	*0,063*	*3,421*
Freq_pur_last6	-0,044	0,12	12,881	0,000	0,957
Constant	*3,099*	*1,105*	*7,862*	*0,005*	*22,167*
Freq_pur_total	-0,5	0,16	10,104	0,001	0,951
Constant	*3,929*	*1469*	*7,157*	*0,007*	*50,85*
Rec_IPT	0,095	0,037	6,646	0,010	1,1
Constant	*-2,32*	*0,44*	*27,786*	0,000	*0,098*
Rec_std_ipt	0,109	0,05	4,798	0,028	1,115
Constant	*-2,13*	*0,408*	*27,25*	0,000	*0,119*
Rec_last6	0,096	0,034	7,768	0,005	1,1
Constant	*-2,2374*	*0,435*	*29,777*	0,000	*0,093*
Rec_lastpur	0,112	0,061	3,343	0,068	1,118
Constant	*-2,054*	*0,389*	*27,809*	0,000	*0,128*
Mon_dif	-2,62	0,449	0,34	0,56	0,77
Constant	*-1,447*	*0,243*	*35,406*	0,000	*235*
Freq_dif	-0,1	0,335	0,089	0,766	0,905
Constant	*-1,456*	*0,244*	*35,654*	0,000	*0,233*
Mon_total_2014	0,000	0,000	3,794	0,0151	1
Constant	*-0,542*	*0,458*	*1,401*	*0,237*	*0,582*
Mon_last6	0,000	0,000	4,776	0,029	1
Constant	*-0,318*	*0,491*	*0,421*	*0,517*	*0,727*

Appendix 8: Descriptive statistics & graphs

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