Universiteit Leiden
ICT in Business

To Churn or Not to Churn: A Comparative Study

Name: Stijn Cornelis Wouter Kievit

Date: 17/05/2019

1st supervisor: Niels van Weeren

2nd supervisor: Peter van der Putten

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Preface

Thank you for reading the preface of “A Comparative study: To Churn or Not to Churn”.
The basis of this study is a comparison between Dutch and international telecommunications providers and operators regarding their churn prediction and prevention capabilities by conducting expert interviews. It was written to fulfill the graduation requirements of the master’s program ICT in Business at the Leiden Institute of Advanced Computer Science (LIACS). I was engaged in researching this topic from February 2019 to December 2019.

This research was conducted in collaboration with Accenture Netherlands, where I undertook my internship. The research questions were formulated together with my supervisors, Rick Bouter, Gandert Pelger and Martijn Wiering, as well as my university supervisors Niels van Weeren and Peter van der Putten. They were of great support during my internship and helped me in every way they could. The biggest challenge during my research was connecting with experts of international telecommunications operators/providers, which the Accenture supervisors and other coworkers tried to relief.

I would like to thank my supervisors, survey respondents, and industry experts that helped me to progress my research. I could not have done it without their help.

To my other colleagues at Accenture: I want to thank you for the great experiences and support I enjoyed during my time at Accenture. I also want to thank my friends, family and especially my girlfriend for the support during this period.

I hope you enjoy this reading!

Stijn C.W. Kievit

Amsterdam, December 1, 2019

Abstract

Telecommunications operators world-wide increasingly face challenges regarding customer churn due to the telecommunications being a very mature market. According to the media, some Dutch telecommunications operators invest heavily in advertising to make up for lost customers, while other operators use quadruple play to increase stickiness and reduce customer churn. Research shows, with multiple case studies across the world, that customer churn prediction can help contest customer churn.

This study aims to identify how well customer churn is currently utilized in the Dutch telecommunications industry and how this can be further enhanced / improved. Building on the currently available work on customer churn prediction, it asks: how can the use of customer churn prediction be accelerated in the Dutch telecommunications industry?

Based on a review of literature on customer churn and customer churn prediction, an online survey was distributed to Dutch citizens to identify important churn drivers. Additionally, expert interviews with operators from multiple geographical regions were conducted to identify to what extent customer churn prediction is used.

The interviews covered the following topics: available data, churn prediction models, integration with other systems and utilization of the churn prediction results (retention). The goal was to compare the findings with the interviewed Dutch operators to identify potential points of improvement.

The results indicate that the use of customer prediction varies widely between operators, also within the Netherlands. However, the maturity of the customer churn prediction seem to differ greatly between the two main types of operators, which are virtual and non-virtual operators.

Finally, the study concludes with the identification of two main obstacles, as well as discussing best practices to implement customer churn prediction.

1 Introduction

The telecommunications industry is one of the most competitive industries existing today. High market maturity and fierce competition forces competitors to use aggressive marketing tactics and invest heavily in advertisement [1]. According to Telecompaper[1], Dutch telecommunications service providers invested a staggering amount of 44 million euros during the first half of 2018. However, the article points out that there are core differences between the telecommunications service providers regarding their spending and tactics. The two major telecommunications providers, KPN and Vodafone, spend significantly less than their competitors on advertising. According to the Telecompaper, this is due to the success of quad play which aims to remove the differences between fixed and mobile networks subscriptions by combining service packages together into one seamless service and providing one coherent customer experience [2]. However, other service providers e.g. T-Mobile and Tele2 try to attract customers by investing heavily into advertising and better offers. This tactic also shows a large growth in customers, but it increases acquisition costs and reduces profit margins.

Yet, there are other techniques to keep a strong customer base and reduce acquisition expenditure and overall customer churn. One of these techniques comes from the artificial intelligence domain, called customer churn prediction (CCP). The goal of CCP is to identify potential churners prematurely and retain them accordingly. The principle behind customer retention is the consensus is that customer retention is several times cheaper than customer acquisition due to setup, promotional and exploratory expenses [3].
Strangely, CCP gets almost no attention in the yearly reports of the major Dutch telecommunications industry[2] despite the amount of case studies available of CCP with telecommunications providers in other geographical regions.

1.1 Problem statement

The Dutch telecommunications industry invests heavily in advertising and quadruple play offerings to contest customer churn, but seems to pay little attention to customer churn prediction while telecommunications service providers in other regions seem to implement customer churn prediction effectively.

1.2 Scope

This research will be mainly focusing on the application of churn prediction by medium / large telecommunications operators / providers. The goal is to investigate three points of interest regarding customer churn prediction, namely (1) the existing challenges regarding customer churn, (2) the use of CCP models and (3) the utilized retention strategies. In this study Dutch telecommunications operators and providers will be compared to operators and providers from other geographical regions including East Asia, United States, Scandinavia and Oceania. Additionally, a field study will be conducted to map the important churn related variables for the Dutch population.

In regard to customer churn, the scope of this study is limited to post-paid residential subscriptions, excluding the prepaid and business services and subscriptions.

The duration of this research has been a period of eleven months, starting February 2019 and ending December 2019.

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[1] News article from the Telecompaper, retrieved: 18th of September 2019, url:https://www.telecompaper.com/nieuws/t-mobile-en-tele2-adverteren-veel-om-klanten-uit-fmc-val-bij-kpn-en-vodafone-te-lokken--1255430

[2] Yearly reports of KPN, Vodafone, and Tele2 in 2017/2018

1.3 Research questions and objectives

The following chapter provides the main research questions, as well as the secondary questions and the research objectives of this study.

1.3.1 Research question

The main research question of this study is: “How can the adoption of customer churn prediction be accelerated in the Dutch telecommunication industry?”.

1.3.2 Secondary questions

1. What techniques are currently utilized by telecommunications providers to reduce customer churn?
2. What is the state of art in customer churn prediction?
3. What is the status of customer churn prediction in the telecommunication industry?
4. What improvements can be done to increase the effectiveness of the application of customer churn models in the Dutch telecommunication industry?

1.3.3 Research objectives

1. Gain insights in methods used by telecommunications providers in different regions to reduce churn;
2. Research the state-of-art in churn prediction by use of literature;
3. Reflect the state-of-art in churn prediction on the current state of the telecommunications industry over different regions;
4. Compare churn related insights of the telecommunications providers in different regions to evaluate the performance of every region;
5. Identify the most important areas of improvement for the Dutch telecommunications industry based on the comparison between the different regions and survey insights.

1.4 Relevance

The following chapter indicates the importance of this study from an academic and business perspective.

1.4.1 Academic Relevance

Churn prediction received a lot of attention in the academic world. There are multiple papers researching different churn classifiers by comparing their accuracy, precision and overall effectiveness.

Additionally, there is a lot of research into feature selection for the churn prediction problem. However, there is almost no research regarding the connection between the churn prediction outcome and the implementation of churn prediction into the retention strategy.

The research-gap this study aims to fill in is between churn prediction modeling and marketing literature. This study tries to identify to what extend telecommunications operators are using churn prediction and if retention strategies are used effectively. Examples of the described types of papers are listed below in Table 1: churn related papers.

Table 1: churn related papers

Paper title	Author	Subject
Time-sensitive Customer Churn Prediction based on PU Learning	Li Wang, Chaochao Chen, Jun Zhou, Xiaolong Li [4]	Time-sensitive customer churn prediction framework, using a real-life experiment to demonstrate how it outperforms rule-based models and traditional supervised learning models.
A comparative analysis of data preparation algorithms for customer churn prediction: A case study in the telecommunication industry	Kristof Coussement Stefan Lessmann, Geert Verstraeten [5]	Examination of data-preparation alternatives based on their performance and how it effects churn prediction performance.
Customer Churn Prediction in Telecommunications Industry using Data Mining Techniques – A Review	Kiran Dahiya, Kanika Talwar [6]	Presents a state-of-art review of various methods and research about churn prediction in the telecom. Assessment of frequently used data mining procedures to categorize customer churn patters in the telecommunications industry. The paper describes advantages of different data mining procedures and provides some insights into the application of churn prediction for telcos.
Computer assisted customer churn management: State-of-the-art and future trends	John Hadden, Ashutosh Tiwari, Rajkumar Roy, Dymitr Ruta [7]	The paper assesses a five-stage model for developing a customer churn management framework, which dives mostly into the accuracy of techniques for predictive modelling, data identification, data semantics, and feature selection. Explains the expenses of customer retention efforts and proposes that there should be a focus on accuracy. However, the paper does not go into the retention efforts.
Customer Churn Prediction in Telecommunications	Bingquan Huang, Mohand Tahar Kechadi, Brian Buckley [8]	The paper presents a set of features for land-line customer churn prediction. It compares seven prediction techniques based on prediction rates (TP, FP & AUC).

1.4.2 Business Relevance

As described in the introduction, customer churn is a major challenge for telecommunications providers worldwide. They invest much resources into maintaining a strong userbase. However, based on the information available in literature, the news article cited in the introduction and yearly reports of major telecommunications operators indicate that not all telecommunication providers seem to utilize customer churn prediction. Instead, they rather invest resources into customer acquisition.

This study aims to identify to what extend customer churn prediction is utilized by telecommunications providers of different regions including the Netherlands. The study also tries to identify what retention strategies are utilized. The goal of identifying customer churn prediction and retention strategies of different regions is to establish an overview of the currently used methods and identify best practices of all regions, which potentially can help Dutch telecommunications providers develop more effective customer churn prevention measures.

2 Literature Review

The goal of the literature review is to gain insights into the telecommunications industry, as well as getting familiar with the concept of churn prediction and its related concepts. This literature study will be the foundation for the expert interviews later on in this research. The literature review will also assist in answering the research questions.

2.1 Telecommunications industry

The focus industry of this thesis is the telecommunications industry, which is within the sector of information and communication technology. This industry sells, operates and maintains telecommunications network infrastructure and services.

2.1.1 Value chain

The value chain of the telecommunications industry exists of five chains [9]:

1. Infrastructure and platform vendors
2. Device vendors
3. Operators
4. OTT, content advertising services
5. Retail and distribution

As of 2015, according to EY, the industry's revenue is split between the chains as visualized in Figure 1.

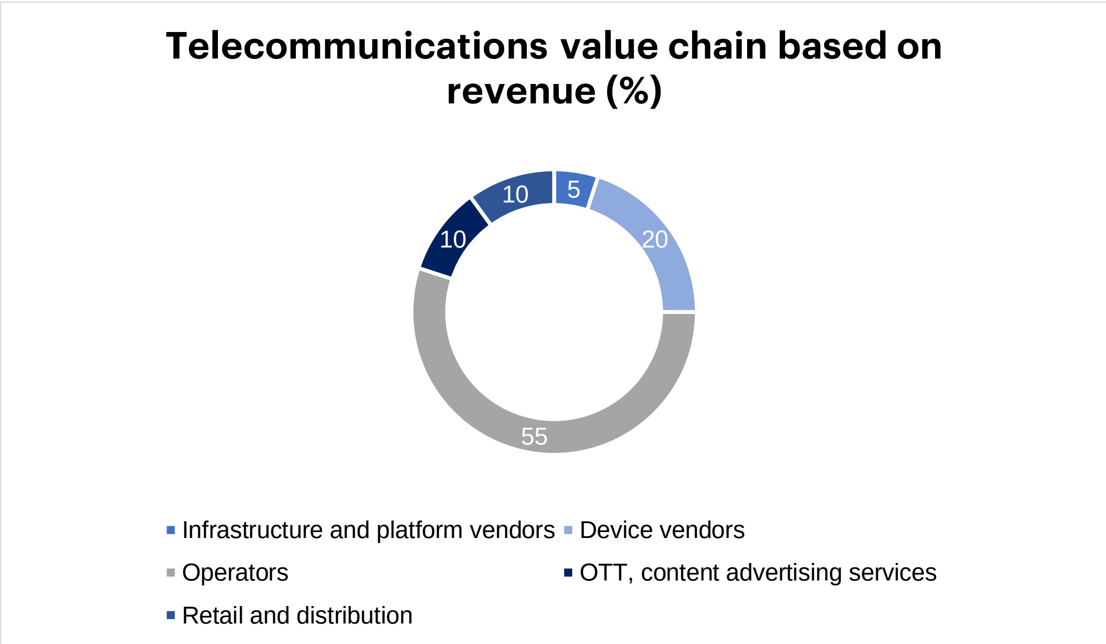


Figure 1: value chain of the telecommunications industry based on revenue percentage

As shown in the figure, the value chain of the telecommunications industry is split into the following types of enterprises.

Infrastructure and Platform vendors

Infrastructure and platform market consists of a variety of companies that provide equipment that telecommunication operators need to operate. This equipment includes switching equipment, transmission equipment, signaling equipment, database equipment, content equipment, applications, OSS / BSS platform (services) etc. [10].

Device vendors

Device vendors refer to the manufacturers that create end-user devices e.g. smartphones, tablets and other hardware that use telecommunications services.

OTT and Content advertising services

OTT refers to “Over The Top”, which in the telecommunications industry refers to third party content for the end-user, in which case the ISP only handles the data traffic. OTT providers are not technically or commercially associated with the ISPs and can provide their services no matter which ISP the end-user uses. Examples of OTT content are YouTube, Spotify, Netflix, Skype WhatsApp and FaceTime.

Retail and distribution

Retail and distribution refer to selling the telecommunications services to the end-user. Dutch telecommunication operators handle the retail and distribution of their services mostly on their own. However, online platforms that help users choose a specific service package offer the functionality to contract the operator for the end-user. Additionally, there are enterprises that resell telecommunications services from operators in prepacked packages.

2.1.2 Telecommunications products and services

Telecommunications operators provide multiple products and services to business (B2B) and consumer (B2C) clients. In this research, the focus is on the business to consumer market, therefore business products and services are left out of the equation.

Consumer telecommunications services, as described by the Dutch “Autoriteit Consument & Markt”, can be divided into two groups: residential services and wireless services [11].

Residential

As the name suggests, residential services are services provided at a customer’s residence, including broadband internet, television and land-line for telephone services. However, most providers provide additional services like email accounts, anti-virus security software, more television channels and OTT content[3].

In most cases, residential services come with the dedicated hardware included e.g. modems, routers and television receivers. Customers can rent additional units for an additional fixed monthly fee.

Wireless services

Wireless services refer to services that require the use of wireless communications infrastructure e.g. 4g network. These services can be ordered separately from the residential services and include wireless phone service, text messages and mobile data. Additionally, most providers offer a service to rent or finance a mobile device. Mobile services subscriptions without a mobile device are referred to as SIM-only subscriptions.

With a wireless service subscription customers receive a SIM-card which is inserted into a mobile device in order to connect to the provider’s network.

Bundling of products

Telecommunications providers mostly bundle their services into packages and can be referred to as triple and quadruple play. Because of this, customers have multiple services with the same operator.

Double play
Refers to the selling / delivery of phone and broadband internet services to a single customer by one provider.

Triple play
Refers to the selling / delivery of phone, broadband internet and television services to a customer by one provider.

Quadruple play
Refers to the selling / delivery of triple play services and wireless services to a customer by one provider. Quadruple play is also referred to as quad play.

[3] Examples can be found when ordering residential services at KPN, Tele2, T-Mobile and VodafoneZiggo

2.1.3 Operators in practice

This thesis mainly focusses on the enterprises that offer telecommunications services to consumers including operators / providers. In practice, operators do not provide all the possible telecommunications services, because they either cannot provide it or choose to they choose focus on a specific set of services. Also, some of these operators own the infrastructure to provide such services, while others lease, using wholesale constructions, the infrastructure from other operators to provide services to their customers. This means that there is a lot of diversity between the operators and this chapter will focus more on the types of operators that operate in the Dutch telecommunications industry.

Dutch operators and market share

According to a report by "Autoriteit Consument & Markt' the 2017 Dutch telecommunications operator residential retail revenue was a total of €5.218.912 and an additional €486.477 in wholesale revenue [11].

The retail mobile market had a yearly revenue of €4.749.624 and an additional €343.722 wholesale revenue. There is a distinctive differentiation between the mobile and residential market, because of the different required infrastructure and players that operate in these markets.

Concluding remark

The residential and wireless market are almost equally large in revenue. Therefore, operators that operate in both markets can take a larger part of the overall revenue compared to operators that specialize in one of the two markets.
However, operating in both markets comes with additional costs, such as infrastructure costs.

As described in the previous sub-chapter, telecommunications operators provide both residential and wireless services. Most smaller-sized operators provide only one of the two types of services.

In contrast, generally larger operators provide both types of services. To illustrate, the five main Dutch operators are large in both the wireless and residential market.

However, there are different major players in the two market segments. The market share in the two markets is split between major Dutch network operators (NO) and smaller virtual network operators (VNO).

Table 2: market share residential services in the Netherlands

Residential services

Operators	Land-line (%)	Broadband (%)	Television (%)
KPN	45 – 50%	40 – 45%	30 – 35%
VodafoneZiggo	40 – 45%	40 – 45%	50 – 55%
Tele2	0 – 5%	0 – 5%	5 – 10%
Other	5 – 10%	5 – 10%	5 – 10%

*market share in 2017 based on active connections / active subscriptions

Table 3: market share mobile services in the Netherlands

Mobile services

Operators	Market share (%)
KPN	30 – 35%
T-Mobile	15 – 20%
VodafoneZiggo	20 – 25%
Tele2	5 – 10%
MVNOs	20 – 25%

*market share in 2017 based on active connections

While looking very similar from a consumer perspective, there are some distinct differences between the two main types of operators: virtual and non-virtual.

Network operators

The network operators own and manage their own infrastructure. They have their own customer relationship management and billing systems. Most network operators license their infrastructure to other enterprises (VNOs). The main Dutch network operators are KPN, VodafoneZiggo, T-Mobile and Tele2. The differentiation between the network operators and virtual network operators is the ownership of telecommunications infrastructure. Additionally, there is a differentiation for mobile network operates, referred to as MNOs, which own mobile network equipment and provide wireless network services.

Virtual network operators

Virtual network operators do not own their own infrastructure but lease capacity from network operators. This is mostly achieved through wholesale constructions. The virtual network operators sell their services to consumers just like network operators. Billing, consumer service, sim-card distribution and other hardware distribution is also handled by the VNOs themselves and customers are not aware that they are using another operators' network infrastructure. VMNOs that only provide mobile network services are called mobile virtual network operators.

Some enterprises are partially MVNOs, since they do not own all the necessary infrastructure to provide their services and need to lease a part of a MNO's infrastructure. For example, Tele2, a Dutch mobile network provider, owns their own 4G network, but still must lease network capacity for other networking technologies, making it a combination of the two types.

Table 4: simplified overview of operator types based on target market

Mobile		Residential	
MNO	**MVNO**	**NO**	**VNO**
Provide mobile networking services. Owns and manages their mobile networking infrastructure	Provide mobile networking services. Leases infrastructure from an MNO.	Provide residential telecommunications services including: landline, broadband internet and television. Own and manage their infrastructure.	Provide residential telecommunications services including: landline, broadband internet and television. Leases the infrastructure from a NO.

Concluding remark

This chapter gave insights in the industry focused on by this study. The study mainly focusses on the operators and this chapter showed that the operators take the largest cut, 55 percent, of the industry revenue. They do this by providing telecommunications services to businesses and consumers, such as landline, television, broadband internet and wireless services.

All operators are unique regarding the way they operate and services they provide. Some operators specialize in residential services, while others focus mainly on the wireless market. In addition, not all operators own their infrastructure, but instead have to lease capacity from operators. These operators are called virtual operators and can therefore fully focus on the service they provide to customers. Others build their own infrastructure and provide all kinds of services to consumers, businesses and other operators.

Even with the large diversity of operators, there is one problem all telecommunications operators face, namely customer churn.

2.2 Customer churn

This chapter will help to answer the research question “what is the current state of art in customer churn prediction” by looking at churn from a literature perspective. In order to understand what churn prediction is, it is necessary to understand the concept “customer churn”.

a) According to multiple studies [12], [13], customer churn is a basic unit of the telecommunications industry used to describe customer loss. It is defined as the gross rate of customer attrition during a given period. Customer churn assesses a telecommunications provider’s customer retention efforts and provides insights into the growth or decline of the subscriber base.
b) A study by Xubing Zhang, Kim & Srivastava [14] describes customer churn as a behavior phenomenon: the act of leaving or abandoning a service provider for another.
c) A study by Au, Chan & Yao [15] describes churn both as the loss of subscribers who switch form one carrier to another, and refers to churn as churn rate, which is in line with the description of customer churn as provide by the studies described in option a.

Taking these multiple perceptions of customer churn, we can identify that customer churn can be either a measurement referring to a churn rate as well as the behavioral action of a customer leaving one service provider for another.

The management of customer churn is of great concern to telecommunications service companies and it is becoming a more serious problem as the market matures and telecommunications service companies compete over the same existing customers, which leads to further forcing down prices [16].

2.2.1 Customer churn as a measurement

To measure customer churn, the first step is to identify the change in subscribers, which is derived from the subscribers (s) at the start of the period (t) minus the subscribers (s) at the end of the period t. It can also be interpreted as the change in subscribers over a period, given that leaving subscribers are specified as churners (c).

$$C_{\Delta t} = s_{t\,start} - s_{t\,end}$$

Equation 1: churners over period (t)

$$\Delta S_{\Delta t} = s_{t\,start} - s_{t\,end}$$

Equation 2: change in subscribers over period (t)

Customer churn as a measurement describes the churn rate. It measures the number of subscribers that have discontinued their contract (C) in a given time period (t) and is expressed as a percentage of a company's average subscriber base (ASB) over this period [14].

$$Customer\ churn\ (\%) = \frac{C_{Period\ t}}{ASB_{period\ t}} * 100\%$$

Equation 3: customer churn rate

Concluding remark

When referring to customer churn, it can either mean the measurement of the gross rate of customer attrition in a given period, or a behavioral phenomenon in which a customer decides to leave or abandon a service provider for another.

However, not every customer is the same and customer churn should not be different.

So, why do customers churn and are there different types of customer churn behavior? Additionally, how big is the customer churn problem really and how is it in other industries?

2.2.2 Customer churn statistics

With the definition of customer churn rate defined, statistics can provide an answer to how big the customer churn problem in the telecommunications truly is. For context, other industries are compared to the telecommunications industry and insights in the Dutch telecommunications industry are provided.

Spotify is an iconic music streaming service provided by Spotify AB. According to a study by Statista the annual churn rate was 7.7% in 2015, 6.6% in 2016 and just 5.5% in 2017 [21]. Compared to other industries based in the U.S., churn rate is much higher in retail (27%), financial (25%) and online retail (22%) than Spotify. The same study also looked at the telecom industry with a churn rate of 21% in 2018 [22].

A study by the "Autoriteit Consument & Markt", a government institute, investigated the Dutch telecommunications industry and conducted a survey with the major Dutch telecommunications providers. The study looked at multiple telecommunications services, including broadband, telephony single line, telephony double line and television [11].

Broadband, which includes DSL, Cable and Fiber, have a collective churn rate of 11,98% over the fiscal year of 2017. Telephony single line has a collective churn rate of 11,24% and double line has a collective churn rate of 19,06%. Television has a collective churn of 13,54% over the same fiscal year. The report did not show any insights in the mobile churn rate. However, according to a study by TM Forum, the mobile post-paid customer churn is between 5% to 32% globally [23]. The churn figures are displayed in Table 5: churn rate in the Dutch telecommunications industry .

Table 5: churn rate in the Dutch telecommunications industry

Dutch telecommunications industry 2017: churn rate per service (%)

Broadband	Telephony: single line	Telephony: double line	Television	Mobile*
11,98%	11,24%	19,06%	13,54%	5% - 32%

*mobile figures are global, due to the lack of information regarding Dutch mobile churn rate

2.2.3 Types of customer churn

Behavioral customer churn comes in many different forms and can have a multitude of reasons why it occurs. The first paper from the Journal of Theoretical and Applied Information Technology that will be discussed regarding customer churn in the telecommunications industry describes two main types of churning customers: involuntary churners and voluntary churners [17].

A study by Jahanzeb & Jabeen [12] identified besides involuntary and voluntary churn the differentiation between internal and external churn. This study defines internal churn as switching of a customer from one service to another within the same service provider company e.g. from post-paid to a pre-paid service, whereas external churn is defined as the switching from one service provider company to another and consists of two sub-types: involuntary and voluntary.

1. **Involuntary churners**
   Involuntary churners are churners that are not actively trying to end their service agreement and do not have any problem with the services they are being provided, but get their subscription canceled by the telecommunications service provider mainly due to issues in the billing / payment process such as customers having insufficient funds or commit fraud [17].

2. **Voluntary churners**
   In contrast with the involuntary churners, voluntary churners decide to end the service agreement themselves. Voluntary churn is more complex due to the many different reasons a customer can decide to leave a company. For example, due to poor customer service a customer can decide to terminate the service agreement with the provider [18] [17].

According to another study by Lazarov & Capota [19], customer churn can be divided in three main groups: active / deliberate, rational / incidental and non-voluntary. This expends the voluntary churners category with two variants.

1. **Active / deliberate**

   Deliberate churn is the focus of most churn management solutions [18]. With this type of churn the customer decides to quit his contract and switch to another provider. Reasons to quit can be separated into three main types: technology-based, quality and economic reasons. This may include dissatisfaction with the quality of service, high costs, uncompetitive price plans, no rewards for loyalty, not understanding the service, bad support, privacy concerns, lack of information provision for service problems, no continuity or fault resolution, etc. [19]. It could be argued that the customers have a low perceived value of the services provided by the service provider.

   1.1 **Economic** reasons describe a financial incentive for customers to switch to a competitor's services. This might be due to uncompetitive price plans of a provider, but it boils down to the customer finding the product at a better price at a competing company.

   1.2 **Technology** reasons describe the technology incentive for a customer to switch to a competitor's services. This might be due to competitors' offerings of the latest products, while the existing provider cannot provide them, or the competitors use of newer technologies in their services compared to the existing provider e.g. 4G plus offerings, 4K video streaming, video OnDemand, etc.

   1.3 **Quality** reasons describe the incentive for a customer to switch to a competitor that provides better quality services and products compared to the existing provider. An example is poor call quality, poor coverage or a bad customer service [1].

2. **Rational / incidental**

   The customer quits contract without the aim to switch to a competitor. Reasons for this are changes in the customer's circumstances that prevent him from further requiring the service, such as moving to a different geographical location where the provider nor service is present. Another reason could be financial problems that lead to the impossibility of payment. Differently put, incidental churn happens when the customer's circumstances prevent the customer from further requiring the provider's service [18].

   2.1 **Financial** reasons are caused by the financial circumstances of the customer. This occurs when a customer can no longer afford the service and is forced to terminate the service agreement.

   2.2 **Geographical** reasons are caused by the unavailability of a service when a customer moves to another geographical location and can only use a competitor's services.

   2.3 **Life change** reasons are caused by a multitude of different unforeseen factors and may include death, change in family and parents terminating their children's contracts at some point.

Incidental churn usually explains a small part of a company's voluntary churn [18]. Therefore, considering the small representation of the total churn and many unforeseen factors that causes incidental churn, it is much more interesting to focus on active / deliberate and non-voluntary churn.

3. **Passive / non-voluntary**

The provider discontinues the contract itself, due to reasons explained previously as involuntary churners. This can be separated into two groups:

3.1 Passive churn occurs when a customer drops out of a subscription without any parties, customer and / or provider, wanting to do so. Causes for this type of churn might be payment failures due to an expired credit card, misleading communications or changes in customer data [20].

3.2 Non-voluntary churn occurs when a provider deliberately wants to end the service agreement. Reasons to do so include violation of service agreement, non-payment of service, bad debt, etc.

Combining the differentiations by the two studies [17], [18] result in two main categories of behavioral churn; voluntary and non-voluntary churners. Voluntary churners can be divided in two subgroups, namely deliberate and incidental churners. The result of combining these five types is visualized in Figure 2: types of customer churn.

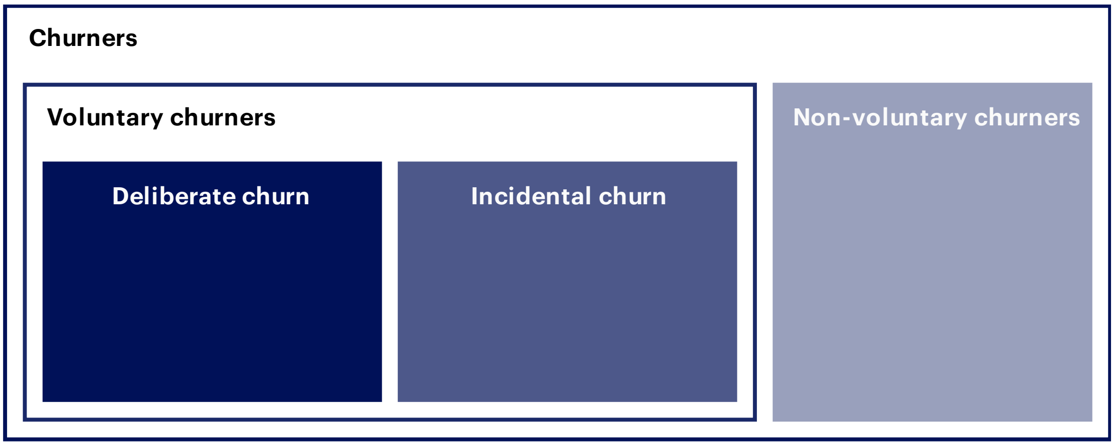


Figure 2: types of customer churn

Furthermore, churn can be described by three other categories that describe the state of churn [19]:

1. **Total** - The service agreement is fully terminated;
2. **Hidden** - The service agreement is not ended, but the customer is not using the service for an extended period;
3. **Partial** - The service agreement is not cancelled, but the customer is not using the service completely, only partly, and is using a competitor’s service instead.

In contrast to the earlier categorization, this state categorization says nothing about the motivation of a customer to churn but rather explains the stage / degree of churning. A total churn occurs when a customer fully leaves a provider; a lost customer.

Both hidden and partial churners are still customers and might churn fully later. This is illustrated in Figure 3: degree of customer churn.

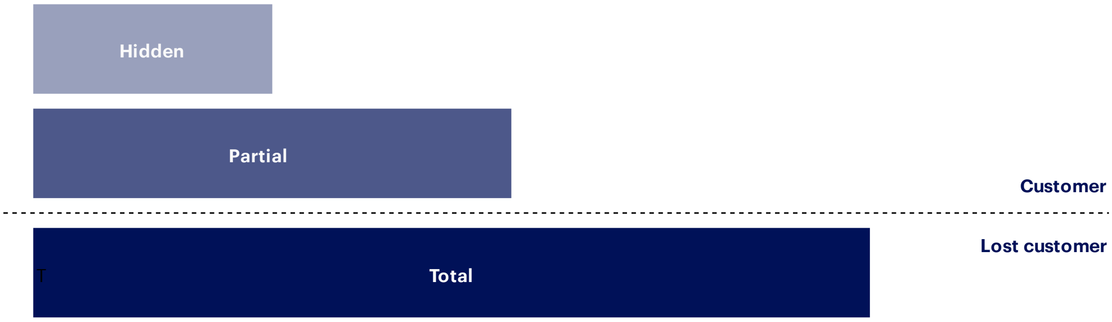


Figure 3: degree of customer churn

A full overview of churn types based on literature described in this chapter can be found in Appendix 7: customer churn overview.

Concluding remark

Customer churn exist in many forms, of which the most important are involuntary and voluntary churn. Involuntary churn refers to a customers churning without wanting to do so. Voluntary churn describes a customer actively trying to end the relationship with an enterprise.

There is also a degree of churn in which, on the one hand, a customer is not using the service / product but still pays for it, and, on the other hand, a customer fully ends the relationship with an enterprise. In between there is partial churn. In that case the customer is still paying for a service or product but is partially using it and uses a competitors' product as well.

Churn can have many reasons. Voluntary churn occurs due to dissatisfaction which can have economic, technology or quality related reasons. An important note is that churn mostly occurs after multiple dissatisfaction scenarios.

Yet, sometimes customers have no choice but to churn. This is called rational / incidental churn and is responsible for a very small part of the total customer churn.

Involuntary churn happens when the operator ends a service agreement with a customer. This can have financial or contractual reasons.

This study focuses on voluntary churn. Some explanations for customer churn are already provided. However, are there any additional churn determinants that are important to identify?

2.2.4 Customer churn determinants

The study by Olanrewaju Adebiyi [24] indicated that many previous studies focused on churn prediction itself using different statistical tools like data mining, survival analysis [25] and logistic regression [1], but most of them did not aim to identify churn motivations. This may serve as a good indicator for real churn forecasting. The focus on churn determinants is shared by Lee & Jo [26].

A study by Ahmed & Maheswari [27] states that churn mainly occurs due to customer dissatisfaction with a service or product. However, a customer does not churn due to a single dissatisfaction scenario. Therefore, it is important to note that usually there are more dissatisfaction cases before a customer decides to churn [28].

A study by Ahn et al. [16] proposed a conceptual model for customer churn with mediation effects. This study is about churn in general, but primarily focusses on active / deliberate churn.

This model exists of five determinants that influence customer churn:

1. Customer dissatisfaction
2. Switching costs
3. Service usage
4. Customer status
5. Customer-related variables

According to this model, the customer status is viewed as a mediator for the other determinants as well as being a determinant itself. This model is virtualized in Figure 4.

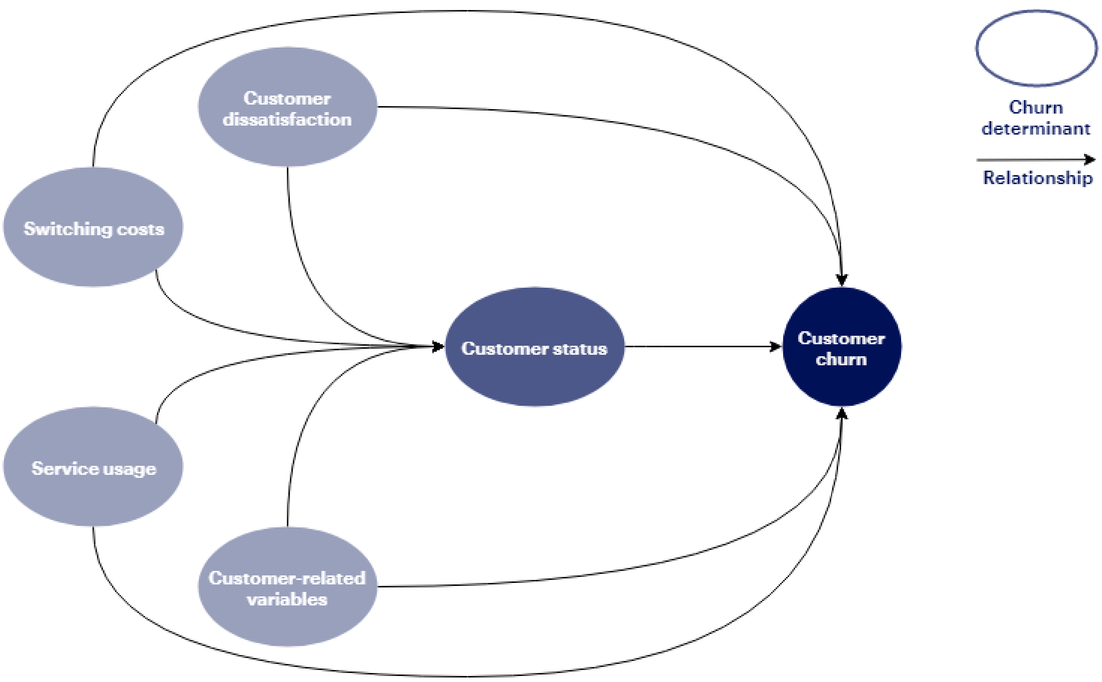


Figure 4: conceptual model for customer churn with mediation effects as proposed by Ahn et al. [16].

1. **Customer dissatisfaction**
   Research suggests that core service failures may be related to customer churn. Network quality and call quality are key drivers for customer satisfaction in the mobile communications industry [16]. Besides network quality and call quality there are more core service factors that influence customer satisfaction. Service failures have been accelerating a customer's decision to discontinue the service of the service provider [29]–[32].
   However, already in 1987 Fornell & Birger [33] argued that well-managed complaint management programs (CMP) that address the complaints by users with core service issues can lower the total marketing expenditure by substantially reducing customer churn. Nevertheless, this is only true if enough of the complaining customers can be persuaded to remain a customer by the CMP.

2. **Switching costs**
   There are two possible reasons for customers to maintain a relationship with a service provider, namely constraints or loyalty. In the case of constraints the customer forced to stay in a relationship with the service provider. In the case of telecommunications providers this might be due to switching costs or contract periods.

3. **Service usage**
   Service usage refers to the total use of a service by a customer. In the telecommunications industry service usage concerns the use of television, landline, broadband, mobile and OTT services and can be measured in frequency, duration and amount of usage.

4. **Customer status**
   Not all customers suddenly churn from a service provider. Some customers might decide not to use a service on a temporary basis or are suspended by the service provider due to payment issues. Customer status mostly referrers to the status change in an internal company customer database if this applies. Ahn et al. [16] grouped all different kinds of customer status into three main groups: active use, non-use and suspended. Active refers to the customer using the service on a regular basis. Non-use refers to a customer that is not using a service but has not churned. Suspended refers to the provider suspending the service of a customer due to payment issues. As described in the chapter "Types of Churn", non-use can indicate that a customer is a hidden or partial churner.

5. **Customer related variables**
   These variables refer to all the business-related variables that a provider knows about a customer e.g. gender, payment method, handset information, type of contract, etc.

The study found that customer dissatisfaction regarding call drop rate has a positive correlation with customer churn as well as the number of complaints. Loyalty points, in this study referring to switching costs, reduced the chance that a customer will churn.

The monthly billed amounts are associated with the probability a customer will churn: the higher the billed amount the more likely a customer will churn. This is also known as bill shock. Additionally, customers with a non-use or suspended status are considered more likely to churn compared to active customers.

Furthermore, a high call failure rate does not seem to be associated with a high churn likability. This is in contrast with the found results of the call drop rate.

Call drop rate and call failure rate seem at first sight very similar. However, they are quite different. Whereas call drop rate refers to the phone connection dropping during an active call, call failure rate refers to not being able to get an active call. Nonetheless, this might indicate that not all quality related variables influence the churn likability.

In contrast to loyalty points, only being a member of a loyalty program does not reduce the likeability a customer will churn. Unpaid balances and the number of unpaid monthly bills are also not associated with the churn likability. These results are summarized in Table 6.

Table 6: churn determinants overview based on the study by Ahn et al. [16]

Factor	Does have an effect on customer churn?	Effect direction
Customer dissatisfaction	Yes	Positive
Switching costs	Yes	Negative
Billed amount (bill shock)	Yes	Positive
Non-use or suspended customer status	Yes	Positive
Call failure rate	No	-
Call drop rate	Yes	Positive
Loyalty program membership	No	-
Unpaid balances / unpaid bills	No	-

Concluding remark

There can be multiple reasons why customers decide to churn (or not), including customer dissatisfaction, switching costs and service usage. Additionally, the current customer status is a strong indicator of customer churn.

However, the correct action of an operator can prevent customers from churning as customers generally churn due to multiple dissatisfaction scenarios.

An important note is that not necessarily all factors that have to do with the identified churn reasons are equally relevant in indicating whether a customer will churn or not. Also, studies tried to use customer related variables to indicate if a customer will churn.

The important question is: how do we indicate that a customer will churn?

2.3 Customer churn prediction

Now that churn is defined, it is possible to look at the way customer churn might be predicted. This will help to answer the research question "What is the current state-of-art in churn prediction?" and can provide useful context for the expert interviews.

Customer churn prediction (CCP) is a key enabler for targeted retention programs and is used to identify customers who show a high tendency to end their relationship with a company [34] [35]. Churn prediction is the practice of estimating the churn probability of each customer in the company's database [34]. This is done using the customer's historical data to find patterns that can predict the future churning behavior. By doing so, customers can be ranked from least likely to churn to most likely to churn, which allows companies to target their marketing retention campaigns.

2.3.1 Churn prediction procedure and process

To help the decision-making process, it is vital to come up with powerful techniques of data analysis and interpretation as well as develop tools that can identify hidden patterns [13]. This is also referred to as data mining.

A well-established process to do data-mining is the Cross-Industry Standard Process for Data Mining (CRISP-DM) by Shearer [36]. This process breaks datamining down into six stages:

1. Business understanding
2. Data understanding
3. Data preprocessing
4. Modeling
5. Evaluation
6. Deployment

For a better understanding of the process flow, the process is visualized in Figure 5.

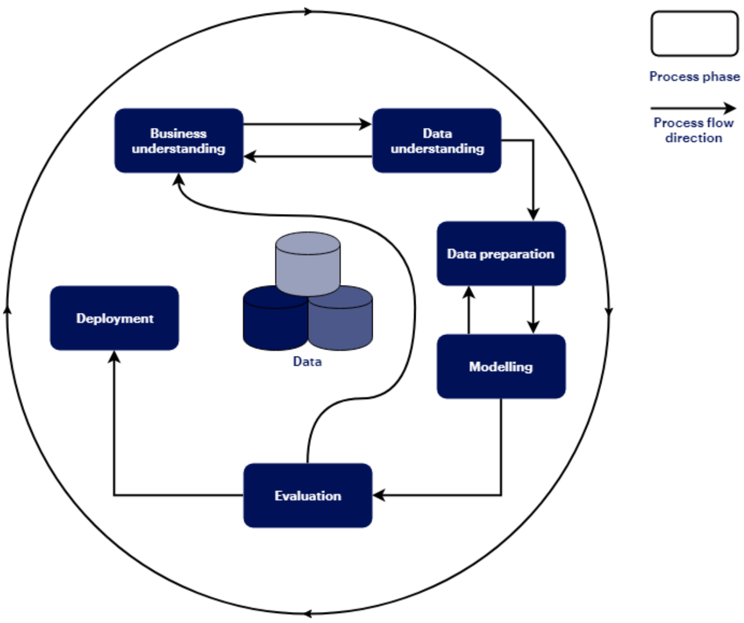


Figure 5: CRISP-DM model

Business understanding

To successfully create a machine learning model, it is important that there is a clear understanding of what the goals of the project is. For example, for churn prediction the goal is to identify potential churning customers in a timely manner, so that a fitting (cost effective) retention strategy can be targeted. The initial phase focuses on understanding the project from a business perspective by identifying project business objectives and requirements. This is converted into a data mining problem definition (MPD) and a preliminary project plan is designed to achieve the business objectives and meet the requirements [37].

Data understanding

Now that there is a business understanding, it is important to understand the available data. This phase starts with the initial data collection and proceeds with getting familiar with the data, identifying data quality problems, discovering insights or detecting interesting subsets to form hypotheses about hidden information.

There is a close link between data understanding and business understanding, since the formulation of the DM problem and project plan require some understanding of the available data.

In this phase a process starts to extract the relevant data from the online transaction process (OLTP). In the case of a telecommunications provider this can include data from the Operational Support Systems (OSS) and Business Support Systems (BSS). This process is called the ETL-process (Extract Transform and Load-process) which allows for transactional data to be stored in a useful manner in a data warehouse. This data can then be analyzed further to identify the available data.

Data Preparation

Most of the ETL-process takes place in the data preparation phase. This phase covers all activities to construct the final dataset from the raw data. Data preparations tasks are usually performed multiple times. Preparations tasks include (1) table-, record- and attribute selection, (2) data cleaning, (3) construction of composed attributes and (4) transformation of data [37]. These tasks can all be placed in the different steps of the ETL-process as shown in Figure 6.

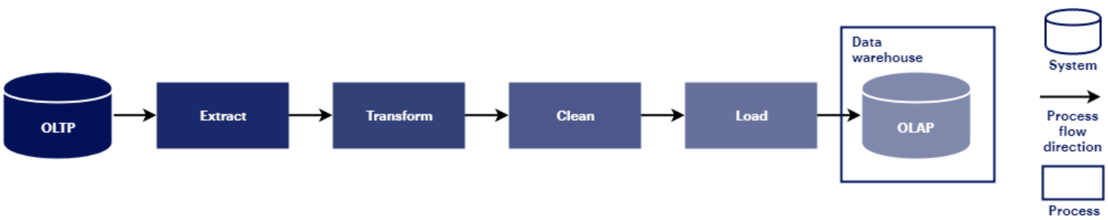


Figure 6: ETL-process

These tasks are executed in different phases of the process. The order of execution and corresponding process phase is as follows:

1. Table-, record- and attribute selection in the extract phase;
2. Construction of composed attributes and transformation of data e.g. date formatting, integer to Boolean transformation etc. in the transform phase;
3. Data cleaning in the cleaning phase which is necessary because real world data is mostly dirty, which refers to data being incomplete, noisy or inconsistent;
4. Inserting the prepared data into the data warehouse so it can be used for online analytical processing (OLAP) is done in the load phase. There are different types of loading, with all their own use cases.

   These types of loading include:
   a) Delta load: only the changed records are taken from the source systems and processed systematically;
   b) Integral load: All records are taken and processed by comparing them with the existing records;
   c) Full load: the load replaces all OLAP tables completely.

However, with the growth of available data over the last decade, more modern approaches are utilized to master the big data challenges.

One of these approaches is the use of a “data lake”. A data lake is a methodology that uses an immense data repository based on low cost technologies that improves the capture, refinement, archival and exploration of raw data within a firm. In contrast to a data warehouse, a data lake contains raw unstructured or multi-structured data that has little to no recognized value to the enterprise.

According to Fang [38] a data lake supports the following capabilities:

- Capture and store raw data at scale for a low cost; the volume of data continues to grow sharply, therefore the costs of data storage becomes more important;
- Store many types of data in the same repository; including traditional DBMS, multi-structured data e.g. text, graph and media;
- Perform transformation on the data; a main use case for a data lake is to perform post-processing and ETL transformation of data for further exploration by other systems;
- Define the structure of the data at the time it is used, also known as schema on read. This avoids costly data modeling and data integration;
- Perform new types of data processing; the nature of a data lake should support all the data and all ways of data processing;
- Perform single subject analytics based on very specific use cases.

As shown in this study the data lake supports the ETL transformation. However, instead of extracting data from a transactional system the data is extracted from the data lake itself. The data lake itself can be fed with data from the transactional enterprise systems as well as available meta-data or third-party data. When visualized the process will look like Figure 7.

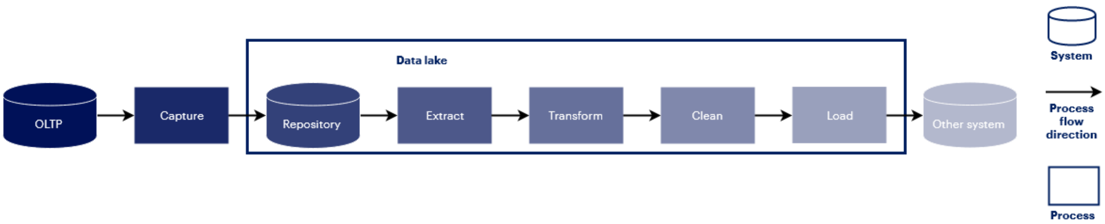


Figure 7: ETL-process with a “data lake”

A modern approach to ETL that is used by enterprises is the use of ELT. In this process flow the order of processes changes. Data is extracted and loaded directly in a “data lake”-like environment. This allows for data to later be transformed and cleaned for specific use-cases.

A major advantage of this approach is the isolation of the load process from the transformation process, because it removes any inherent dependency between those stages [39]. However, this can also be achieved by staging the extracting data into another environment for transformation purposes to later load it into a data warehouse environment.

Furthermore, ETL is highly scalable and parallelized according to the available data sets. The transformation process is done in the final data environment, reducing stress on the network.

Even though there are many benefits to ETL, there are limited tools available with full support for ELT. ETL-vendors provide many features and more mature solutions compared to currently ELT solutions. This, however, might change in the future. An example of the ELT process is visualized in Figure 8.

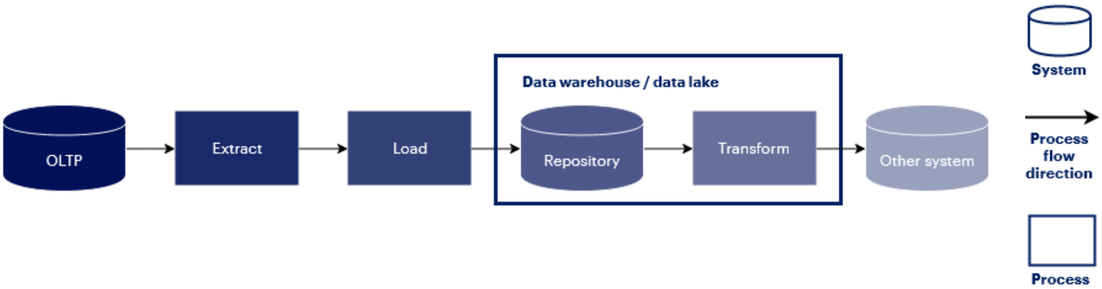


Figure 8: ELT-process with a “data lake”

Modeling

Now that the data is extracted, transformed, cleansed and loaded into a data warehouse, the next phase can begin. This is the modeling phase, which is concerned with the selection and application of various modeling techniques. Typically, there are several techniques for the same data mining problem types and some require specific types of data [37]. When looking into churn prediction literature, this mostly refers to the different types of algorithms and models used in this process. However, this phase is concerned with the following tasks:

- Select (a) modeling technique(s)
- Generate a test design
- Build the model
- Assess the model

Evaluation

After the modelling phase, a set of seemingly high-quality models should have been created. In the evaluation phase we look back at the business objectives and requirements to evaluate if they are met by the models created in the modeling phase. Evaluation can be done using sample tests. A key objective is to determine if there are important business issues that are not sufficiently considered. If everything seems fine, it is important to determine what to do next e.g. how should the model be implemented / deployed.

Deployment

Now that there is an agreement that the model is positively evaluated and that there is a clear understanding of what must be done, it is time to deploy the model. It is important to create a deployment, monitoring and maintenance plan as well as to produce a final report. Once this is done, it is time to deploy the model as described in the deployment plan and from now on monitor and maintain the deployed model accordingly.

2.3.2 Churn prediction techniques

Looking back at the previous chapter "Churn Prediction Procedure and process", this chapter dives into the modeling phase of the CRISP-DM model.

There are multiple machine learning algorithms that are proposed by the scientific community to tackle the churn prediction problem. These techniques include, but are not limited to, artificial neural networks, decision trees, regression analysis, logistic regression, super vector machines, naïve Bayes, sequential pattern mining and market basket analysis, linear discriminant analysis and, finally, rough set approach [40].

According to a study by Kiran Dahiya and Kanika Talwar these data mining techniques can be separated into eight different types of methods [6].

These methods include:

- Decision tree-based methods
- Naïve Bayes-based methods
- Neural network-based methods
- Regression-based methods
- Logistic regression-based methods
- Covering / rule-based methods
- Statistical data analysis-based methods
- Genetic algorithm-based methods

However, according to Vafeiadis et al. [40], the five most well established and popular techniques used for churn prediction regarding reliability, efficiency and popularity in the research community are:

1. Artificial neural network
2. Support vector machine
3. Decision tree learning
4. Naïve Bayes
5. Regression analysis-logistic regression analysis

Most of the popular classifiers are supervised classifiers e.g. Naïve Bayes. Supervised classifiers, also referred to as supervised learning, use training data sets with a target variable to identify patterns which allows the classifier to estimate the target variable when provided with new data.

Another common type of classifiers are unsupervised classifiers, also referred to as unsupervised learning. In unsupervised learning, no labels or target variables are provided to the learning classifier. The algorithm must find structure in the input that is provided. This is widely used to discover hidden patterns in data by clustering data.

All techniques have their own benefits and drawbacks which are summarized in Table 7. A more in-dept explanation for every technique can be found in Appendix 6: datamining algorithms and classifiers.

Table 7: overview benefits and drawbacks of the most popular churn prediction classifiers

Techniques (classifiers)	Description	Advantages	Disadvantages
Artificial neural network	Model based on a biological neural network e.g. the human brain	Very accurate	Requires lots of training data, computational heavy, hard to understand, due to black box nature, high risk of overfitting
Support vector machines	supervised learning models with the associated learning algorithms that analyze data points and recognize patterns. SVMs are based on the structural risk minimization principle	Can be used in high dimensional feature space, kernel trick allows for fine tuning, more accurate than decision trees and in some cases almost as accurate as artificial neural networks	Long training time, difficult to interpret, memory heavy
Decision trees	A model, which splits of an instance into subgroups until a specified criterion has been met. The result looks like a tree	Easy to understand, commonly used	Prone to overfitting
Naïve Bayes	Naïve Bayes is a supervised-learning module that contains examples of the input-target mapping which the model tries to learn. It is based on the Bayes' theorem	Short computational time for training, good performance, removes irrelevant features	Assumption of independent predictors, requiring feature selection
Regression analysis-logistic regression analysis	a well-known type of analysis in statistics and the process of estimating the relationships between variables. It tries to find the correlation between the independent and dependent variables and can use a multitude of techniques	Can perform as well as decision trees	Needs proper data transformation in order to work well

Concluding remark

The results from this literature study can help answering the secondary question: “What is the current state of art in customer churn prediction?”. The literature study identified that the CRISP-DM process by Shearer [36] is a widely accepted data mining process for the use of data analysis tasks such as churn prediction. According to scientific literature the current state of art in customer churn prediction is the use of the CRISP-DM process to create and implement a churn prediction model which uses either a single classifier or a combination of supervised and / or unsupervised classifiers.

2.3.3 Churn prediction evaluation

As shown in the CRISP-DM process, it is important to evaluate the machine learning models used in the data mining process. These evaluations measures are used to adjust parameter of the classifiers until a reasonable performance is achieved. It is important to note that these evaluation measures, in most cases, measure the performance based on how well the classifiers can predict churn correctly and do not measure computational costs or usability.

Churn prediction results can be separated into categories as shown in Table 8: churn prediction categories.

Table 8: churn prediction categories

	Actual Churners	Actual Non-Churners
Predicted Churners	True Positive (TP)	False Positive (FP)
Predicted Non-Churners	False Negative (FN)	True Negative (TN)

The performance indicators that are mostly used are accuracy, sensitivity and specificity [15], [19], [41], [42].

Accuracy

Accuracy is the proportion of the total number of predictions that were correctly identified. This is calculated using the following equation:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Equation 4: churn prediction accuracy

Sensitivity

Sensitivity describes the actual proportion of positive cases that were correctly identified. It can also be referred to as recall. This is calculated with the following equation:

$$Sensitivity = \frac{TP}{TP + FN}$$

Equation 5: churn prediction sensitivity

Specificity

Specificity, in contrast to calculating the proportion of true positives, refers to the actual proportion of true negatives; in this case, correctly identified non-churners. This is calculated using the following equation:

$$Specificity = \frac{TN}{TN + FP}$$

Equation 6: churn prediction specificity

It is important to note that there are other performance indicators that can be used to measure the performance of a classifier, which include precision, F-measure, miss rate, false alarm rate, and top 10% decile lift.

Precision

Precision refers to the proportion of accurately predicted positive cases. In the case of churn prediction, this refers to correctly identified actual churners. This is calculated using the following equation:

$$Precision = \frac{TP}{TP + FP}$$

Equation 7: churn prediction precision

Precision or recall alone cannot describe the efficiency of a classifier, since good performance in one of the two performance indicators does not necessarily imply that the classifier is performing well. Therefore, it can be useful to use the F-measure, which is a popular commonly used single metric for evaluating classifier performance [40]. It is the harmonic mean of precision and recall and is calculated using the following equation:

$$F\ Measure = \frac{2 * \ Precision * Recall}{Precision + Recall}$$

Equation 8: churn prediction F Measure

Other less commonly used measures are (1) the miss rate, which refers to the percentage of churners that the classifiers fail to predict, (2) false alarm rate, which refers to the percentage of non-churners defined as churners [43] and (3) the area under the ROC curve (AUC) is used as an aggregated measure of the sensitivity of all possible thresholds of a classifier.

Additionally, the top n% decile lift is used, which is derived from sorting the results of the classifier based on the churn likelihood. The ratio of the percentage of correct classifications of the churners in the top n% of the sorted results of the actual churners of all the results provides the top n% decile lift [41].

Depending on the actions based on the churn prediction results, it can be worthwhile to adjust the classifier parameters to optimize for cost effectiveness. This principle is described in a study by [44] regarding credit card churn problems.

Concluding remark

To illustrate: if the retention costs are significantly lower than the costs of losing a customer, it is more important to reduce the number of false negatives (wrongly identified churners as non-churners) over false positives (wrongly identified non-churners as churners). This is true, because the lost investment in false positives is made up by the savings of reducing the number of false negatives. This, however, is completely dependent on the business requirements, costs regarding retention strategies and Average Revenue per User (ARPU).

Although it is important to be aware of potential churners, this information only becomes useful when it can be applied in order to prevent customer churn from happening. This is where customer retention marketing comes in.

2.4 Customer Retention

This section will help understand how a churn prediction model should be used once created. As the study by Coussement, Lessmann and Verstraeten [5] explains, the application of customer churn prediction is irrelevant if no appropriate marketing tactics are developed. However, it is important to firstly understand what customer retention means.

This chapter will also serve as input for the expert interviews to determine the effectiveness of their customer churn prediction implementation.

2.4.1 Customer retention construct and related constructs

Customer churn related marketing tactics are mostly part of a customer retention strategy. However, what is customer retention? The construct of customer retention focuses on repeat patronage of a marketer and is closely related, sometimes confused, with the repeat-purchasing behavior variable as well as the loyalty construct. However, there are differences between customer retention and both other constructs.

The customer retention construct in contrast to the loyalty construct, which is a multidimensional construct comprised of three distinct constructs - behavioral loyalty, attitudinal loyalty and composed loyalty [45] - does not contain any attitudinal aspects [46]. Furthermore, in customer retention the marketer is seen as the initiator (i.e. retaining), whereas the behavior-based construct repeat-purchase concept pays no attention to such underlaying behavior factors [46]. Thus, customer retention aims to achieve repeat purchase behavior triggered by the marketer’s activities.

Loyalty as described earlier is a higher dimensional construct comprised of three clear constructs: behavioral loyalty, attitudinal loyalty, and composite loyalty [47].

1. Behavioral loyalty refers to the willingness to continue buying a service or product;
2. Attitudinal loyalty refers to the willingness to recommend a product or service. The customer has a positive attitude towards the service or product;
3. Composite loyalty takes both types of loyalty in consideration.

The third construct in relation to customer retention is repurchasing behavior, which refers to the customer repurchasing a product or service from an enterprise. The three constructs are visualized in Figure 9 by (1) type of construct, (2) attitudinal and behavioral connection and (3) by actor.

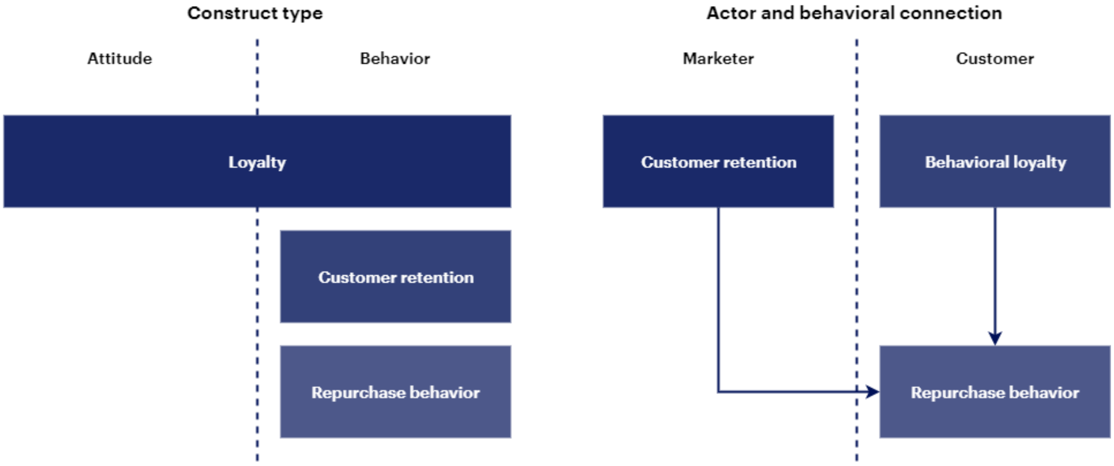


Figure 9: construct overview: loyalty, retention and repurchase behavior

Another construct that research relates to previously discussed construct is satisfaction, especially the relation between satisfaction and loyalty [35], [45], [48], [49].

2.4.2 Preventing churn by encouraging repurchase behavior

A study by Jahanzeb & Jabeen [12] explains that there is no single way of reducing churn across all customer segments, since all segments will respond differently based upon their needs and situation. A predictive churn model might be designed to target likely churners by segmenting them into customer profiles. This allows marketeers to focus on customers through exclusive service packages e.g. specifically tailored packages [50]. It also helps a service provider to retain customers by well handling of complaints, enquiries, brand-reputation, promotional tie-ups and a wide range of value-added services (VAS).

A study by Lim, Widdows & Park [51] identified that two dimensions of perceived value have a significant influence on customer satisfaction and loyalty intention within the mobile telecommunications industry.

These two dimensions of perceived value are:

1. Economic value
2. Emotional value

Economic value is related to perceived economic benefits received in comparison to a monetary cost of the service or product. Multiple researchers found a significant role of customer's perceived monetary value in satisfaction and future decisions [51].

Emotional value refers to the utility derived from feelings or affective states that a service provider stimulates [52]. The emotional value includes consumer's affective behavior to service stimuli in a cognitive-oriented means-end model. In a retailing context, Sweeney and Soutar [52] identified that emotional value is the strongest predictor of consumers' purchase intention in a particular store.

2.4.3 Advantages of customer retention

A study by van den Poel and Larivière [25] summarized the economic benefits of customer retention as follows:

- Retention lowers the need to seek new and potentially risky customers, which allows focusing on the demands of existing customers;
- Long-term customers tend to buy more;
- Positive word of mouth from satisfied customers is a good way for new customers' acquisition;
- Long-term customers are less costly to serve because of a larger set of records of their demands and actions. This information allows enterprises to target long-term customers with tailored marketing messages. In contrast to customer acquisition, no explorative costs have to be inquired;
- Long-term customers are less sensitive to competitors' marketing activities. This means that long-term customers are less likely to churn;
- Losing customers results in less sales and an increased need to attract new customers, which is five to six times more expensive than the money spent for retention of existing customers;
- People tend to share more often negative than positive service experiences with friends, resulting in negative image of the company among possible future customers.

Concluding remark

In order to make the implementation of customer churn prediction relevant, operators will need to develop marketing strategies to retain customers. All customers are different and therefore multiple retention strategies are needed to fulfill the customer's needs. Since customers mostly churn because of dissatisfaction scenarios, retention strategies should try to aim to resolve / compensate dissatisfaction scenarios as quickly as possible. An important factor regarding satisfaction is economic and perceived value by the customers. Therefore, operators should try to aim to provide good value to customers in order to increase loyalty.

Also - not mentioned in this literature study - operators should try to evaluate how much they are willing to invest to retain a customer, since some customer are worth more than others and operators remain commercial entities.

2.5 Privacy concerns and regulations

A key ingredient for the creation and implementation of churn prediction models is customer data. However, large-scale data collection has heightened consumer's concerns about their privacy. As a result, governments are considering new privacy regulations to restrict the collection and use of customer data by firms [53]. In the United States, the Federal Trade Commission (FTC) considered moving to regulate the use of customer data for targeted online advertising. In the European Union, the General Data Protection Regulation (GDPR) is in full effect since 2016, forcing enterprises that operate in Europe to be compliant or otherwise they will face fines [54].

The GDPR expands the original directive of 1995, which originated from an era when 1% of the world's population was using the Internet. The GDPR data protection scope is that anyone or any organization that collects and processes information related to EU citizens must comply with the regulation, no matter where their head office is based or their data is stored.

The GDPR updated the definition of personal data. It states that personal data includes information from which a person could be identified, directly or indirectly. The GDPR introduced mandatory breach notification and individual rights to EU citizens.

The individual rights state that [54]:

- EU citizens must unambiguously give their consent for their data to be processed. This consent must be informed and must be voluntary;
- EU citizens have the right to access information held on them;
- EU citizens have the right to object to the processing of their data where there are legitimate grounds for doing so;
- EU citizens have the right to be forgotten, requiring data controllers and processors to remove data that is irrelevant, inadequate or no longer relevant. This requires that organizations know what information they hold and where it is sored.

The European GDPR regulation also affects the adoption of these new privacy standards in other regions, since it affects international companies. To illustrate, The United States' state of California passed the California Consumer Privacy Act, which grants rights to transparency and control over the collection of personal information by companies in the same manner as the GDPR [55].

Especially the individual rights of citizens require companies to update their data systems in order to stay compliant. Data mining, in many cases, requires historical data to train and to use models. Allowing citizens to object to data processing or to use the right to be forgotten can limit the available data and / or the use of churn prediction for that specific citizen.

2.6 Concepts

This section helps identifying the key concepts for answering the main and secondary research questions based on the findings of the literature study.

Based on the research questions, at least the following concepts must be well understood in order to answer the research questions:

1. Customer churn
2. Customer churn prediction

Additional concepts that prove useful to be defined in order to answer the research question are:

3. Customer retention
4. Customer churn drivers

2.6.1 Customer churn and churn drivers

Customer churn as a concept can refer to a metric as described by Almana et al. [13]. This metric describes the percentage of customers that leave a service provider compared to the entire provider's customer base over a period of time. Additionally, customer churn can refer to the act of leaving or abandoning a service provider for another as described by Xubing Zhang et al. [14].

In this study, the appropriate definition of customer churn is: "The act of leaving or abandoning a service provider and / or its services".

However, multiple studies identified sub-types of customer churn [12], [17]–[19]. These types include:

- **Involuntary churners**
  "Churners that are not actively trying to end their service agreement, which is mostly caused by billing issues."
- **Voluntary churners**
  "Churners that are actively trying to end their service agreement."

This research will focus on voluntary churners only. The differentiation between the types of voluntary churners as described by Lazarov and Capota [19] indicates a difference between active / deliberate and rational / incidental churn. Active / deliberate churn describes a churn motivation linked to dissatisfaction of the customers based on economic, technology and quality related aspects. Rational / incidental churn refers to churn that occurs when the customer's circumstances prevent the customer from further requiring the provider's service.

The focus of this research will be on the active / deliberate churn, because incidental churn is responsible for a very small percentage of the total churn an provider experiences [18].

Concept: customer churn

"The act of leaving or abandoning a service provider and / or its services."

Main focus / additional information
The main focus is on customers that actively try to end their service agreement themselves, referred to as voluntary churners.

Motivations for voluntary churn, including dissatisfaction of the consumer regarding economic, technology and quality related aspects, can be referred to as churn drivers: “The reason and / or motivation why customers decide to churn”.

Besides the drivers derived from the different churn types, studies used in the literature study found more specific churn drivers, including:

- Customer dissatisfaction
- Switching costs
- Billed amount (bill shock)
- Non-use or suspended customer status

Finally, it has been described that customer churn does not occur after one dissatisfactory experience, but usually occurs after multiple.

Concept: customer churn drivers

“The motivation and / or reason why customers decide to churn.”

Main focus / additional information
Churn drivers are related to customer satisfaction. Low customer satisfaction increases the probability a customer will churn. Dissatisfactory experiences can have economic, technology and quality related aspects.

2.6.2 Customer churn prediction

Customer churn prediction as a concept used in this research is: "The identification of customers who show a high tendency to end their relationship with a company [34]".

According to multiple studies this identification of customers is done by using data-mining techniques [5], [19], [58]–[60].

The data mining process is first standardized and officially published by Shearer in 2000 as the CRISP-DM model. The model describes six steps for the data mining process [36].

These steps include:

1. Business understanding
2. Data understanding
3. Data preprocessing
4. Modeling
5. Evaluation
6. Deployment

It is important to note that all these steps must be fulfilled in order to fully utilize a churn prediction model. The entire process is an iterative process and certain steps are also linked in an iterative manner.

The prediction of customer churn is achieved by churn prediction models, which are created in the modeling phase. In order to do this, data mining models use one or more classifiers / methods.

These methods and related classifiers include:

- Decision tree-based methods
- Naïve Bayes-based methods
- Neural network-based methods
- Regression-based methods
- Logistic regression-based methods
- Covering / rule-based methods
- Statistical data analysis-based methods
- Genetic algorithm-based methods

According to Vafeiadis et al. [40] the five most well established and popular techniques used for churn prediction regarding reliability, efficiency and popularity in the research community are:

- Artificial neural network
- Support vector machine
- Decision tree learning
- Naïve Bayes
- Regression analysis-logistic regression analysis

Therefore, the current state-of-art in churn prediction is the use of data-mining, setup according to the CRISP-DM model, in order to identify customers who show a high tendency to end their relationship with the service provider by using any supervised or unsupervised learning classifiers such as of the five types of popular techniques as described in Appendix 6: datamining algorithms and classifiers.

Concept: customer churn prediction

“The identification of customers who show a high tendency to end their relationship with a company.”

Main focus / additional information
The identification of customers is a data mining problem and can be solves using data mining modeling. To successfully create and utilize a churn prediction model it is advised to use the CRISP-DM model and select methods and classifiers that are well suited for the business and technical understanding of the problem. Well known methods used for customer churn prediction are artificial neural networks, support vector machine, decision tree learning, naïve Bayes and regression- and logistic regression analysis.

2.6.3 Customer retention

Customer churn prediction is only effective if the churn prediction results are used in a meaningful way. Since customer churn prediction identifies customers that have a high tendency to end their relationship with a company, it is a logical approach to try and convince these identified customers to stay. Without doing so, the use of customer churn prediction is irrelevant. This idea is supported by Coussement, Lessmann and Verstraeten [5], used in the previous sections.

The convincing of customers to stay at their current service providers is called retention marketing and is one of the tools that marketeers have to their disposal to reduce customer churn.

According to literature, retention as a concept refers to: “A marketeer actively trying to encourage repurchase behavior of a customer”.

An important addition to the literature is that retention can either be pro- or reactive. Proactive retention refers to the marketeer encouraging repurchase behavior when the marketeer anticipates a customer to churn, whereas reactive retention refers to responding to an action by a customer such as a cancellation or upsell request.

Concept: customer retention

“The process of a marketeer actively trying to encourage repurchase behavior of a customer.”

Main focus / additional information

Customer retention can occur both pro- and reactively. In the reactive situation, the marketeer reacts on an action of a customer such as cancellation of a subscription. In the proactive situation, the marketer anticipates on the customers behavior in order to prevent a customer from churning

3 Methodology

In this thesis quantitative and qualitative research is used to find an answer for the question: "How can the adoption of customer churn prediction be accelerated in the Dutch telecommunication industry?".
To achieve this, in addition to the literature study, expert interviews and an online survey with Dutch consumers are performed.

3.1 Research frame

The thesis itself does not entirely follow a design frame. However, a big part of the study will reflect on the current Dutch churn prediction implementation of telecommunications providers in comparison to other geographical regions, like Asia, Oceania and the Americas, which as a study is comparable to a comparative study. A comparative study is useful because it allows for new insights since other regions generally do things differently and can offer new insights for ideas and development [56].

3.2 Data collection

The research data in this thesis is drawn from three main sources: literature, surveys and expert interviews.

3.2.1 Survey

The goal of the survey is to verify the churn determinants and the motivations of the Dutch population to churn in comparison to the literature study. This is done by identifying how satisfied the respondents are with their mobile subscription and mobile provider and how likely they are to churn once their contract ends. The focus on the mobile segment has two motivations. First of all, this focus will simplify the survey by focusing on just one segment of the Dutch telecommunications sector. Second of all, the mobile sector is responsible for a big portion of the yearly revenue of telecommunications providers.

This survey tries to include as many factors as possible that are relevant for a mobile subscription and is roughly divided in four parts: customer related variables, customer satisfaction, service usage and churn motivations.

1. The customer related variables describe demographic information about the participant e.g. age and sex, but also include questions about their current mobile subscription e.g. monthly costs, type of subscription, current provider, customer lifetime and device acquisition.

2. The customer satisfaction section is concerned with general satisfaction of the subscription and provider and ends with a matrix consisting of a satisfaction Likert scale for multiple aspects of a carrier and mobile subscription. This is based on the hypothesis that there is a difference between the satisfaction of a provider and the satisfaction of a certain subscription plan.

3. Service usage is concerned with the participant's subscription usage based on mobile data, call minutes and text messages.

4. The final section about churn motivations asks the participant how likely it is he / she will churn once their contract ends and concludes with a matrix with a Likert scale that describes how important the same carrier and subscription aspects are, which is related to the customer satisfaction section regarding motivations to churn.

Table 9: customer related factors used in the survey

Factor	Descriptive	Measured variable type
Age	The age of the respondent	Ordinal
Gender	The gender of the respondent	Nominal
Type of subscription	The type of subscription: postpaid / prepaid	Nominal
Device acquisition	Whether or not the respondent received a device with his subscription	Nominal
Provider	The current provider of the respondent	Nominal
Loyalty	How long the respondent has been a customer of his current provider	Ordinal
Subscription costs	How much the respondent pays monthly for his subscription	Ordinal

Table 10: satisfactions factors used in the survey

Factor	Type of factor	Influences variable	Measured variable type
Monthly subscription costs	Economic / financial	Subscription satisfaction	Ordinal
Bundle size: national, international	Economic / financial	Subscription satisfaction	Ordinal
Rates outside bundle: national, international	Economic / financial and Geographical	Provider satisfaction / Subscription satisfaction	Ordinal
Network reception	Quality and Geographical	Provider satisfaction	Ordinal
Call quality	Quality	Provider satisfaction	Ordinal
Internet speed	Technology	Provider satisfaction / Subscription satisfaction	Ordinal
Mobile app from carrier	Quality	Provider satisfaction	Ordinal
Cancellation period	Economic / financial	Provider satisfaction	Ordinal
Extra services	Quality	Provider satisfaction	Ordinal
Family benefits	Economic / financial	Provider satisfaction	Ordinal
Customer service	Quality	Provider satisfaction	Ordinal

Table 11: service usage related factors used in the survey

Factor	Descriptive	Measured variable type
Usage: call minutes	How many call minutes of the respondent's subscription plan are used	Ordinal
Usage: text messages	How many text messages of the respondent's subscription plan are used	Ordinal
Usage: data	How much data of the respondent's subscription plan is used	Ordinal

The survey questions are, if possible, transformed to an ordinal scale to make it easier for respondents to fill in the survey and increase the response rate. The survey is created in a survey tool by Qualtrics as approved by the University of Leiden. In order to increase the potential respondents, the survey has been shared using social media, including Facebook, WhatsApp and LinkedIn. Once respondents used the link, the last activity was tracked and they had one week to finish the survey. The survey was available from May 13th to June 26th and concluded in a sample size of n=121 with a target of n=100 and a completion rate of 0.876 for a total of 106 valid recorded surveys.

The focus of the analysis is on the correlation between the customer satisfaction and the probability the customer will churn. Additionally, the correlation between customer related variables and subscription usage regarding the customer churn probability will be analyzed. Finally, there will be looked at factors that customer deem to be important churn motivations.

Due to the ordinal nature of the questions the survey will be analyzed using the Spearman's rho correlation coefficient, since Spearman's correlation coefficient is appropriate for both continuous and discrete ordinal variables [57]. The analysis will be done using Jamovi v1.0.0.0 by jamovi.org which is an open source statistical software built on the R statistical language.

Validity and reliability

To ensure validity, the survey is created based on the conducted literature study. Therefore, the satisfaction factors are labeled by the type of factor they represent regarding deliberate churn. Additionally, the survey was first verified with the supervisors of the company and university. The first week, starting May 13, 2019, social media responses were monitored for additional feedback. This led to the addition of the factor "benefits for families".

Before publication of the survey, Accenture colleagues were asked to fill in the survey to identify unclarities and measure the response time. This led to most question response options being transformed to an ordinal scale. The used tool by Qualtrics provided usability metrics that help design a survey as well as providing pre-created 5- & 7-point Likert scales. Finally, to ensure respondents are not hindered by language the survey is multi-language: English and Dutch.

To increase the reliability of the survey, a target sample size of at least n = 100 was required. The survey concluded with a sample size of n=121 and a completion rate of 0.876 for a total of 106 valid recorded surveys.

Table 12: survey descriptive(s)

Survey Descriptive(s)

	Age	Gender	Subscription type
N	119	110	119
Mean	3.33	1.55	3.12
Median	3	2	3
SD	1.41	0.500	0.906
Variance	2.00	0.821	0.250

Additional insights in the survey population can be found in the figures below (a full-size version can be found in the Appendix 8: survey population).

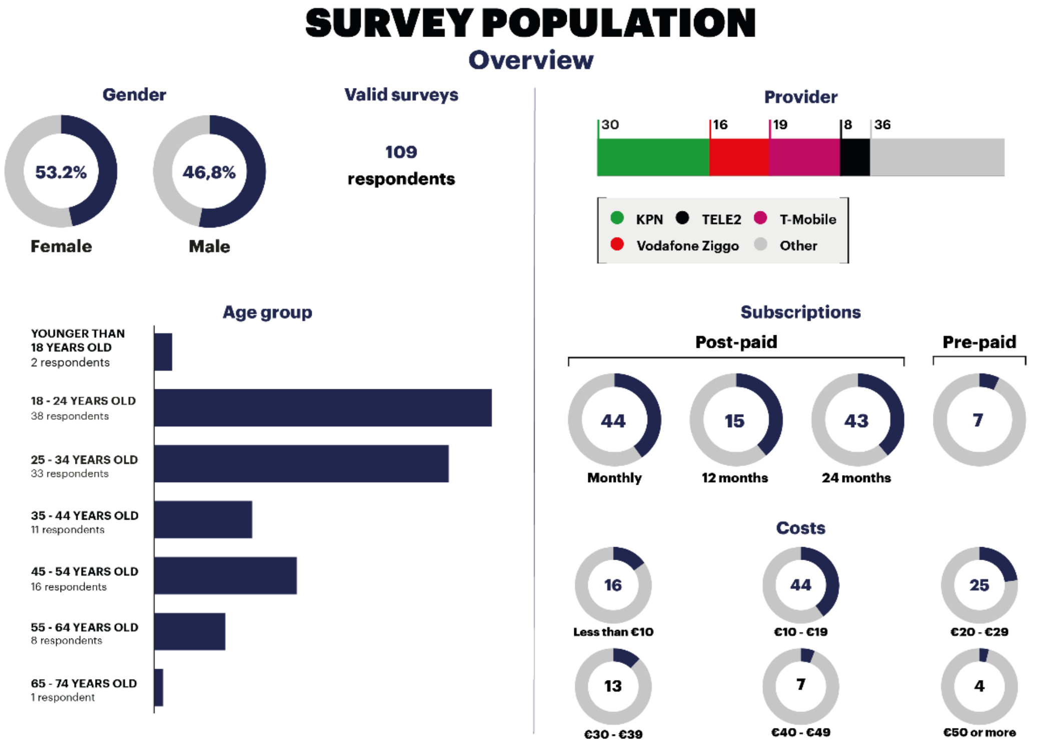


Figure 10: survey population - overview

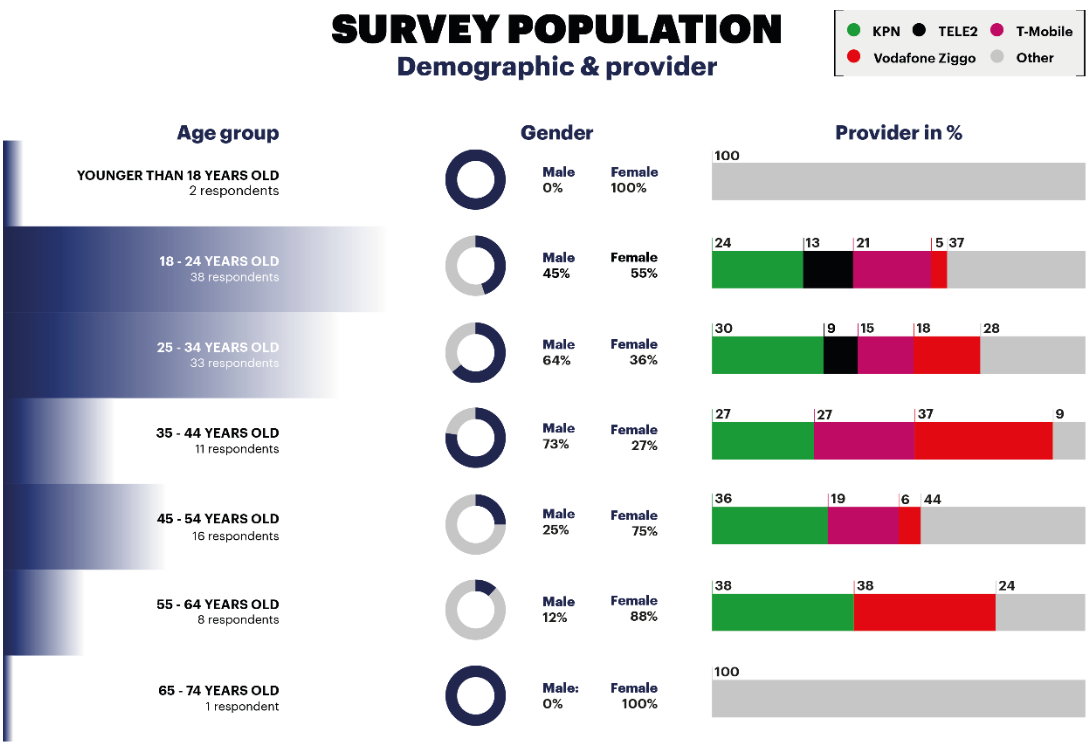


Figure 11: survey population - demographic and provider

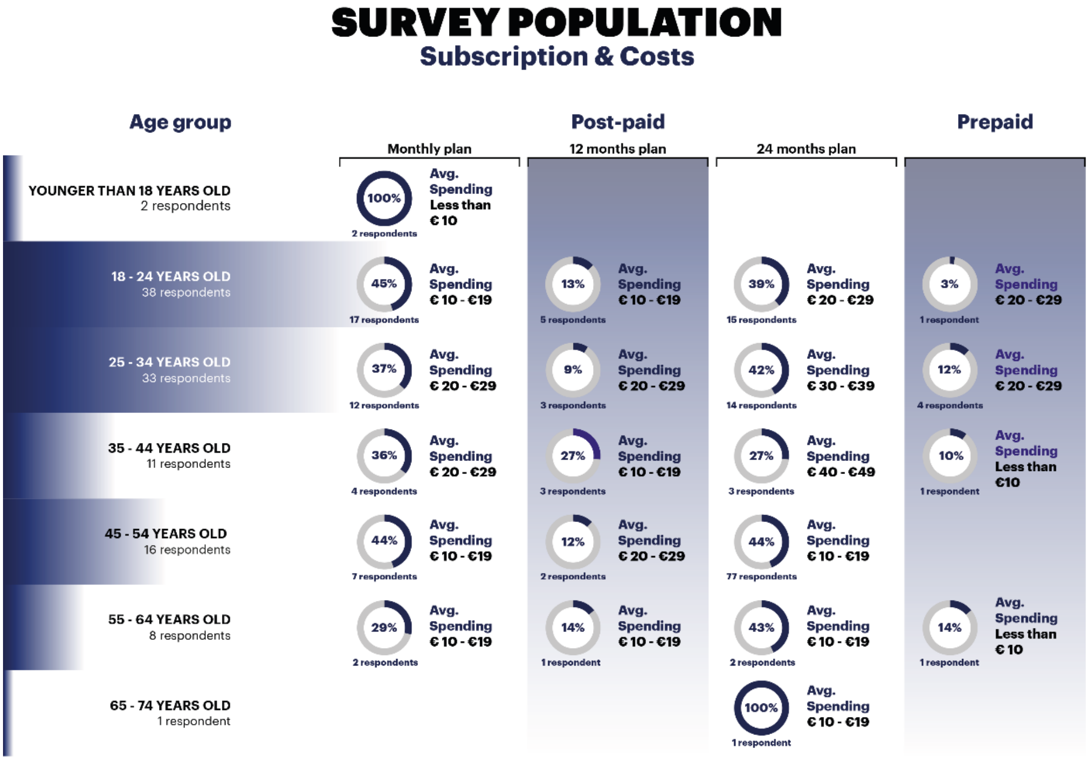


Figure 12: survey population - subscription and costs

Generalizability

The survey's generalizability is not optimal due to the age, subscription costs and provider of the surveyed population. The average age of the population is 25 - 34 years old. However, most of the population is in the age groups of 18 - 24 and 25 - 34 categories, which introduces bias towards younger people into the survey results. The subscription costs average sits at 2,6, which is between the categories €10 - €19 and €20 - €29. However, the largest part of the population is located between €10 - €19. This is rather low.

Another potential bias is introduced by the telecommunications provider. According to the Telecommonitor 2017, the retail market share should be, in order of size, KPN 30 - 35%, MVNOs 20 - 25%, VodafoneZiggo 20 - 25%, T-Mobile 15 - 20% and Tele2 5 - 10%. In the survey population, MVNO's have the biggest share followed by KPN. Additionally, T-Mobile is better represented than VodafoneZiggo in contrast to the Telecommonitor 2017.

3.2.2 Expert interviews

The expert interviews of this research are utilized to identify the degree of adoption of churn prediction across multiple regions.

Experts who worked on churn prediction / data analytics project, internally or externally, are interviewed regarding a telecommunications operator. Experts were selected based on their professional work experience with operators within the Accenture portfolio. The preferred professional roles were data scientists, marketeer or (industry) manager.

The goal is to cover at least three other regions than The Netherlands.

The interviews were conducted in a semi-structured format, since this allows for additional context if the interviewee's response which allows for follow-up questions. The interview questions are separated into three main themes:

1. **Customer churn**
   This theme dives into the effects of churn on the telecommunications operator and how it is perceived from an operator point-of-view.
2. **Churn prediction**
   This theme is about the analytical and churn prediction capabilities of a telecommunications operator.
3. **Customer retention**
   This theme is about the retention processes of a telecommunications operator once a customer shows churn behavior. If applicable, this will discuss the implementation of churn prediction in the retention processes.

The structured questions can be found in the appendix. Due to the large distances between regions, most interviews were conducted digitally by use of digital communication services, including Microsoft Teams and Skype. The interviews took approximately 30 - 45 minutes each. The interviews were recorded if the interviewee agreed upon this. Otherwise, the interview notes were transformed into a summarized format and sent to the interviewee for validation. The recorded interviews were transcribed and summarized and ultimately combined in an overview in order to be able to answer the appropriate research questions.

Validity and reliability

In order to increase the reliability of the expert interviews, all interviews are conducted by using a research protocol with predefined questions and subjects that have to be covered. This research protocol ensures that all survey results can be compared based on the answers to the questions and subjects. This is done so to increase reliability and validity, since the questions are based on findings in the literature reviews.

It is important to note that the research protocol has changed over time due to interviewees providing extra information alongside the initial interviews questions. This additional information would prove to be valuable.

Later, gained knowledge was translated into three main topics that are discussed during the expert interview results: (1) data and data availability, (2) churn prediction models and integration and (3) churn prevention. This shift in focus might have harmed the reliability and validity of the expert interview slightly.

The expert interviews are conducted with a limited pool of experts with different backgrounds, including marketeers, data scientists, consultants and managers. The results showed to have some consistency across the results regarding the topics. However, the different backgrounds of the interviewees might have introduced bias towards the expert's field of expertise.

The limited number of experts from other geographical regions than The Netherlands - in all cases one or two experts - provide a very one-sided story for those regions. However, this does not directly harm the results of the study since the regions are used as a comparison to the two Dutch operators that this research evaluates. However, it would have been better to interview multiple experts per region to further increase the reliability of the interview results.

Finally, the highly qualitative / explorative approach to the expert interviews limits the quantifiability of the results. This also limits the ability to compare the research. In this study, the analysis is based on relative comparison between the interviews and the used literature.

Generalizability

The expert interviews are conducted in the context of telecommunications operators of multiple sizes globally, including smaller virtual network operators and large incumbent operators. Therefore, the results of the expert interviews are strictly applicable to (virtual) telecommunications operators only but might be useful for other service industries as well.

However, all expert interviews discuss major global telecommunications operators and / or their subsidiaries. These operators are globally widely spread to increase generalizability. However, considering the sample size of operators on a global scale, it is hard to defend the generalizability of the results in the context of all telecommunications operators existing worldwide.

4 Research Results

This chapter provides the findings of the customer survey and expert interviews conducted during this research.

4.1 Survey results

The goal of the survey was to identify whether there is a correlation between customer satisfaction and churn probability. The survey addresses the customer satisfaction in general regarding their subscription and the provider as well as the satisfaction of all aspects of a Dutch mobile telecommunications service and service usage.

Analysis of the general customer satisfaction and likeliness a respondent will churn after the contract period ends (churn probability) shows that provider satisfaction has a stronger negative correlation with the churn probability (-0.522) compared to subscription satisfaction (-0.347). However, it is important to note that subscription satisfaction has a moderate positive correlation with provider satisfaction (0.575), which affects churn probability moderately (see Appendix 3: survey results, Table 19).

Analyzing the correlation between subscription usage, satisfaction and churn probability indicates that there is a significant negative correlation between data usage and subscription satisfaction, which indicates that a lower usage of data translates into a higher subscription satisfaction. However, this is only a low correlation. The same is true for the correlation between text message, data usage and provider satisfaction. Text message usage does not correlate with subscription satisfaction. Additionally, there is no correlation between subscription usage and churn probability in this survey (see Appendix 3: survey results, Table 20).

Diving deeper into the individual satisfaction factors, the survey shows a more complete picture of how everything correlates with the churn probability (see Appendix 3: survey results, Table 21). Most significant correlations are low to moderate correlations and almost none are as strong as the correlation between the satisfaction of customers about their providers and the churn probability (-0.522). Also, some factors do not affect churn probability directly but do so through either provider or subscription satisfaction. Examples of this are:

- Subscription costs
- Bundle size data
- Bundle size text messages
- Bundle size call minutes
- Rates outside bundle
- Rates outside of the EU

Other factors influence churn probability directly as well as subscription satisfaction and provider satisfaction. These factors are:

- Network reception
- Network reception abroad
- Call quality
- Internet speed
- Mobile application of the provider
- Customer service

Some of these correlations are stronger regarding churn probability in contrast to satisfaction. This concerns network reception abroad. In contrast, contract termination period has a stronger correlation to provider satisfaction than to churn probability.

It is interesting that the factors that directly correlate to churn probability have the strongest correlation as well as the most significant one, while having a somewhat equal correlation with provider and subscription satisfaction. These factors with the strongest correlation (ρ > 0,396) to churn probability as well as satisfaction are:

- Network reception
- Call quality
- Internet speed
- Mobile application of the provider
- Customer service

Referring to the methodology and customer churn chapter, all these factors are quality and technology related satisfaction factors.

Some factors, however, only influence subscription and provider satisfaction. In this case, the degree of satisfaction acts as a mediator between those variables and churn probability. These are in general economic and financial related factors. All correlations between the different factors and satisfaction / churn probability are summarized in Figure 13: survey results - factor correlations.

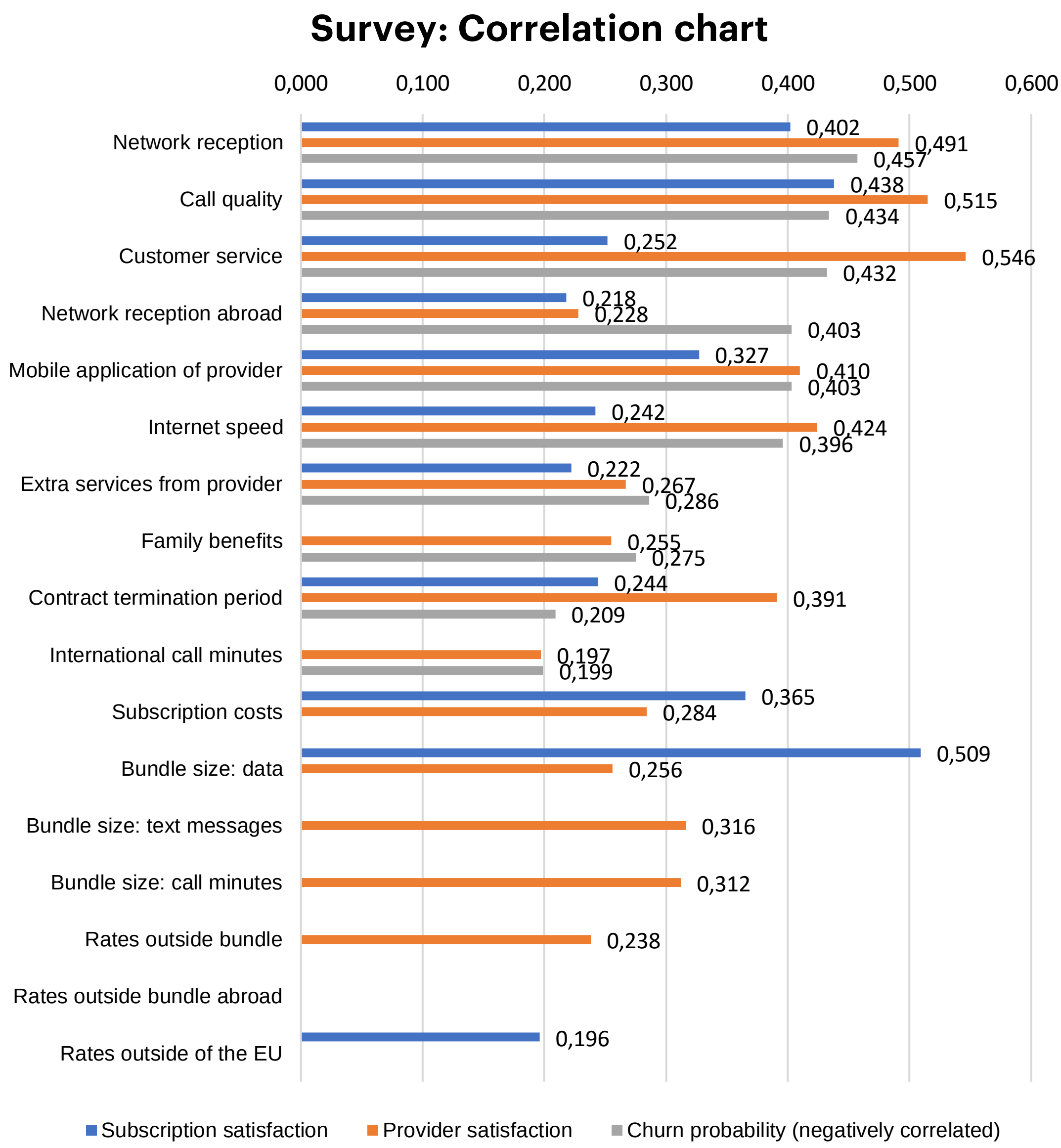


Figure 13: survey results - factor correlations

4.2 Expert interview results

The results of the expert interviews are categorized in two main subjects: churn prediction and churn prevention. The specifics for every geographical region are qualitatively described based on these two main subjects.

1. Churn prediction results focus on the data availability for each region as well as the use of churn prediction models by the respective telecommunications operator(s).

2. Churn prevention results focus on the current customer retention strategies in relation to churn prediction as well as other means region's telecommunications operator(s) deal with the churn problem.

Due to confidentiality requirements, the interviews are re-written without personal identifiable information and enterprise names. The interviews are labeled as shown in Table 13.

Table 13: expert interviews - overview

Label	Region*	Type**	Operator type***
NED1	Netherlands – West Europe	Single	Network operator
NED2	Netherlands – West Europe	Single	Virtual network Operator
USA1	United States	Multiple	Network operator
USA2	United States	Multiple	Cable company
NOR1	Norway – Scandinavia	Single	Virtual network operator
AUS1	Australia – Oceania	Single	Network operator
JAP1	Japan – Oceania	Single	Network operator

*Describes the geographical region of operation of the operator(s) discussed during the interview.
**Describes the number of operators discussed during the interview.
*** Describes the type of operator(s) discussed during the interview.

The interview results will be qualitatively compared in the following areas: (1) market of operation, (2) data and its availability, (3) churn prediction models and integration between churn prediction models and existing systems, and (4) the strategies utilized by the operator to reduce customer churn.

The operators are grouped relative to each other regarding their performance within each of the previously described facets.

The performance grouping is split into:

1. Low performers
2. Medium performers
3. High performers

Low performers have a large performance gap between them and the majority. Medium performers form the majority and their actions can be easily linked to existing literature. High performers perform better than the majority regarding their strategy, work methods, capabilities, etc.

4.2.1 Market of operation

Across all interviews, the participants described their market of operation as very mature and highly competitive. The market is generally divided into a group of major operators and smaller virtual operators.
The key differences between the markets are discussed in the following section.

The United states market is still mainly focused on acquisition (USA1a; USA2g). Operators face high levels of full customer churn in the wireless segment and high levels of product churn in their residential services on the television product (USA2i).
Operators are shifting their business to content creation besides providing traditional telecommunications services by acquiring large content creators.

This is caused by pressure from online streaming platforms and increasing costs of content rights (USA2f). Furthermore, the United States' market is divided between high population areas with many competitors e.g. West Coast and rural areas e.g. Texas with limited competition (USA2a; USA2b; USA2c).
In the United States, telecommunications services are mostly sold as 12- or 24-month contracts, but there is a slight shift to monthly contracts (USA1o).

The European market (NED1c, NOR1a, NOR1b) are similar with 2 - 3 major operators and many smaller operators competing in a saturated marketspace. Competition is strong and the larger operators started out as state-owned enterprises.
Norway is very digitalized, reducing switching efforts by providing SIM pickup points and simple activation (NOR1e). In The Netherlands the wireless and residential markets are converged to a single market by quad play offerings of the major operators. However, in terms of players, the wireless and residential market are very different (NED1c).

The Japanese telecommunications market is very similar to Europe, with a small number of large operators and multiple smaller operators (JAP1a; JAP1b). However, the Japanese largest operators are part of enterprises that operate in multiple different industries e.g. healthcare and ecommerce (JAP1b).

The Australian market is very similar to the European market in terms of players. However, due to aggressive marketing the value of post-paid subscriptions has decreased to such an extent that pre-paid subscriptions offer better value to the customer, causing a shift from post-paid to pre-paid (AUS1v).

4.2.2 Data and data availability

Low performers	Average performers	High performers
NED1	USA2	JAP1
USA1	NED2	AUS1
		NOR1

NED1
The operator has no clear indication who their customers are on a customer level and therefore lacks the ability to serve customers personally (NED1g; NED1l). This lack of insights is caused by poorly integrated systems, which are caused by the multi-service nature of larger operators (NED1l). The operator is aware of this issue and is actively working to resolve this issue (NED1m).

USA1
The discussed major US operators have a very siloed business environment and therefore poorly integrated systems (USA1b). Operators have difficulties identifying customers and their products on a personal level, because information is poorly shared between departments and poorly integrated (USA1c). However, some operators ask customers to provide personal information in return for a small financial incentive which is very effective (USA1f).

NED2
The operator has access to personal variables, which include demographic information, service agreement information, product ownership, customer lifetime and customer touchpoints (NED2c). However, the operator cannot use personal identifiable information such as usage data because of the GDPR (NED2d). The operator is partly mitigating this by interpreting such information using the sources that are available (NED2d). It is possible to have customers opt-in in order to use personal data, but the interviewee explained that the operator is not actively trying to pursuit this at the moment.

USA2
US operators have their own data warehouses and data scientists. However, there is still a lot of room for improvement regarding data quality (USA2n). Demographic and usage data is still of concerning quality. However, operators are actively trying to resolve this (USA2t). Additionally, the European General Data Protection Regulation has huge impact on the US. California is the first state to pass a similar regulation and other states will most likely follow, which further challenges data availability for US operators (USA2u).

JAP1
The operator set up a joint-venture to create an analytics platform (JAP1c). The joint-venture created a data lake and all departments of the operator and subsidiaries forwarded their data (JAP1d). All subsidiaries within different industries use the same customer identifier for the same individual, making it easier to integrate data sources (JAP1e). The joint-venture has access to all customer data of its subsidiaries, including more than 363 data points just from the wireless service (JAP1f).

AUS1
The Australian operator has access to more than 140 data points on its customer, including interaction sentiments, usage data, demographics, contract status and current handsets (AUS1f). The operator aggregated the available data points into 30 bigger data pieces to help identify types of churners (AUS1g). However, not all data is being used because, according to the interviewee, not all data is relevant for churn prediction and should not be included into the model or analysis (UAS1i).

NOR1
The small operator used to have no available customer or marketing data a few years ago (NOR1f). However, the operator currently has a CRM system with very detailed information on its customers (NOR1g). The operator has 60 - 70 data points on its customers (NOR1h). Norway is also part of the European Economic Area (EEA) and therefore has to be compliant with the GDPR. Because of this, the operator automatically opt-in every newly acquired customer (NOR1i). Currently, the CRM data is updated once a month (NOR1o).

Performance indication
In order to compare the results of the expert interviews in relation to each other, the following three levels of performance are used:

1. **Low performance**
   The operator / provider has no or poor access to customer related data.
2. **Medium / average performance**
   The operator / provider has access to customer related data.
3. **High performance**
   The operator / provider has access to many customer related data sources or uses other means to gain additional usable data compared to other operators / providers.

4.2.3 Churn prediction modeling and integration of relevant systems

Low performers	Average performers	High performers
NED1	JAP1	AUS1
USA1	NOR1	NED2
USA2		

NED1
The operator has rudimentary churn prediction models based on the frequency a customer contacts the service desk (NED1j). Furthermore, the operator has difficulties integrating churn prediction models into their retention strategies because of lack of knowledge on how to do this (NED1k).

USA1
US operators create rule-based environments built on the analysis of their data environment (USA1g). Rules are created by identifying churn drivers using regression and decision trees (USA1j). Regarding the active use of churn prediction models, US operators are immature (USA1i).

USA2
US operators have basic churn prediction models as well as data warehouses and data scientists. However, there is still room for improvement regarding data quality and actioning (USA2n). The quality of demographics and usage data makes it challenging to create churn prediction models (USA2t). The business is unable to act based on the models because the models do not provide additional insights such as churn drivers besides a churn probability and accuracy score (USA2o).

JAPO1
The joint-venture combines multiple analysis into one churn prediction models of which the results are passed down to the different departments (JAP1g). The joint-venture tried to make the model as accurate and efficient as possible in order to be able to use it effectively (JAP1n). This allowed them to identify potential churners six months in advance (JAP1k). However, the models do not provide insights in what the churn reason is and what it takes to retain a churner. To do this, the joint-venture required additional data sources such as customer touchpoints (JAP1p).

NOR1
The Norwegian provider used a supervised learning approach to create churn prediction models (NOR1j). When creating churn prediction models, the provider focusses on (1) the time-frame to identify when a customer is about to churn and (2) available data to exclude customer groups that have not enough data available to be accurately predicted by the models (NOR1k).
The provider integrated churn prediction models and retention strategies by business ruling in their CRM systems (NOR1n).

It is important to note, that most business rules are linked to customer related variables, which are found to be related with churn in their CRM system instead of churn prediction model output. Model output is used less frequently in business rules because the churn prediction model runs once a month (NOR1o) while customer related data is updated more frequently.

AUS1

The Australian telecommunications operator identified eight types of churners (AUS1h). The churn prediction model identifies (1) the churn probability, (2) most likely churn reason based on these eight types of churners and (3) an accuracy score regarding the churner type prediction (confidence) (AUS1k). This is done for every customer, new and existing, since it is important to identify churners as early as possible to increase the chances of success (AUS1k; AUS1l).

NED2

The Dutch provider uses multiple churn prediction models to identify potential churners and cluster these churners based on characteristics (NED2b). Model output is integrated using business rules in the provider's marketing system (NED2e). The models update daily, identifying customers with a higher churn probability than usual and labels them based on churn related characteristics (NED2q).

Performance indication

In order to compare the results of the expert interviews relative to each other, the following three levels of performance are used:

1. **Low performance**
   The operator / provider has no usable or very rudimentary churn prediction models.
2. **Medium / average performance**
   The operator / provider has access churn prediction models that can identify potential churners.
3. **High performance**
   The operator / provider has access to churn prediction models that provide additional insights besides churn probability.

4.2.4 Churn prevention and customer retention

Low performers	Average performers	High performers
USA1	NED1	NED2
JAP1	AUS1	NOR1
	USA2	

USA1
The United States operators are focusing more on acquisition instead or retention / churn prevention. However, operators do use churn prevention call centers. Customers are connected to these call centers when they indicate that they are going to churn. Churn prevention call centers give customers retention offers in order to retain them. The problem with this strategy is that customers have already left the provider emotionally speaking, requiring a big discount in order to keep them. However, operators are focusing more on customer churn in the B2C environment.

JAP
The enterprise's joint-venture prediction results are forwarded to the enterprise's departments. These departments are themselves responsible for the retention strategies (JAP1h). The retention strategies themselves have not changed because of churn prediction. However, the retention strategies are better targeted because of churn prediction resulting in reduced costs (JAP1i). The operator used to have issues tracking the effectiveness of these retention strategies, which entailed sending coupons to high risk customers, but later identified the strategy was ineffective. However, the operator shifted its focus from sending out coupons to improving customer experience by e.g. onboarding campaigns (JAP1m).

NED1
The Dutch operator's main strategy in reducing churn is the use of quadruple play, bundling triple play offerings with mobile services. The operator provides benefits to customers that use quadruple play offerings to increase loyalty (NED1b). However, the operator is very immature regarding their retention strategies and its ability to serve customers personally (NED1h). The used retention strategy is the save-desk, which is a specialized call center that provides a final retention offer in order to keep the customer from churning. The problem the operator faces with this strategy is that they have no clear indication of which customer they are dealing with, resulting into a generic offer to every churner including defaulters (NED1g).

AUS1
The Australian operator used to send standard retention packages to the top percentile churners, including discounts or any retention package available (AUS1e).
Currently, the operator predefined types of churner to support the marketing team developing retention strategies. The current challenge the operator faces is translating these predefined types of churners into actionable retention strategies (AUS1n). The next step would be to run pilot programs to experiment with retention strategies (AUS1q). However, their current implementation of their CRM system is not yet capable of tracking such programs (AUS1r).

USA2

The US operators have difficulties actioning the churn prediction models because the models do not provide the necessary insights into churn drivers (USA2p). However, the use of customer churn prediction has changed the retention strategies over the years. This change is mainly in the targeting of high-risk customers with retention packages instead of sending out offers randomly (USA2q). Currently operators are unable to target customers with a personalized offer based on the churn driver / root cause, but this is a long-term goal (USA2r).

Operators are starting to focus more on customer experience, putting KPI on metrics such as NPS in order to identify issues with the customer experience and use this to resolve experience related issues one step ahead of churn (USA2s).

Also, US operators are focusing on content creation, providing their own online streaming services, providing ITV and acquiring media companies (USA2l). They do this to fight the increasing television product churn and cut the increasing costs content providers ask for content licensing.

NED2

The provider uses multiple strategies to reduce customer churn including the use of quadruple play, service improvements and technical improvements to build loyalty and one-tone retention campaigning (NED2a).

Quadruple play, the combination of land-line, television, broadband and wireless services into one package, have been the biggest driver in reducing churn for the Dutch provider (NED2m).

In one-to-one retention campaigning, churners are automatically selected and targeted with a relevant retention strategy based on characteristics and churn prediction model output (NED2e). The operator's marketing team is constantly trying to identify blind spots to create new relevant retention campaigns (NED2f). The effectiveness of the retention campaigns is actively measured (NED2h). The provider is currently working on an algorithm that automatically identifies the next best offer for a customer without marketeer interference (NED2j).

The next step is to make the campaigns even more personalized using machine learning (NED2k). This is more challenging for larger operators because of a more complex enterprise landscape compared to smaller operators (NED2l).

Additionally, telecommunications services are becoming more of a commodity, forcing operators / providers to specialize (NED2n). However, a focus on content creation, such as in the US, is impractical in the Netherlands because of the relatively small market size (NED2o).

NOR1

The Norwegian operator uses in- and out-bound actions. In-bound actions are always active and trigger when a customer interacts with the provider through e.g. online environment or application. Out-bound actions are based on churn prediction model outputs and include text-messages and emails (NOR1p). Out-bound actions can be pro- and reactive. Proactive actions are based on triggers related to customer churn e.g. bill shock. Reactive actions are based on the output of the churn prediction model, this is reactive because the model only runs once per month (NOR1o).

The interviewee states that to effectively use churn prediction, it is not necessary to use state-of-art algorithms. Finding effective treatments is what matters the most (NOR1u). The operator uses pilots to test retention strategies on multiple thresholds based on churn probability in order to identify the best strategy to use (NOR1m).

Performance indication

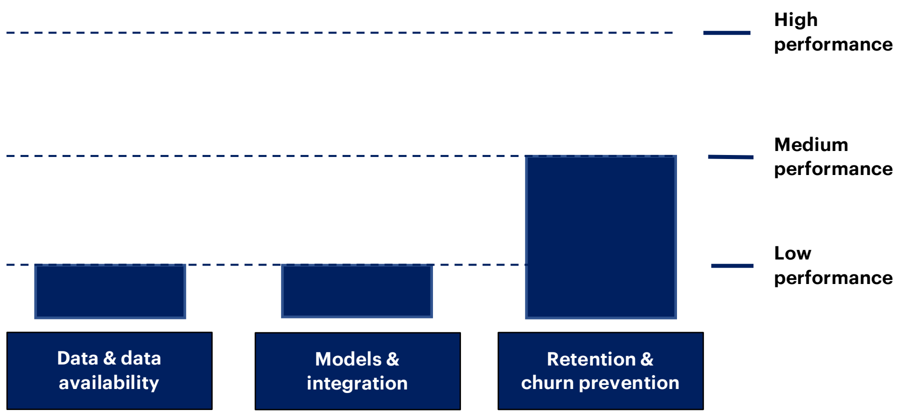
In order to compare the results of the expert interviews relative to each other, the following three levels of performance are used:

1. **Low performance**
   The operator / provider has no effective retention strategies in place and / or has no other means of reducing customer churn.
2. **Medium performance**
   The operator / provider uses targeted retention strategies and / or has other means of reducing customer churn.
3. **High performance**
   The operator / provider uses multiple retention strategies and / or other effective means of reducing customer churn.

4.2.5 Complete overview and additional insights by interviewees

Based on the information provided in the paragraphs of the previous chapters, a visual representation of the operator's performance per focus area is provided in this chapter. The key information from the interview is summarized per focus area. Additional insights from the experts is also summarized besides the key information.

The Netherlands – NED1



Data and availability

- Data systems are poorly integrated;
- There is an unclear picture of customers due to poorly integrated systems.

Models and integration

- Rudimentary churn prediction models are used, based on service desk contact frequency;
- There is no integration between churn prediction models and other systems.

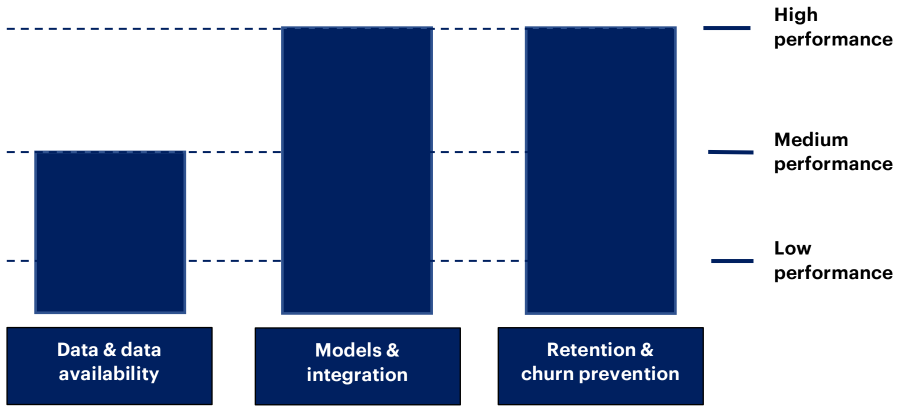
Retention and churn prevention

- Quadruple play offerings are used as an effective strategy to increase loyalty;
- There is a lack of targeted and personalized retention campaigns. However, customers receive a retention offer when they leave.

Additional insights

- Viewing behavior is changing: people are switching to online streaming services. However, exclusive content can play an important role in countering this (NED1p);
- The biggest potential of churn prediction is the effective use of churn prediction models output instead of improving the models themselves (NED1n).

The Netherlands – NED2



Data and availability

- There is access to personal variables such as demographics, service agreement information, product ownership, customer lifetime and internal customer touchpoints;
- There is no access to usage data because of GDPR;
- Interpretation of usage data is based on available data.

Models and integration

- Multiple models are used to identify and cluster churners based on characteristics;
- Model output is integrated with campaigning systems.

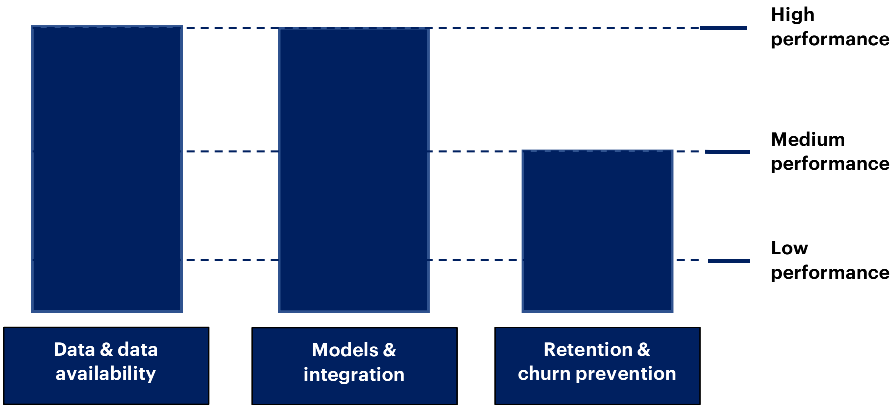
Retention and churn prevention

- Multiple strategies are used to reduce customer churn, including quad play offerings, service improvements to build loyalty, technical improvements and one-to-one retention campaigning;
- Churners are automatically targeted based on model output when a suitable retention campaign is active. This is achieved by business ruling in the campaigning system;
- The marketing team is actively trying to identify blind spots and create appropriate campaigns.

Additional insights

- The output of a churn prediction models is an assumption of the reality (NED2p);
- Targeted campaigns can cause a wake-up effect on a sleeping customer, causing a customer to churn as the customer becomes aware of current market offerings (NED2g).

Australia - AUS1



Data and availability

- The operator has access to 140 data points on its customers, including interactions, usage data, demographics, contract status, current handset and related variables;
- The operator uses aggregation of multiple data sources into fewer but bigger data pieces that help identifying types of churners.

Models and integration

- Models are used that provide churn probability, churn reason based on predefined churn types and accuracy score;
- Every customer is scored by the models;
- Models are integrated in a CRM system by business rules.

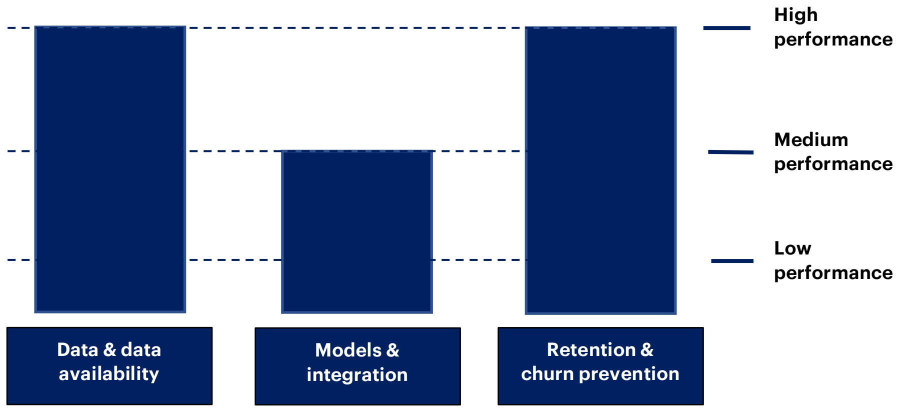
Retention and churn prevention

- Well targeted, but standard retention packages are used;
- Marketing related teams have a hard time identifying retention strategies;
- The CRM system is not yet capable of tracking campaigning pilots.

Additional insights

- The most important step in churn prediction is what you do once you have a churn score (AUS1a);
- Operators do not treat churn prediction and retention separately. However, they are two different concepts: churn prediction is the identification of churners and retention is the prevention of churn (AUS1c);
- Building loyalty with customers can help making them stay in the long-run (AUS1p);
- Providing a good service to customers increases their willingness to pay more and to stay longer (AUS1w);
- Poor use of prediction scores (targeting top x percentile of churners) might not be useful, since customers are targeted that will leave nonetheless (AUS1s);
- A retention strategy does not need to make things cheaper, it just needs to add additional value (AUS1t).

Norway - NOR1



Data and availability

- The operator as access to a CRM system with very detailed customer information;
- New customers must actively opt-in, which allows the provider to use usage data;
- The operator has access to 60-70 data points on its customers.

Models and integration

- The churn prediction model provides a churn probability;
- The model is integrated in the CRM system by business ruling;
- The model runs once a month due to frequency of data updates;
- There are triggers on customer related variables that have found to be churn drivers.

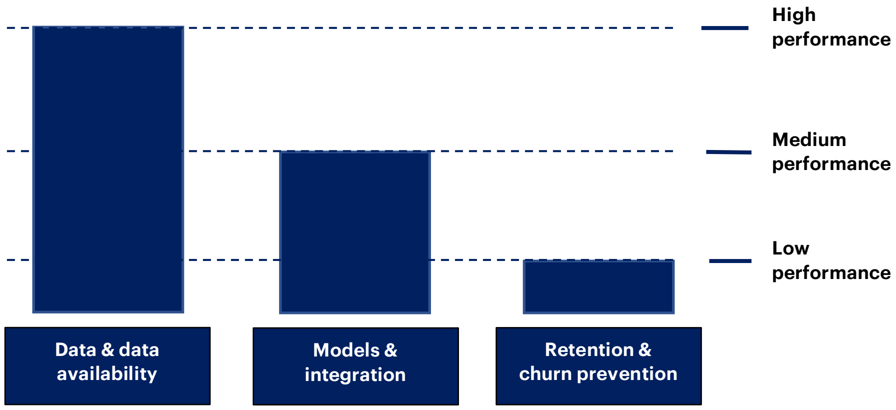
Retention and churn prevention

- Different churn probability thresholds are used for retention strategies;
- There is an emphasis on testing of retention strategies by running pilots;
- There is in- and outbound communication with customers to reduce customer churn.

Additional insights

- Innovation of the product portfolio can help reduce churn (NOR1s);
- In order to effectively use churn prediction state-of-art algorithms are not needed. Finding an effective treatment is what matters the most (NOR1u);
- In order to effectively use churn prediction, it is important to combine analytics with business sense and testing (NOR1t).

Japan - JAP1



Data and availability

- There is access to data lake with customer data of all different departments and enterprise subsidiaries;
- Customers share the same unique identifier over all subsidiaries.

Models and integration

- Multiple analyses are combined into one model;
- Lists with model output are passed down to all departments;
- There is an early identification of churn (6 months).

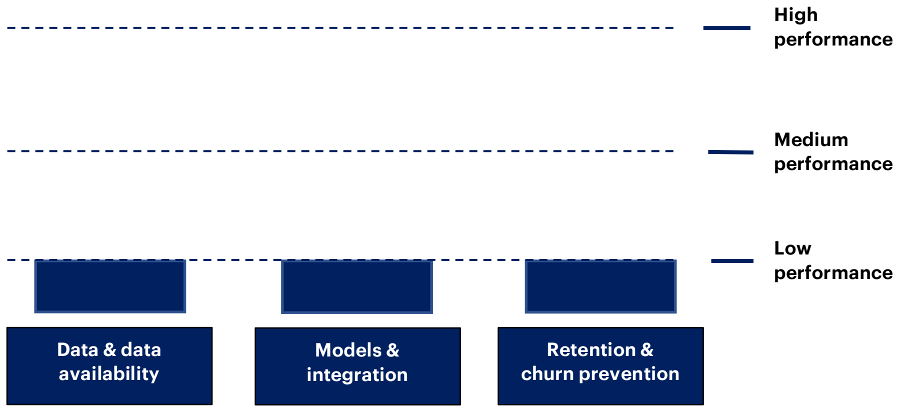
Retention and churn prevention

- Departments themselves are responsible for retention strategies;
- Use of CCP has not changed retention strategies, but allowed for better targeting and cost savings;
- The retention strategy is to send coupons, but this is found to be ineffective;
- The operator starts to focus more on customer experience instead of retention.

Additional insights

- The identification of who is going to churn is easy compared to identifying what it takes to retain customers (JAP1q);
- Churn prediction is not always useful, since identified customers might have already decided to leave (JAP1l);
- Churn prediction models should be accurate and efficient in order to be used effectively (JAP1n).

United states - USA1



Data and availability

- Systems are poorly integrated due to a siloed environment;
- There are difficulties to identifying customers and their products.

Models and integration

- The operator has very basic models and / or has in most cases a business rule system based on churn analysis.

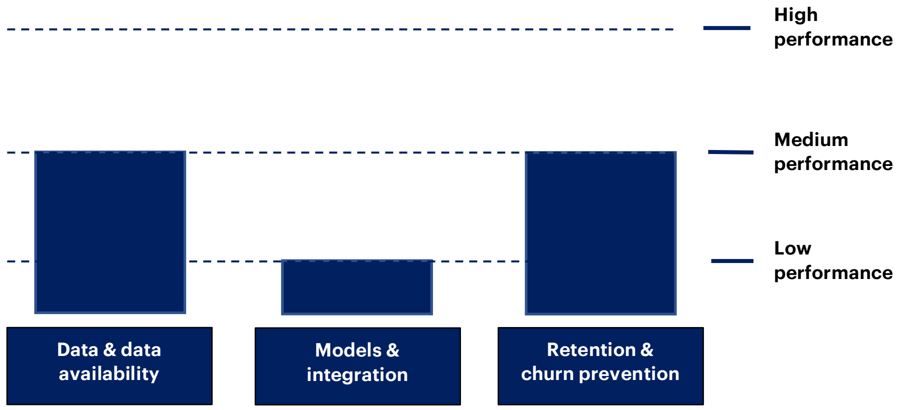
Retention and churn prevention

- There is a strong focus on customer acquisition;
- Customers get a retention offer once they indicate they will churn.

Additional insights

- Actively trying to reduce customer churn improves customer satisfaction, which increases brand recognition and brand scoring (USA1u);
- The ideal situation would be to monitor customer related variables and to identify whether there are any variables related to churn drivers that give a red flag to pro-actively trying to retain a customer (USA1n).

United states – USA2



Data and availability

- The operator has access to data warehouses and data scientists;
- The data quality is poor in most cases.

Models and integration

- There is access to models that provide churn probability and accuracy score;
- Models are not actionable by business due to lack of churn drivers.

Retention and churn prevention

- The focus is on customer acquisition;
- Exclusive content and streaming platforms are used to reduce churn and costs;
- Retention strategies are better targeted due to the use of customer churn prediction;
- The operator is unable to provide personalized retention offers to customers.

Additional insights

- Quadruple play is not as popular in the United States compared to triple play offerings (USA2e).

4.2.6 Strengths and challenges

This chapter will illustrate the strengths and weaknesses of the operators in context to each other. The operators are plotted in a set of matrixes and radar plots with the main areas of interest: data and availability, models and integration, retention and churn prevention. Additionally, the operators are color labeled to visualize their type. The color coding can be found in Table 14.

Table 14: operator matrix color-coding

Operator type	Color
Network operator	Dark blue
Virtual network operator	Light blue
Cable company	Purple

In order to calculate the average performance of operator types, the performance values have to be translated into a numeric value. Table 15 shows the numeric value of the different performance values.

Table 15: performance indication in integer

Relative performance	Numeric value
Low performance	1
Medium performance	2
High performance	3

Table 16 shows the numeric performance values of all the operators based on the information gathered during the expert interviews.

Table 16: performance per operator(s)

	AUS1	JAP1	NED1	NED2	NOR1	USA1	USA2*
Data and data availability	3	3	1	2	3	1	2
Churn prediction models and integration	3	2	1	3	2	1	1
Customer retention and churn prevention	2	1	2	3	3	1	2

*Cable companies

Combining the performance values of the different types of operators (virtual and non-virtual operators) results in the following two tables:

Table 17: performance per operator incl. average

	Data and data availability	Churn prediction models and integration	Customer retention and churn prevention
AUS1	3	3	2
JAP1	3	2	1
NED1	1	1	2
USA1	1	1	1
Average	2	1,75	1,5

Table 17 shows the performance of the non-virtual operators and the average. As shown in the table, the values of the non-virtual operators range from the lowest (1) to the highest (3) possible scores in the first two categories. Churn retention and churn prevention never reaches a score of three with the lowest average of 1,5.

Table 18: performance per virtual operator incl. average

	Data and data availability	Churn prediction models and integration	Customer retention and churn prevention
NED1	2	3	3
NOR1	3	2	3
Average	2,5	2,5	3

Table 18 shows the performance of the virtual operators and the average performance. As shown in the table, the performance values from the virtual operators are in contrast to the non-virtual operators that are all between the medium (2) and highest possible score (3).

In Figure 14 the averages of the different types of operators are plotted in a radar graph. This shows that virtual network operators perform better overall compared to the other operator types.

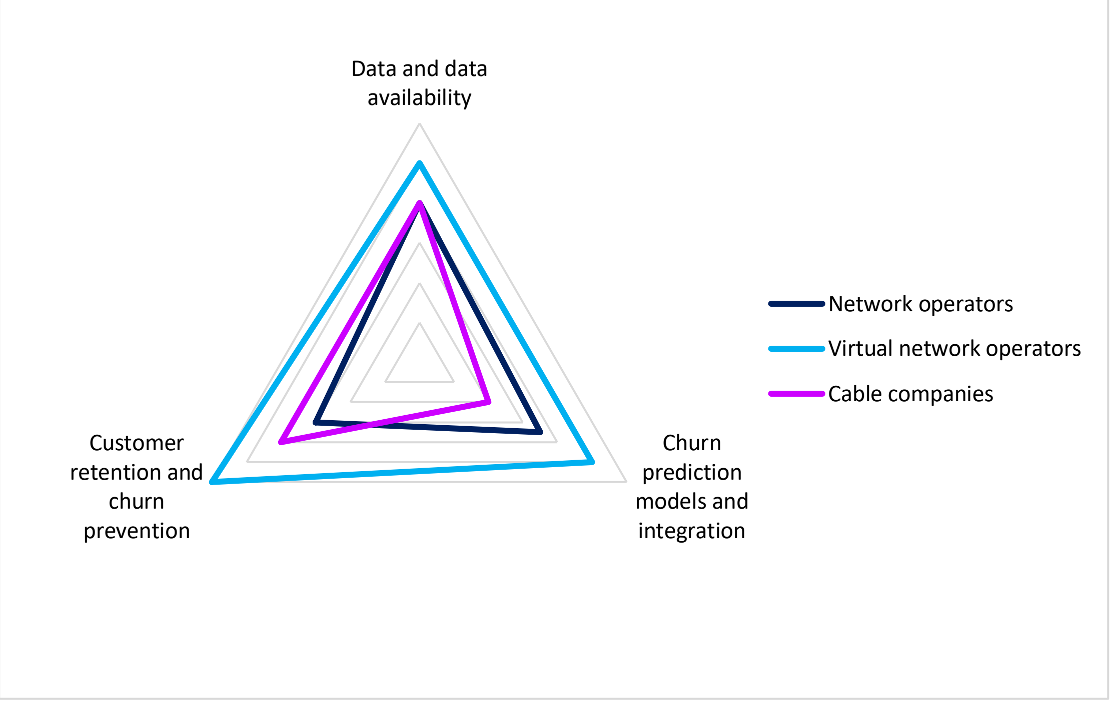


Figure 14: overview operator performance

Figure 15 shows the performance of all non-virtual operators. There does not seem to be a relation between the operators except for the fact that all are not performing high in customer retention and churn prevention. However, operators that score high in data and data availability seem to score higher in churn prediction models and integration.

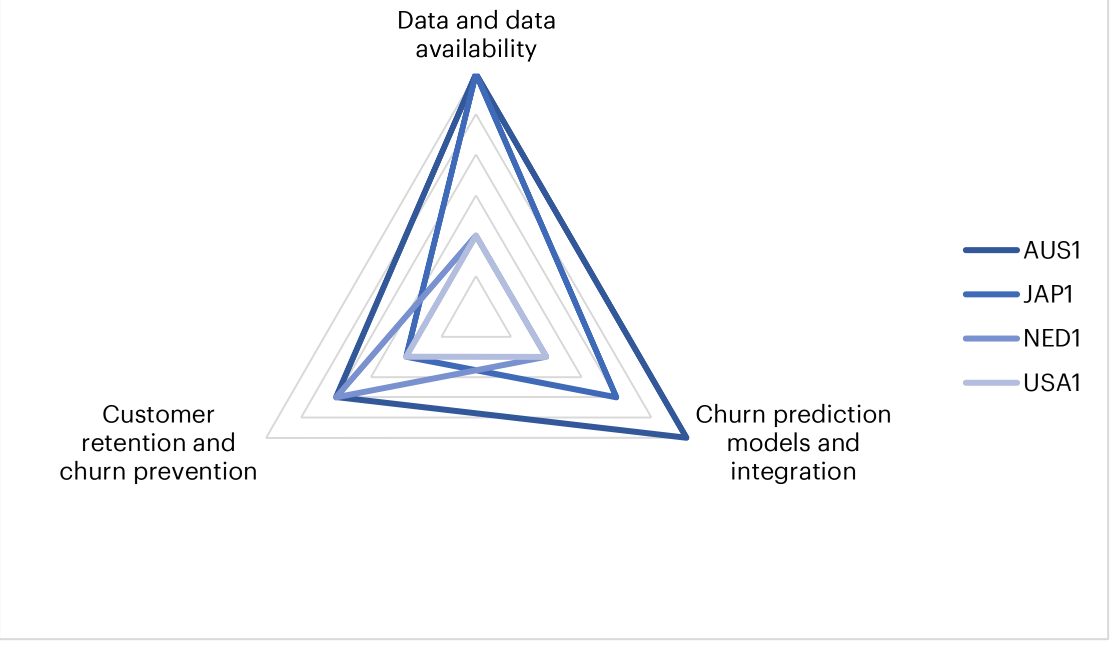


Figure 15: overview network operator performance

Figure 16 shows that all virtual network operators perform high in customer retention and churn prevention even with differences in the second highest performing category.

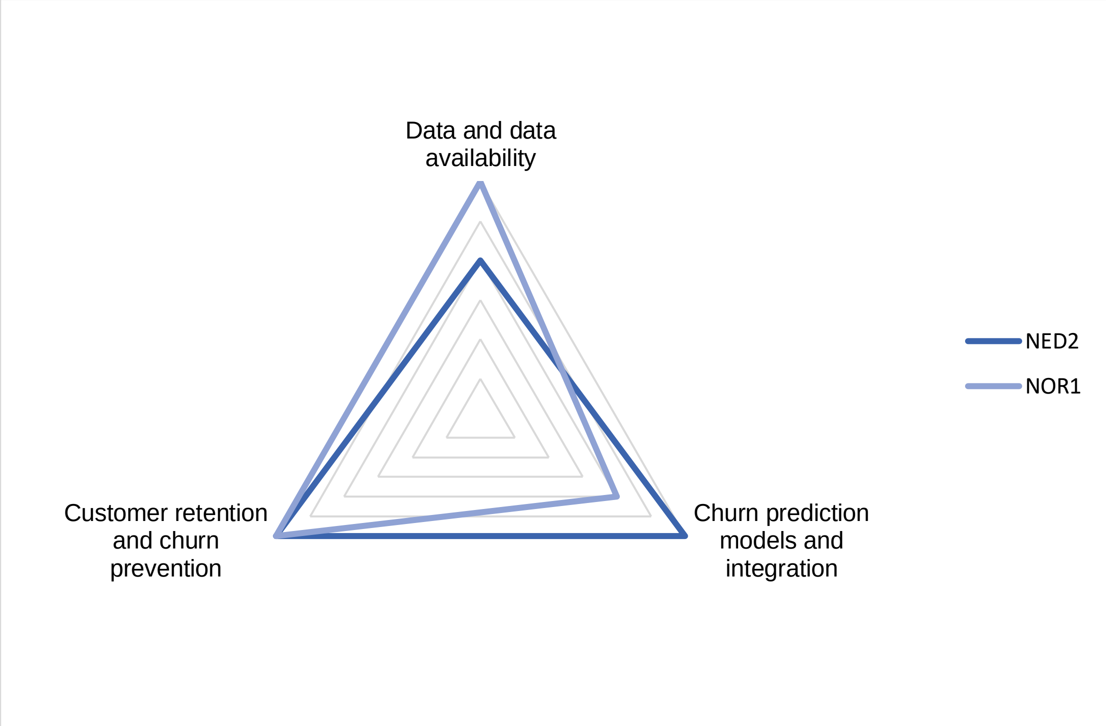


Figure 16: overview virtual network operators' performance

Figure 17 plots the operators in a matrix with data and data availability as the y-axis and churn prediction models and integration as the x-axis. As visible in the figure, the network operators (dark blue) are scattered over the entire plot. The two virtual network (light blue) operators are displayed in the higher quadrant.

An important observation is that there is no operator in the quadrant of (1) low data and availability and (2) high level of churn prediction models and integration.

Figure 17: matrix overview of operators - variant A

Concluding remark

This matrix's observation is logical, since data is necessary to develop any type of machine learning model. Therefore, it is safe to conclude from this matrix that proper data systems are necessary in order to have good churn prediction models and integration.

Figure 18 plots the operators in a matrix with “data and data availability” as the x-axis and “retention and churn prevention” as the y-axis. As visible in the figure, the network operators are again scattered over the entire plot. The two virtual network operators are displayed in the higher quadrant.

An important observation is that both virutal operators are on the right side of the matrix. This indicates that virtual operators are, in this sample, better in retention and churn prevention compared to larger operators.

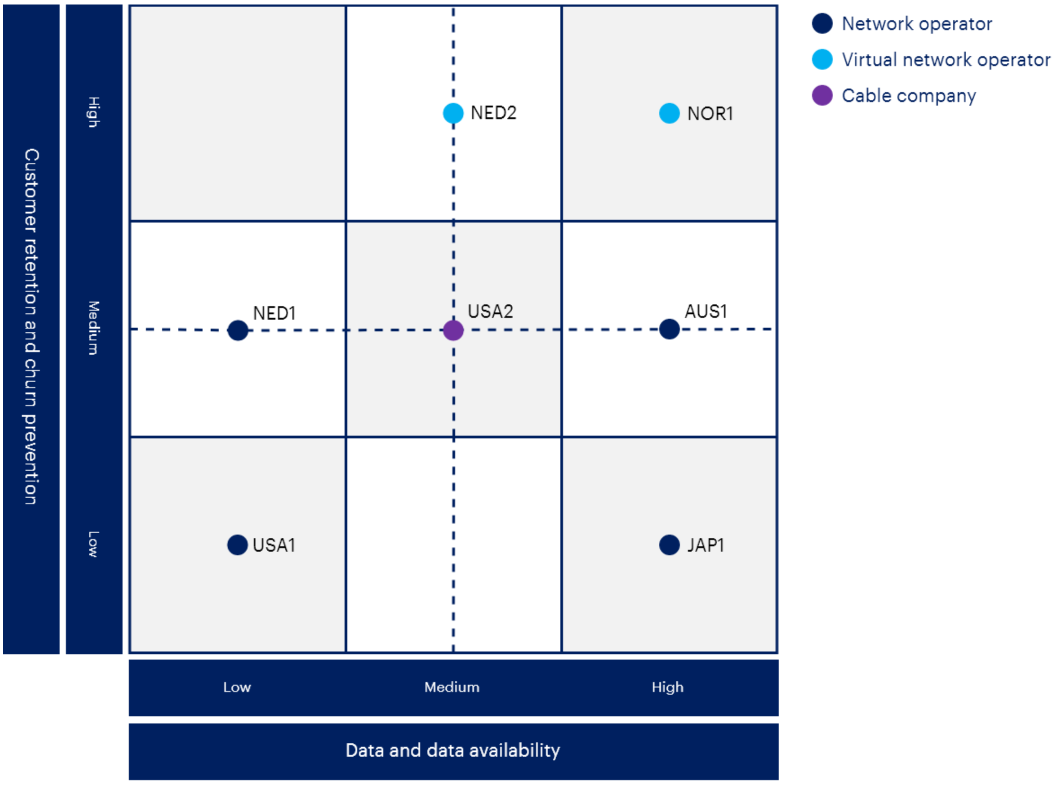


Figure 18: matrix overview of operators - variant B

Concluding remark

Virtual operators seem to perform better in customer retention and churn prevention than non-virtual operators even if their data situation is the same or worse. An explanation for this could be the scale and / or focus of virtual operators. Virtual operators, in general, tailor their services to a specific segment, making it more straightforward to develop effective retention campaigning strategies. Additionally, not having to manage infrastructure allows the virtual operators to fully focus on their customers and product offerings.

Figure 19: matrix overview of operators - variant C

Figure 19 plots the operators in a matrix with “churn prediction models and integration” as the x-axis and “retention and churn prevention” as the y-axis.

An important observation is that operators are split in two groups: the operators that are located in the higher quadrant and the operators that are placed in the lower segment. This indicates that there is a correlation between how wel operators use and integrate models and how well they perform in retention and churn prevention.

Virtual operators seem te perform better compared to larger operators on both axis. The exception is the operator from Austrlia.

Concluding remark

This matrix shows that there is a relationship between the development and integration of churn prediction models and the use of customer retention and churn prevention strategies. Operators that perform well with their churn prediction models and integration of these models in other systems are likely to perform better at customer retention as well.

This might be explained because these operators have a better data situation in the first place, which allows them to use analytics to create better tailored campaigns. Additionally, well created and integrated models allow for additional insights that marketeers can use to create better and (more) personalized retention strategies.

5 Discussion

The research of this thesis originated from the identification that the Dutch telecommunications industry invests heavily in advertising and combination products to contest customer churn but seems to pay little attention to customer churn prediction while, according to literature, telecommunications service providers in other regions do.

The research question derived from this problem statement was: "how the use of customer churn prediction can be accelerated within the Dutch telecommunications industry". This chapter discusses the results of the survey and expert interviews, as well as the answers to the secondary and main research questions.

5.1 Survey discussion

To identify churn drivers specific for the Dutch population a survey was created. The survey asked participants for:

- Demographic information, including gender and age;
- Subscription related information, including type of subscription, monthly costs, contract period, current provider;
- General satisfaction of participants with their mobile subscription and provider, as well as participants' satisfaction with every aspect of a normal Dutch mobile subscription;
- Likeliness that participants will end their mobile subscription after the contract period;
- Subscription aspect that participants find important in their consideration to churn.

5.1.1 Results and implications

The survey showed that there is a medium correlation between subscription satisfaction and provider satisfaction ($\rho = 0{,}575$). Provider satisfaction showed a stronger correlation with churn probability ($\rho = -0{,}522$) than subscription satisfaction ($\rho = -0{,}347$).

The survey also found that the factors with the strongest correlation to churn probability ($\rho > 0{,}396$) also have a strong correlation with satisfaction. These factors include:

- Network reception
- Call quality
- Internet speed
- Mobile application of the provider
- Customer service

As described in the methodology and customer churn chapter, all these factors are quality and technology related satisfaction factors. Some factors, however, only influence subscription and provider satisfaction, in which case the degree of satisfaction acts as a mediator between those variables and churn probability. These factors mostly include economic / financial related factors, including:

- Subscription costs
- Bundle size data
- Bundle size text messages
- Bundle size call minutes
- Rates outside bundle
- Rates outside of the EU

The survey results show that customer satisfaction and churn probability are significantly negatively correlated. This means that low customer satisfaction is a strong driver for churn within The Netherlands, especially how satisfied customers are with the provider itself. The level of satisfaction is correlated with economic / financial related factors. This result can be explained as value being an indicator of customer satisfaction. This value consideration is also in line with some of the expert interviews conducted during this research.

In contrast to economic / financial related factors, quality / technology related factors directly influence customer churn probability. This can be explained as how customers experience the services are a strong indicator of customer churn. This focus on experience is in line with some of the expert interviews conducted during this research.

Reading guide

The results discussed in the discussion that have implications for the main or secondary research questions are highlighted. These implications are later used to answer the main and secondary questions. The first implication for the research questions is highlighted below.

Service value and customer experience are important factors to consider when implementing customer churn prediction models and creating retention strategies.

5.1.2 Research limitations

It is important to acknowledge that the survey only takes the wireless subscription and full churn, as opposed to partial (downgrade or reduced usage) customer churn, in consideration. Most telecommunications service providers also provide residential services including land-line, broadband internet and television, which are not taken in consideration. It is likely that customers might have different churn drivers for residential services. Additionally, the survey does not take partial churn, such as quitting a data plan, in consideration. Including partial churn in the survey might have provided additional insights.

However, the use of wireless services creates an equal baseline, since the introduction of a multitude of residential services might introduce too many variables to be able to get anything meaningful out of the survey analysis.

Regarding the survey population, it is important to note that most of the population is between 18 and 34 years old. This introduces a bias towards younger people. This might be explained by the methods of sharing, since the survey is shared on social media to reach the largest possible population in the given time-frame.

5.2 Expert interview discussion

Literature showed that customer churn prediction is a data mining process. Therefore, this requires data- and business understanding, data, models and proper deployment. Literature studies also identified that actioning, based on the churn prediction results, is as important as the prediction itself. The actioning on churn prediction results refers to retention, which is the act of encouraging repurchase behavior of a customer.

As discussed during the survey results in chapter four, the findings of the literature are simplified into the following three categories:

1. **Data and data availability**
   What data is available on customers and how usable is it?

2. **Churn prediction models and integration**
   Does the provider actively use churn prediction models, what are they capable of and how well are they integrated in business systems?

3. **Customer retention and churn prevention strategies**
   What retention strategies are used and does the provider utilize other strategies to prevent customers from churning?

Levels of performance within these categories are based on the following assumptions:

- The results can be compared between all interviews;
- Scoring is done based on relative performance as interpret by the researcher, given the researcher has adequate knowledge about the topic based on literature study and interviews.

The results of the expert interview will help formulate an answer to the main research question as well as the following secondary questions:

- What techniques are currently utilized by telecommunications provider to reduce customer churn?
- What improvements can be done to increase the effectiveness of the application of customer churn models in the Dutch telecommunications industry?

5.2.1 Results and implications

When analyzing the results of the expert interviews, it can be clearly identified that every operator / provider performs differently in the three main categories. This is also true when comparing operators of the same region. Based on the interviews it seems that Australia, The Netherlands and Norway perform well in most categories. Interviews with experts from Japan and the United States indicated medium performance in all categories. Finally, interviews with another Dutch- and United states-based operator indicated low performance in most categories.

This information rejects the hypothesis that the Dutch providers and operators are lacking behind operators from different regions as derived from the main research question and problem statement. However, it shows that operators and providers from every region need to be assessed separately.

Every operator performs differently on all categories. Therefore, a conclusive answer to "How can the adoption of customer churn prediction be accelerated in the Dutch telecommunication industry?" cannot be given.

However, guidelines to accelerate customer churn prediction can be provided for every operator.

Virtual operators versus major operators

A pattern found in the expert interviews is that virtual operators, apart from Australia and Japan, seem to perform better over all categories compared to larger incumbent operators. These larger operators seem to perform well in both (1) data and data availability and (2) models and integration, but are lacking in (3) retention and churn prevention.

Virtual network operators perform better in customer churn prediction and retention than non-virtual operators.

Other major operators mainly have challenges regarding their data (NED1, USA1, USA2), which limits their ability to build and use churn prediction models and to offer personalized retention packages. Smaller virtual operators (NED2, NOR1) seem to have better organized data sources in general. The better organized data sources allow for better models and can support identifying effective retention strategies that can be linked to model output.

Issues regarding available data limit the ability to build and use churn prediction models. A lack of customer data also limits the ability to offer personalized retention packages.

Operators that have well-organized data sources are more likely to have better churn prediction models and are more likely to identify effective retention strategies.

Data and data availability performance

Providers / operators performing poor in data and data availability have poorly integrated systems and / or a siloed environment limiting the information they can use. Well performing providers / operators have access to multiple data sources on customers, which are well organized and suited for the churn prediction models.

Examples from well performing providers / operators from the expert interviews include:

- Access to 140 data points on its customer, including interactions, usage data, demographics, contract status, current handset and related variables;
- Aggregation of data points into larger data pieces that help identifying types of churners;
- Access to a CRM-system with very detailed customer information;
- Automatic customer opt-in, because of privacy regulations, in order to be able to use customer usage data;
- Access to a data lake with customer data of all departments and enterprise subsidiaries.

Access to multiple data points on customers, including interactions, usage data, demographics, contract status, current handset and related variables, are beneficial for customer churn prediction.

Aggregation of multiple data points helps identification of different types of churners.

Access to data environments, e.g. data lake or detailed CRM-system, is beneficial for customer churn prediction.

Operators limited by privacy regulations can choose to have customers opt-in so that they can use their data for customer churn prediction.

Model and integration performance

Poor performing providers / operators seem to have difficulties building and implementing customer churn prediction models. They either do not have churn prediction models, but instead have a rule-based system based on statistics analysis. Another observation is that they have churn prediction models that are not integrated with other systems which makes them unusable.

Well performing providers have models that provide additional insights besides churn probability that helps marketeers with creating retention strategies and / or have churn prediction models that are well integrated in other systems.

Examples from well performing providers / operators from the expert interviews include:

- Usage of models that provides a churn probability, churn reason based on predefined churn types and accuracy score;
- The scoring of every customer by churn prediction models;
- The integration of churn prediction models in a CRM-system by use of business rules;
- Usage of multiple models to identify churners and to cluster them based on characteristics;
- The integration of model output with campaigning systems.

Churn prediction models should be integrated in other systems, e.g. campaigning systems and CRM systems, to be used effectively.

In order to assist marketeers, churn prediction models should provide additional insights besides a churn probability such as churn driver or churn types.

Retention and churn prevention

Poor performing operators have either no or ineffective retention strategies. Some operators are mainly focusing on customer acquisition over retention. Well performing operators have multiple targeted retention strategies and are constantly trying to introduce new strategies, which are tested by using pilots. Moreover, well performing operators have additional strategies to reduce churn besides retention offerings.

Examples from well performing operators from the expert interviews include:

- Usage of multiple strategies to reduce customer churn, including quad play offerings, service improvements, technical improvements and one-to-one retention campaigning;
- Automatic targeting of potential churners based on model output when a suitable retention campaign is active. This is achieved by business rules in the campaigning system;
- Identification of blind spots by marketing teams to create appropriate retention campaigns;
- Usage of different churn probability thresholds for retention strategies;
- Emphasis on testing of retention strategies by running pilots;
- In- and outbound communication with customers to reduce customer churn.

Operators should use multiple strategies to reduce and prevent customer churn, including in- and outbound communication, retention offerings and product offerings such as quadruple play.

Active identification of new types of churners and their motivations can help creating appropriate retention campaigns.

Testing and running pilots for campaigns can help to create appropriate retention campaigns for churners.

Automatic selection of the right retention strategies based on churn prediction model output can be achieved by using business rules.

5.2.2 Research limitations

The way experts are selected might have introduced some bias, since all experts are either Accenture consultants / data scientists working on internal projects at a client of Accenture, or they are Accenture client's employees with roles such as data scientists or marketeer. However, due to the global nature and field of operation of Accenture, it allowed for a global perspective on the matter. This adds additional insights over solely regional interviews.

Due to confidentiality requirements the translations are re-written into a format excluding enterprise and participant names. The downside of this method is that interview information might get lost in the translation. This translation was done based on the sentences of the transcription to ensure objectivity. However, the key information gathered from the translation and transcription (included into Appendix 5: expert interview results) is an interpretation of the provided information by the interviewee and might introduce researcher's biases.

5.3 Research discussion

The main research question of this study is “How can the adoption of customer churn prediction be accelerated in the Dutch telecommunication industry?”. This section of the discussion will try to give an answer to this research questions by using the information gathered in this research.

Globally, the current level of customer churn prediction implementations varies from operator to operator, which is also true for the Netherlands. Therefore, there is no conclusive answer for the Dutch telecommunications industry.

The expert interview showed that most operators face challenges regarding the creation, implementation and / or use of churn prediction models. Operators will need to overcome these challenges to adopt customer churn prediction successfully and use it effectively.

However, smaller virtual network operators seem to perform better in customer churn prediction and retention than non-virtual operators. This seems to origin from smaller virtual operators having better organized data sources.

This can have a multitude of reasons e.g. virtual operators are, in general, newer and therefore are less likely to have technical / design debt. In addition, virtual operators do not have to manage and maintain infrastructure and can exclusively focus on their customers and focused customer segments. Finally, virtual operators are less established than the main large operators, forcing them differentiate and provide good value to the customer in order to keep afloat.

Nonetheless, operators need to assess their current capabilities regarding customer data, churn prediction models, integration between models and other systems and retention strategies of which all are necessary to effectively use customer churn prediction.

Concluding remark

Analysis of the expert interviews shows that (1) availability of usable customer data and (2) the translation from the churn prediction results to actionable retention strategies are the major obstacles operators face when implementing customer churn prediction.

These main obstacles need to be over won in order to successfully implement customer churn prediction and ultimately accelerate the adoption of customer churn prediction within the telecommunications industry.

Identifying the best performing operators from the expert interviews, the following key information regarding the use of customer churn prediction was formulated:

1. Operators that have well-organized data sources are more likely to have better churn prediction models and are more likely to identify effective retention strategies;
2. Access to multiple data points on customers, including customer interaction, usage data, demographics, contract status, current handset and related variables, are beneficial for customer churn prediction;
3. Aggregation of multiple data points helps identification of different types of churners;
4. Access to a data environment, e.g. data lake or detailed CRM-system, is beneficial for customer churn prediction;
5. Operators limited by privacy regulations can choose to have customers opt-in in order to use their usage data for customer churn prediction;
6. Churn prediction models should be integrated (by e.g. business rules) in other systems, for instance campaigning systems and CRM-systems, in order to be used effectively;
7. Well performing churn prediction models provide additional insights besides a churn probability, such as churn drivers or churn types, in order to assist marketeers;
8. Operators should use multiple strategies to reduce and prevent customer churn, including in and outbound communications, retention offerings and product offerings such as quadruple play;
9. Active identification of new types of churners and their motivations can help creating appropriate retention campaigns for customers;
10. Testing and running pilots for campaigns can help to create appropriate retention campaigns for churners;
11. Automatic selection of the right retention strategies based on churn prediction model output can be achieved by using business rules.

These statements, key findings of the expert interviews provide insights on how the two main obstacles in implementing customer churn prediction could be tackled. The key information from the expert interviews is structured in **Fout! Verwijzingsbron niet gevonden.**.

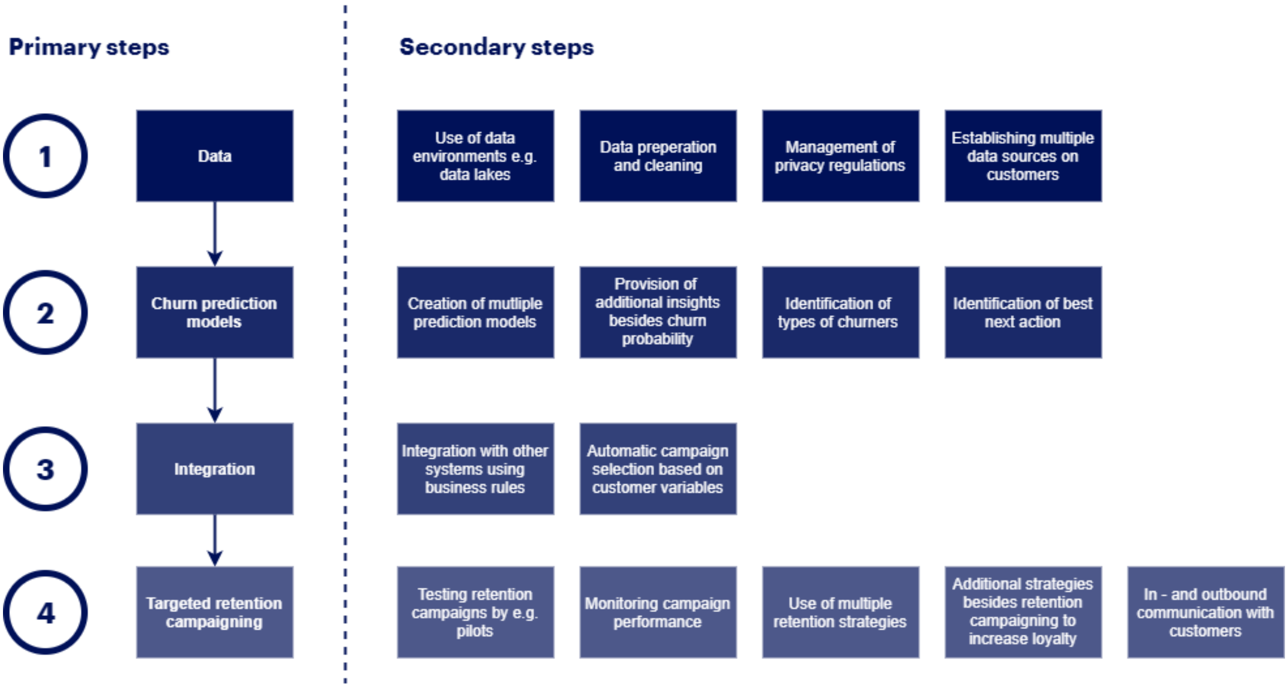


Figure 20: steps to fully utilize customer churn prediction based on expert interviews

This figure shows a model that contains the necessary steps to fully utilize and implement customer churn prediction. These steps are based on the CRISP-DM model and result from the expert interviews. The first step is the acquisition of enough usable data to do analysis and train churn prediction models. The second step is the creation of churn prediction models. Different types of models can be created in this step to fulfill different roles for the retention process later on e.g. churn probability, types of churners and best suitable retention campaign. The third step is the integration of the churn prediction models with other systems, such as CRM-systems, which allows the prediction results to be used and combined with business logic e.g. customer value evaluation.
The last, arguably most important step, is the development and execution of effective campaigns to keep the identified customers from churning. In this final step it is important to consider which types of customers are churning and what it takes, in terms of value, to retain them as well as whether customers are worth it to retain.

The figure also shows the secondary steps necessary in every primary step. These secondary steps indicate best practices and important considerations based on the experts interviews that operators should try to focus on when implementing customer churn prediction.

Concluding remark

According to the survey, when customer churn prediction is implemented in the marketing and retention strategies, Dutch operators should focus on (1) customer satisfaction in relationship to the operator themselves, (2) service quality and (3) service value.

Secondly, not mentioned in this discussion, it is important to understand that customer churn prediction and customer retention is not the holy grail when it comes to reducing customer churn. Some of the experts clearly have stated that customer churn prediction and customer retention are just some of the tools marketeers can use to reduce customer churn. Therefore, customer churn prediction should be used alongside other marketing strategies e.g. quad play in order to increase stickiness. Additionally, operators should focus on providing good value services and quality to increase customer satisfaction and to build loyalty.

6 Conclusion & Further research

This is the concluding section of the thesis. This section first formulates conclusive answers to the secondary questions and provides a short explanation on how the adoption of customer churn prediction can be accelerated with some meaningful considerations. The chapter ends with interesting topics for further research.

6.1 Secondary questions

In order to answer the main research questions, the following secondary questions need to be answered first. The answers provided for the secondary questions are in a condensed representation. The full representation can be found in the relevant chapters of each secondary question.

6.1.1 First secondary question

Question: “What techniques are currently utilized by telecommunications providers to reduce customer churn?”

Based on the expert interviews the following methods of churn reduction are identified:

- Use of exclusive content
- Bundling of service products (triple- and quad play)
- Service improvements
- Technical improvements
- Focus on customer experience
- Targeted retention packages / targeted offers
- Retention call center

More information regarding these methods can be found in the chapter “Expert interview results” of the Research results chapter.

6.1.2 Second secondary question

Question: “What is the current state of art in customer churn prediction?”

According to scientific literature the current state of art in customer churn prediction is the use of the CRISP-DM process to create and implement a churn prediction model which uses either a single classifier or a combination of supervised and / or unsupervised classifiers.

An important note is that the state of art of customer churn prediction is based on the used machine learning classifiers and related methods.

More information regarding customer churn prediction, classifiers, CRISP-DM and the underlying processes can be found in the chapter “Customer Churn Prediction” of the literature study.

6.1.3 Third secondary question

Question: “What is the status of customer churn prediction in the telecommunication industry?”

According to the expert interviews, the status of customer churn prediction varies within the telecommunications industry. Smaller virtual operators seem to be ahead compared to larger operators regarding the use and implementation of customer churn prediction.

More information regarding these methods can be found in the chapter “Expert interview results” of the research results chapter.

6.1.4 Fourth secondary question

Question: “What improvements can be done to increase the effectiveness of the application of customer churn models in the Dutch telecommunication industry?”

According to the expert interviews, the application of customer churn models in the Dutch telecommunications industry varies per operator. Therefore, operators require different improvements based on their current performance. According to the best performing operators from the expert interviews, operators are required to have the following prerequisites in order for them to be able to effectively use customer churn prediction:

1. Have clean and sufficient customer related data;
2. Have prediction models that provide additional insights next to a churn probability, such as churn drivers or customer segment;
3. Integrate between churn prediction models and CRM-systems and / or campaigning systems;
4. Be able to track and test retention campaigns in order to find effective retention campaigns for different types of churners.

More information can be found in the chapter “Expert interview results” and the literature review regarding customer churn and customer retention.

6.2 Main research conclusion

This research's aim was to find an answer to the research question "How can the adoption of customer churn prediction be accelerated in the Dutch telecommunication industry?". The adoption of customer churn prediction by telecommunications operators has many benefits. It enables the use of targeted retention campaigns and can provide additional insights that marketeers can use to improve their customer relationship. This does not only reduce costs significantly, since retention is several times less expensive than customer acquisition, but, besides other benefits, it also builds customer loyalty by proactively resolving customer's dissatisfaction, which reduces customer churn in the long run.

The idea of this study was to identify the main obstacles that operators face when implementing customer churn prediction and to provide best practices to ease / accelerate the adoption of customer churn prediction in The Netherlands.

The study identified that operators encounter difficulties when implementing customer churn prediction. According to this study, the two main obstacles telecommunications face are:

1. Lack of sufficient and high quality data on customers;
2. A knowledge / experience gap in translating prediction results into real-world retention campaigns.

This study provides a model based, on the insights of experts, that illustrates essential ordered steps to successfully implement customer churn prediction, namely:

1. Obtaining usable customer data;
2. Modeling of relevant models;
3. Integration of models in business systems;
4. Effective retaining of identified churners.

Mastering all these steps successively supports operators with implementing customer churn prediction effectively. The Dutch operators interviewed during this study varied widely in their maturity, both being at the opposite side of the spectrum. Also, the other operators discussed during this study differ widely. Therefore, operators should self-assess their current capabilities to identify which step they are currently struggling with. Every step of the model builds on the previous one, so operators should build up from the first step where they encounter challenges.

Diving into the Dutch telecommunications industry, the study identified that dissatisfaction regarding service quality and service value are strong churn drivers and Dutch operators should focus on managing these two drivers to reduce customers churn effectively.

Accelerating the use of customer churn prediction in the Dutch telecommunications industry can provide many benefits. This study provides a four-step model that helps operators to implement customer churn and to maneuver identified pitfalls, easing the implementation of customer churn prediction and thus accelerating customer churn prediction adoption.

An important final note is that customer churn prediction in combination with retention marketing is just a part of the solution to customer churn. Likewise, to reduce customer churn operators will need to work on their reputation, provide good quality and value, solve customer complaints and communicate clearly to customers.

6.3 Further research

Further research is needed to investigate how operators should tackle each of the steps described in the conclusion of the research question. This should be done in the context of the operator themselves e.g. by use of case studies.

Additionally, the study uses interviews from operators within multiple geographical regions. These interviews are compared to the Dutch telecommunications operators' interviews. Within the same geographical regions, other operators could be interviewed to identify whether there are any disparities between the findings of this study and theirs.

Furthermore, research could be done to identify how other geographical regions besides Australia, Japan, Norway and the United States compare to each other. To illustrate, similar comparative studies can look at developing regions or regions that are predominantly pre-paid service oriented.

Also, more research is needed to close the gap between churn prediction and retention strategies. Most of the interviewed operators seem to find it challenging to utilize churn prediction results effectively in their retention strategies.

Finally, during one of the expert interviews an interviewee identified that the Australian market is transforming from a post-paid to pre-paid market. This transformation could be an interesting topic for further research, since most markets transform from pre-paid to post-paid markets.

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Appendix

The appendix contains all additional information used to conducts this research.

The appendix contains:

1. Survey questions
2. Survey results
3. Expert interview research protocol/ template
4. Expert interview results

Appendix 1: survey questions

Ref.	Identifier	Question	Coding
1	D1	What is your age?	1 = Younger than 18 years old 2 = 18 - 24 years old 3 = 25 - 34 years old 4 = 35 - 44 years old 5 = 45 - 54 years old 6 = 55 - 64 years old oud 8 = Older than 75 years old
2	D2	What is your gender?	1 = Male 2 = Female 3 = Prefer not to say
3	SUB1	What type of mobile subscription do you have?	1 = Pre-paid 2 = Post-paid (12 months) 3 = Post-paid (24 months) 4 = Post-paid (monthly)
4	SUB2	Did you receive a device with your current mobile subscription?	1 = Yes, I received a device with my subscription 2 = No, I have a sim-only subscription
5	SUB3	Which mobile carrier do you have? - Selected Choice	1 = KPN 2 = Vodafone 3 = T-Mobile 4 = Tele2 5 = Another carrier
6	SUB4	For how long have you been using your current mobile carrier? (contiguous subscriptions, if applicable)	1 = 6 months or less 2 = 6 to 12 months 3 = 12 to 18 months 4 = 18 to 24 months 5 = 24 months or more
7	SUB5	What does your mobile subscription consist of? (Multiple answers possible)	1 = Telephony 2 = Text messages 3 = Data
8	SUB6	How much do you pay for your mobile subscription each month?	1 = Less than €10 2 = €10 - €19 3 = €20 - €29 4 = €30 - €39 5 = €40 - €49 6 = More than €50
9	INDEP1	How satisfied are you with your current mobile subscription?	1 = Extremely satisfied 2 = Moderately satisfied 3 = Slightly satisfied 4 = Neither satisfied nor dissatisfied 5 = Slightly dissatisfied 6 = Moderately dissatisfied 7 = Extremely dissatisfied

10	INDEP2	How satisfied are you with your current mobile carrier?	1 = Extremely satisfied 2 = Moderately satisfied 3 = Slightly satisfied 4 = Neither satisfied nor dissatisfied 5 = Slightly dissatisfied 6 = Moderately dissatisfied 7 = Extremely dissatisfied
11	SAT1	How satisfied are you with your current mobile subscription/carrier? - Monthly subscription costs	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
12	SAT2	How satisfied are you with your current mobile subscription/carrier? - Bundle size data	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
13	SAT3	How satisfied are you with your current mobile subscription/carrier? - Bundle size text messages	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
14	SAT4	How satisfied are you with your current mobile subscription/carrier? - Bundle size telephony	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
15	SAT5	How satisfied are you with your current mobile subscription/carrier? - International call minutes	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
16	SAT6	How satisfied are you with your current mobile subscription/carrier? - Rates outside bundle	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
17	SAT7	How satisfied are you with your current mobile subscription/carrier? - Rates outside bundle abroad	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied

18	SAT8	How satisfied are you with your current mobile subscription/carrier? - Rates outside the EU	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
19	SAT9	How satisfied are you with your current mobile subscription/carrier? - Network reception	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
20	SAT10	How satisfied are you with your current mobile subscription/carrier? - Network reception abroad	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
21	SAT11	How satisfied are you with your current mobile subscription/carrier? - Call quality	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
22	SAT12	How satisfied are you with your current mobile subscription/carrier? - Internet speed	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
23	SAT13	How satisfied are you with your current mobile subscription/carrier? - Mobile app from the carrier	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
24	SAT14	How satisfied are you with your current mobile subscription/carrier? - Cancellation period	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
25	SAT15	How satisfied are you with your current mobile subscription/carrier? - Extra services from provider, for example: Spotify	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied

26	SAT16	How satisfied are you with your current mobile subscription/carrier? - Benefits for families, for example: family discounts	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
27	SAT17	How satisfied are you with your current mobile subscription/carrier? - Customer service	1 = Very satisfied 2 = Satisfied 3 = Neither satisfied nor dissatisfied 4 = Dissatisfied 5 = Very dissatisfied
28	U1	How many call minutes of your mobile subscription do you use?	1 = Very many 2 = Many 3 = Not many, not a few 4 = A few 5 = Very few 0 = Does not apply
29	U2	How many text messages of your mobile subscription do you use?	1 = Very many 2 = Many 3 = Not many, not a few 4 = A few 5 = Very few 0 = Does not apply
30	U3	How much data of your mobile subscription do you use?	1 = Very many 2 = Many 3 = Not many, not a few 4 = A few 5 = Very few 0 = Does not apply
31	DEP1	How likely is it that you will switch mobile carrier at the end of your contract period?	1 = Extremely likely 2 = Moderately likely 3 = Slightly likely 4 = Neither likely nor unlikely 5 = Slightly unlikely 6 = Moderately unlikely 7 = Extremely unlikely
32	IMP1	What are important motivations for you to switch mobile carrier? - Monthly costs	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
33	IMP2	What are important motivations for you to switch mobile carrier? - Bundle size telephony	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant

34	IMP3	What are important motivations for you to switch mobile carrier? - Bundle size text messages	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
35	IMP4	What are important motivations for you to switch mobile carrier? - Bundle size data	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
36	IMP5	What are important motivations for you to switch mobile carrier? - International call minutes	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
37	IMP6	What are important motivations for you to switch mobile carrier? - Rates outside bundle	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
38	IMP7	What are important motivations for you to switch mobile carrier? - Rates outside bundle abroad	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
39	IMP8	What are important motivations for you to switch mobile carrier? - Rates outside of the EU	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
40	IMP9	What are important motivations for you to switch mobile carrier? - Network reception	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
41	IMP10	What are important motivations for you to switch mobile carrier? - Network reception abroad	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant

42	IMP11	What are important motivations for you to switch mobile carrier? - Call quality	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
43	IMP12	What are important motivations for you to switch mobile carrier? - Internet speed	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
44	IMP13	What are important motivations for you to switch mobile carrier? - Mobile App from carrier	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
45	IMP14	What are important motivations for you to switch mobile carrier? - Termination period	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 1 5 = Very unimportant
46	IMP15	What are important motivations for you to switch mobile carrier? - Customer service	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
47	IMP16	What are important motivations for you to switch mobile carrier? - Additional benefits of other carriers, for example: Spotify	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
48	IMP17	What are important motivations for you to switch mobile carrier? - Benefits for families, for example: family discounts	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant
49	IMP18	What are important motivations for you to switch mobile carrier? - Reviews of customers	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant

50	IMP19	What are important motivations for you to switch mobile carrier? - New mobile phone	1 = Very important 2 = Important 3 = Neither important nor unimportant 4 = Unimportant 5 = Very unimportant

Appendix 2: survey responses
Source: https://ql.tc/0iyq1c

Appendix 3: survey results

Table 19: correlation matrix - satisfaction and churn probability

		Subscription satisfaction	Provider satisfaction	Churn probability
Subscription satisfaction	Spearman's rho	—		
	p-value	—		
Provider satisfaction	Spearman's rho	0.575 ***	—	
	p-value	< .001	—	
Churn probability	Spearman's rho	-0.347 ***	-0.522 ***	—
	p-value	<.001	<.001	—

Note. * p < .05, ** p < .01, *** p < .001

Table 20: correlation matrix - usage, satisfaction and churn probability

		Subscription satisfaction	Provider satisfaction	Churn probability
Usage: call minutes	Spearman's rho	0.183	0.041	-0.028
	p-value	0.062	0.683	0.778
Usage: text messages	Spearman's rho	0.004	-0.214 *	0.124
	p-value	0.968	0.029	0.209
Usage: data	Spearman's rho	-0.325 ***	-0.257 **	0.038
	p-value	<.001	0.008	0.699

Note. * p < .05, ** p < .01, *** p < .001

Table 21: correlation matrix - satisfaction factors, subscription satisfaction, provider satisfaction and churn probability

		Subscription satisfaction	Provider satisfaction	Churn probability
Subscription costs	Spearman's rho	0.365 ***	0.284 **	-0.161
	p-value	< .001	0.003	0.100
Bundle size: data	Spearman's rho	0.509 ***	0.256 **	-0.136
	p-value	<.001	0.010	0.171
Bundle size: text messages	Spearman's rho	0.175	0.316 **	-0.188
	p-value	0.073	0.001	0.233
Bundle size: call minutes	Spearman's rho	0.156	0.312 **	-0.114
	p-value	0.113	0.001	0.246
International call minutes	Spearman's rho	0.186	0.197 *	-0.199 *
	p-value	0.057	0.046	0.042
Rates outside bundle	Spearman's rho	0.132	0.238 *	-0.078
	p-value	0.179	0.015	0.428
Rates outside bundle abroad	Spearman's rho	0.155	0.159	0.004
	p-value	0.115	0.110	0.971
Rates outside of the EU	Spearman's rho	0.196 *	0.130	-0.125
	p-value	0.045	0.189	0.203
Network reception	Spearman's rho	0.402 ***	0.491 ***	-0.457 ***
	p-value	<0.001	<.001	<.001
Network reception abroad	Spearman's rho	0.218 *	0.228 *	-0.403 ***
	p-value	0.027	0.021	<.001

		Subscription satisfaction	Provider satisfaction	Churn probability
Call quality	Spearman's rho	0.438 ***	0.515 ***	-0.434 ***
	p-value	<.001	<.001	<.001
Internet speed	Spearman's rho	0.242 *	0.424 ***	-0.396 ***
	p-value	0.013	<.001	<.001
Mobile application of provider	Spearman's rho	0.327 ***	0.410 ***	-0.403 ***
	p-value	<.001	<.001	<.001
Contract termination period	Spearman's rho	0.244 *	0.391 ***	-0.209 *
	p-value	0.012	<.001	0.032
Extra services from provider	Spearman's rho	0.222 *	0.267 **	-0.286 **
	p-value	0.023	0.006	0.003
Family benefits	Spearman's rho	0.169	0.255 *	--0.275 **
	p-value	0.093	0.011	0.006
Customer service	Spearman's rho	0.252 **	0.546 ***	-0.432 ***
	p-value	0.010	<.001	<0.001

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 4: expert interview research protocol

Currently, for my master's degree, I am working on a study related to customer churn prediction in the telecommunication industry, which is the early identification of individual customers that are about to switch telco. To get a baseline, I would like to verify if telecommunication providers are able to predict churning customers and retain them. By answering these questions, would help me greatly in my studies, and additionally the identification of new opportunities to research.

Confidentiality Agreement

I agree that the interview is **recorded***	
I want to have my **name anonymized****	
I want to have my **employer**/ business **anonymized*****	
I want to have the entire **interview anonymized******	

*the recording will not be shared with 3rd parties and will **only** be used to make a transcription for research purposes for this specific research. The recordings are kept for a period the university deems necessary.
**the name of the interviewee will not be mentioned in the final paper.
***the name of the company will not be mentioned in the final paper.
**** all identifiable information is removed from the final transcription and won't be used in the final paper.

This interview will be conducted in a **semi-structured** format. Further questions will be askes based upon the answers provided for the structured questions.

Estimated duration: **30 - 45 minutes**

Information

Interviewer	S.C.W. Kievit
Interviewee name	
Interviewee company/client	
Interviewee role/ expertise	

Region:

……………………………………………………………………………………………………..

Interviewee background:

……………………………………………………………………………………………………..

Interviewee specializations:

……………………………………………………………………………………………………..

Themes

1. Market – number of players, rivalry, market maturity
2. Data availability – data systems, information on customers
3. Churn prediction – use of churn prediction models, integration with systems
4. Churn prevention – retention, campaigning

Pre-defined Questions

1. Is your company / client applying retention strategies to retain consumers?

If no retention strategies are applied, explain why. For the following question consider what kind of retention strategies you would apply.

2. What kind of retention strategies are applied?
3. Are these retention strategies considered effective at retaining customers?
4. Are these retention strategies considered cost effective?
5. Would you consider these retention strategies pro-active and why?
6. Do you believe pro- or re-active retention strategies are more effective and why?
7. What kind of information is necessary to be able to effectively retain a customer?
8. What kind of actions are necessary to be able to effectively retain a customer?
9. Are all customers that are about to churn retained or are there business rules in place? If so, what kind of business rules are in place and how are they enforced?
10. At what point are you aware that a customer is about to churn?
11. How many customer churns are prevented?
12. What happens if a customer is about to churn?
13. Are you able to predict which customer is about to churn?
14. How are you predicting customer churn?
15. Do you feel it is beneficial to predict customer churn and why?
16. If your company/ client is not able to predict customer churn
17. What prevents you from predicting customer churn?
18. If your company/ client can predict customer churn
19. What were the biggest challenges during the realization of churn prediction?
20. What information should be provided to effectively retain a predicted customer?

Appendix 5: expert interview results

The results of the expert interviews do not include transcriptions due to confidentiality requirements. The information extracted from the expert interviews is re-written in a format without the use of participant's names or client/ employer.

The Netherlands – NED1

Participant M has 8 years of professional work experience in the telecommunications industry and is specialized in lean six sigma and analytics. In these years the participant did projects for a major Dutch operator.

The participant indicated that churn prediction is a classic problem all telecommunications providers face. The most popular strategy to reduce churn and increase loyalty that is used by Dutch providers is the bundling of services.

To illustrate: customers have land-line, television and broadband internet from the same providers, which is called triple play. The major Dutch operators, e.g. KPN and VodafoneZiggo, offer packages that combine the triple play offerings with wireless services, which is called quadruple play. In most cases providers offer benefits to customers that have all their services at the same provider. Applying this principle is the silver bullet to keep customer loyal and reduce churn.

The participant also explained that there is a duopoly in the Dutch telecommunications market. The two largest incumbents are responsible for 80% of the residential and wireless market combined. However, it is slightly different when focusing on the wireless market, with a combined market share of 60%.

The participant indicated that an internal customer survey revealed that around 30% of the customer churn is based on price, with the believe that they can get a better deal elsewhere. Another 30% churn because they are not satisfied with the quality of the services, e.g. reception, internet speeds and television quality. Just 4% of the customers indicated that they left because the content did not meet their expectations. The participant indicated that the results of such surveys can be deceiving, because many customers are using Netflix instead of television, which indicates that content does matter. The other churners are mostly involuntary churners that leave because of circumstances, for example moving away, passing away or payment issues.

The participant indicated that a retention strategy used by a major telecommunications provider is the use of a safe-desk. This is a specialized department within a call center that focusses on the retainment of customers. In case a customer calls to indicate that he/she is churning, the customer is referred to the safe-desk and a final offer is given in order to keep the customer from leaving.

The problem with this strategy is that the safe-desk has a poor understanding of the customer that is on the other side of the line. Therefore, they do not know if the customer is a defaulter or loyal a customer, which leads to the same treatment for all customers, including customers you might not want to keep.

The participant also indicated that this telecommunications provider is immature regarding customer retention. It is also immature in its use of data and business ruling to serve their customers more personally.

The participant indicated that vendors like Salesforce and Pega systems offer packages that are more mature and can track customer touchpoints to help identify how much a customer had contact, indicating which channels were used, e.g. SMS, WhatsApp, phone, and email.

In the past the participant had worked together with the provider to build customer churn prediction models, but they were very rudimentary. The data points used in these models consisted of how often a customer contacted the service desk. The participant indicated that it is very unlikely that they are using these models in their retention strategy, mostly because they found it difficult to apply in their own strategies.

The participant indicated that the provider had a related problem: they had no idea who their customers were. This is a historical problem, since telecommunications providers used to be multi-service companies with their own departments and their own systems. This makes it hard to integrate data. A lot of data is only useful if it is combined in a useful way. Currently the provider is working on creating a correct customer picture, but this takes a lot of time and effort.

The participant believed that the biggest potential of churn prediction is the effective use of churn prediction models instead of trying to improve the models themselves. For example, using the model output with business rules in order to define how a customer should be served.

The participant also indicated that telecommunications services are becoming more a commodity. However, television is still very important for major telecommunications providers, but customers' watching behavior is changing from television to online streaming services. Exclusive content can play an important role in fighting this. The participant also noted that land-line is slowly disappearing.

Key information

From the interview the following key information is gathered:

a) The most popular strategy to reduce churn and increase loyalty by Dutch operators is to bundle services into one package.
b) Most operators provide triple play offerings, and most major operators provide quadruple play, bundling triple play offerings with mobile services. Operators provide benefits to customers that have all their services with the same operator.
c) The Dutch telecommunications market is a duopoly, with the two major operators having 80% of the market share in the residential marketspace. This is lightly shifted in the wireless segment with having 60% market share
d) Internal customer services can be deceiving, not providing a correct image.
e) Price and quality showed to be strong churn drivers based on internal customer surveys by the Dutch operator.
f) The retention strategy used by the Major Dutch operator is the use of a safe-desk, which is a call center that offers a final retention offer once a customer indicates that he/she will churn.
g) The safe-desk strategy has no clear indication of what customer they are dealing with, therefore providing a generic offer to every churner, including defaulters.
h) The Dutch operator is immature regarding their retention strategies and its ability to serve customers personally.
i) Suppliers like Salesforce and Pega Systems can provide more mature solutions regarding personalization than the currently used system by the Dutch operator.
j) The Dutch operator has rudimentary churn prediction models based on frequency of service desk interactions.
k) The Dutch operator finds it difficult to integrate churn prediction models in their retention strategies, because they do not know how.
l) The Dutch operator has issues identifying customers on a customer level, because of poorly integrated systems caused by the multi service nature of larger operators.
m) The Dutch operator is actively working on integrating its data systems
n) The biggest potential of churn prediction is the effective use of the churn prediction model output instead of improving the models themselves
o) An industry trend is that telecommunications services are becoming a commodity.
p) Dutch customers watching behavior is changing, switching to online streaming services. Exclusive content can play an important role in fighting this.

The Netherlands – NED2

Participant K has 13 years of work experience at one of the telecommunications operators in The Netherlands. The participant's main expertise is retention marketing. The participant has been responsible for retention in the wireless / mobile as well as the residential telecommunications services of the consumer segment. The participant also has experience in digital marketing, which includes the use of machine learning and data-driven marketing.

The participant indicated that the operator has an extensive set of strategies to retain churners. The operator has multiple models and churn prediction models. The models are used to identify customer churn, which varies from target group to product ownership and customer lifetime. These can all be reasons why customers churn, and the operator is trying to find a solution for all identified churn reasons.

1. The participant also mentioned that combining services into complete packages (quadruple play) is a major strategy in reducing customer churn. This strategy is based on the principle of increasing stickiness, since the more products you have the more a hassle it becomes to quit.
2. Additionally, the participant mentioned that they focus on loyalty. They do this by using a customer contact strategy, using newsletters, gifts, satisfaction checks and similar campaigns. The participant mentioned that they do this to ensure the customer feels good about their services.
3. Finally, the participant explained that they use churn prediction models to do targeted campaigns. They do this by identifying if a high churn risk customer should be approached or not, as well as using the prediction to target churners with a retention offer, discount etc. They target customers using clustering based on customer features.

The participant explained that they had churn prediction models back in 2011, and that churn prediction models are nothing new. Churn prediction started in 2011, back then the focus was on customer acquisition, but the business realized that it is not efficient to just attract new customers while customers are leaving. Consequently, this is when churn prediction started. The models over the year have become much smarter since then, however the marketing campaigns and the models were not operating together. The data-driven approach in marketing and campaign teams is something of the last two years. This approach includes the use of data modelling to do improved targeted campaigns as well as more personalized campaigns. This showed a positive trend in the conversion rate. However, the participant added that the models are never finished and can always be further developed.

The participant explained that their marketing teams are currently in the transition from marketing as a gut feeling approach to a more data-driven approach, which is challenging due to the different natures of both approaches. In the new approach marketeers must constantly verify their decisions with data.

The participant explained that the data used in the churn prediction models is personal variables, which include: demographic information, agreement information, product ownership, customer lifetime and customer touchpoints. As well as tracking customer behavior in their online environment e.g. service pages. However, data is limited because you need an opt-in in order to use customers personal information, which the operator is not actively pursuing.

The participant emphasized that some information can be interpreted from the available data sources e.g. the invoice. The participant explained that they can legally read till the first page of the customer's invoice. Thanks to the invoice, it is not necessary to have access to a customer's usage data to identify if a customer is constantly outside of the bundle, since these costs are included in the invoice. However, not everything can be easily interpreted, which limits the ability to serve customers on some aspects e.g. international costs. This limitation can be relieved by asking customers to opt-in as described in the GDPR. The participant also emphasized that it is important that you have relevant, enough and correct data.

The participant notes that the prediction models are used for out-bound campaigns, which are campaigns in which the operator approaches the customers pro-actively.

In most cases this is an offer to lock-in the customer for another contract period. In the mobile market this is a matter of price. However, in residential services this is not the case. The participant explained that in residential services, quality and carefreeness are much more important.

Therefore, the campaigns used for residential services are different from the campaigns used in the mobile segment. The residential campaigns include: ensuring a good connection, upgrading hardware and improving Wi-Fi coverage to preventively remove a churn motivation.

The participant explained that this is different from general campaigns, since they are targeted using 1-to-1 communication based on the output of the churn prediction models. Therefore, the campaign is only targeted to customers that are identified as having issues with, for example, their broadband connection.

The participant also explained that such campaigns can also create a wake-up effect, since by asking if customers are still satisfied can encourage them to look at the competitor. Therefore, if a customer is not likely to churn, the customer shouldn't be approached

Targeting is done using business ruling at the marketing side, which uses the output of the churn prediction models. The churn prediction models update daily, identifying customers with a higher than usual churn probability and churn reason. The campaign system updates every morning and if a churner's reason matches a cluster with an active campaign the churner is automatically targeted.

The participant emphasized that this is all based on assumptions. These assumptions are based on qualitative customer research and exit surveys to identify the most important churn reasons.

The participant explained that many campaigns are trigger based, for example calling a customer that is in the process of switching from provider. This call can resolve customer issues and keep a customer from churning.

The participant explained that they are constantly trying to identify new opportunities. This refers to the identification of blind spots, unmatched churners, in their retention campaigns. Campaigns are tracked based on their effectiveness and customer opinion.

The participant emphasized that campaigning is just a part of the solution to customer churn, a big proportion is cross-selling, loyalty and technical improvements e.g. network improvements.

The participant explained that they are currently working on an algorithm that identifies the next best action. This is based on online behavior, customer characteristics etc. The algorithm will try to identify the most suitable offer including service messages as well as promotional offers. Currently, this is done manually and by business ruling with priorities. The business ruling system is custom made.

The participant explained that is it difficult to implement and that they are currently still working on it. This is both a technical and business challenge, since people need to understand the system and it requires a different way of business operations. the algorithm causes the business to lose some control. The algorithm is self-learning and needs some time before it gets better than what we are currently doing. However, even a second-best action can still deliver good results. Therefore, it is hard to justify such an algorithm until it earns itself back.

The participant explained that they are doing pilots. A recent pilot was to profile customers based on their most likely motivation to engage in cross-sell. This required a lot of data, so they had to mail customer with a survey to get to know them better. This had a great response rate.

When asked what the next best thing would be regarding churn and churn prediction the participant responded: that the next best thing would be to make marketing even more personalized. Using machine learning and the algorithm they are currently working on. The participant explained that this is a major challenge due to the difficulties of implementation and the data capabilities. The participant explained that this is easier for start-ups than it is for operators that are existing for a long period, that have a very complex system landscape.

The participant also mentioned that churn has been reduced drastically over the last few years. Combination products and benefits have been the biggest driver in reducing churn. Likewise, the firm has focused on their service quality and network, which further helped decrease churn.

The participant added that it is a difficult and mature industry with a slow growth. Telecommunications services are becoming more a commodity and customer choose to use their own services. The only thing that matters is the broadband connection in the ground. The participant added that you see a global trend that operator is either fully focusing on content like in the united states as well as operators fully focusing on the commodity services providing the best network. The participant added that content creation is difficult in a small country like the Netherlands and a focus on IoT causes competition with, for example, energy suppliers.

The participant ended by emphasizing that it is important to be aware that models are assumptions. Therefore, you never truly know your customer unless the customer tells you.

Key information

From the interview the following key information is gathered:

a) the operator uses multiple strategies to reduce customer churn including: combination products (quadruple play), service improvements (loyalty), technical improvements and one-to-one retention campaigning

b) the operator uses multiple churn prediction models to identify potential churners and cluster churners based on characteristics

c) the operators use personal variables, which include: demographic information, service agreement information, product ownership, customer lifetime and customer touchpoints.

d) due to privacy regulation, the operator cannot use personal data like usage. This requires a customer to opt-in, which is not actively pursued by the operator. Instead, the operator interprets the available data to gain additional insights.

e) Identified churners are automatically selected and targeted, based on characteristics and model output, by business ruling in the operator’s custom marketing system.

f) The operator’s marketing team is trying to identify blind spot to create new relevant retention campaigns.

g) Targeted campaigns can cause a wake-up effect, causing a customer to churn.

h) The operator’s marketing team is actively tracking the effectiveness of their retention campaigns

i) The implementation machine learning algorithms is challenging because it is both a technical as well as a business challenge

j) the operator is currently working on a next best action algorithm, which automatically identifies the next best offer for a customer.

k) the next best developments according to the participant is to make the campaigns even more personalized using machine learning.

l) larger operators have a harder time implementing machine learning, because of a more complex enterprise landscape compared to newer operators.

m) Combination products have been the biggest driver in reducing churn

n) Telecommunications services are becoming more of a commodity, forcing operators to specialize.

o) Focus on content creation is not practical in the Netherlands.

p) The output of a churn prediction models is an assumption of the reality

q) The churn prediction models update daily, identifying customers with a higher than usual churn probability and labels the customer based on characteristics.

r) The campaign system updates every morning and if a churner’s reason matches a cluster with an active campaign the churner is automatically targeted.

Japan – JAP1

Participant S is working in Japan as part of the Applied Intelligence group and has been working with Accenture for the past three years. The participant's background is in neuroscience and used to be a professional researcher. Currently the participant is working for ~~a~~ telecommunications operator in Japan.

The Japanese telecommunications industry has three major players: DoCoMo, Softbank and KDDI. The market itself is very saturated, since every citizen owns a mobile phone of sorts. Therefore, a newly gained customer is the other one's loss. In 2017 they wanted to reduce churn rate of customers, since acquiring a new customer is more expensive than retaining an existing one. The participant indicated that this is true for most developed countries.

The client started a project back in 2017 with the goal to reduce the churn rate within their enterprise. The first step was to identify who is going to churn, thus creating churn prediction models. This project stated with basic analytics e.g. exploratory data analysis. The participant explained that the major players in the Japanese telecommunications industry own many different types of enterprises e.g. ecommerce, healthcare etc. Therefore, have huge amounts of data on their customers which are all managed by a single customer identifier.

The participant indicated that the joint-venture had C-level support and therefore access to a single large data analytics system, which all departments forwarded their data to.

The analysts had access to information from many organizations and covered almost 363 data points just for the mobile services.

The first challenge was to predict who was going to churn, this was done by combining multiple analysis into a single model. This model was expended by predicting who is more likely to churn to another. The model was creating using supervised learning with a target variable.

These models were used to provide churn probability lists for every department that could use these list as they seemed fit with their own retention campaigns.

The participant indicated that the use of churn prediction models did not affect the retention strategies themselves, which stayed unchanged. They were only better targeted to reduce costs.

The participant explained that the departments had issues tracking the effectiveness of their campaigns, because they were sending out direct mails to every potential churner without creating control groups. Once this issue was resolved, the departments found the retention strategies to be ineffective. They would send out coupons to potential churners to renew their contracts and lock them in for another contract period.

The participant told that they can provide long-term churn probability, indicating a potential churner six months in advance. The participant mentioned that this is not always useful, since this is based on consumer behavior and customer would have already decided that he/she would leave. Therefore, the operator is trying to nurture their customers rather than stopping them from churning by sending out coupons, thus investing into customer experience.

The participant found the recent approach better, because larger operators are never able to fight virtual operators on price.

The participant explained that the models they use must be accurate and efficient. Accurate because you do not want to send coupons to low risk customers. Efficient because the model shouldn't take days to train and run if you need it every day. The participant also mentioned a model should be stable, which means the predictor variables shouldn't change too often.

The participant mentioned that contract information was a strong indicator of churn, demographics did not seem to be a good predictor since Japan is a very compact country without much regional differences.

The participant mentioned that it would be helpful to predict what a potential churner wants, but that is very hard based on static data e.g. contract, demographic and asset information. This requires a different type of data, probability customer touchpoints. The participant added, it is easy to understand who is going to churn, but it is very difficult to understand what it takes to stop them from churning.

Key information

From the interview the following key information is gathered:

a) The Japanese telecommunications industry is very mature, with therefore limited growth opportunity.
b) The telecommunications industry has three major players, that have many types of subsidiaries besides telecommunications operators e.g. ecommerce robotics and healthcare.

The operator created a new enterprise to set-up an analytics platform with the goal to reduce churn within the enterprise.

c) The enterprise created a data lake and all departments within the enterprise forwarded their data to the system.
d) The enterprise uses unique customer identification within all the subsidiaries making the data processing easier.
e) The enterprise has access to all customer data of its subsidiaries and departments including more than 363 data points from only the wireless services.
f) The enterprise combines multiple analysis into one churn prediction model of which the results are passed down to the departments.
g) The enterprise departments receive lists with churn prediction results from the joint-venture and are themselves responsible for the retention strategy.
h) The churn prediction models have not changed the retention strategies, which stayed unchanged but better targeting resulted into reduced costs.
i) The operator used to have problems tracking the effectiveness of the retention campaigns, however once this was resolved the use of coupons was found to be ineffective.
j) The enterprise can identify a potential churner six months in advance.
k) Churn prediction are not always useful since identified customers might already decide to leave
l) The operator shifted its focus from sending out coupons to improving the customer experience, because they cannot fight on price with smaller operators.
m) Churn prediction models should be accurate and efficient in order to be used effectively.
n) Demographic information could not be used for churn prediction since there is little differentiation in a small country like Japan.
o) The enterprise find it challenging to identify what a customer wants in order to retain them, based on their current information. In order to do so, the joint-venture requires other data sources such as customer touchpoints.
p) The identification of who is going to churn is easy, compared to the identification of what it takes to retain customers.

Australia – AUS1

Participant MC has 6 years of professional work experience in the telecommunications industry. During this period the participant worked with a wholesale enterprise to work on agile delivery across multiple platforms and technology landscapes. The last two years the participant has been working for one of the largest operators in the Australian market. During these two years the participant worked on their data strategy implementation, including churn and retention.

The participant immediately emphasized that the most important step of churn prediction is what you do once you got a churn likability score.

The participant identified two points of interesting during the participants career in the telecommunications industry. Firstly, there is a gap between how telecommunications operators interpret and action data. Secondly, operators do not treat churn prediction and prevention as two separate entities. The participant explained that identifying that someone will churn is different from trying to prevent someone from churning.

The operator the participant works for was already using churn prediction to predict who had a high probability to churn when the participant started working there. However, the participant helped expending the model by introducing the why into the equation. At this point the operator was using standard retention packages, which they would send to the top percentile of churners. These packages included: discounts and whatever basic retention package was available in the market.

The operator had more than 140 data points on their customers, which they aggregated in around 30 larger pieces to understand in which category a churner fit. The participant explained that they were looking at interaction sentiments, data usage, demographics, contract status, current handset and related variables. They identified 8 churn categories, which the model used to identify churners. The model is predominantly created using supervised learning, since at that time they did not have the capability to do unsupervised learning. The participant also mentioned that they are most likely moving to unsupervised learning now, since they were redoing their big data stack.

The participant mentioned that it is not necessary to include every data point you have, since not all data is relevant for what you want to achieve.

The participant explained that the idea behind the categorization of churners is that it allows the marketing team to come up with interesting propositions for that group specifically in order to retain them.

Currently, this churn reason group is predicted for every customer regardless of their contract duration. The customers will get tagged with a churn reason and accuracy score. The participant explained that this is important, since you want to identify potential churners as early as possible in the customer cycle. This increases the chance of success, since trying a retention strategy at the point a customer is already leaving is almost too late.

The participant explained that knowing that they are going to leave and why allows for decision making. The business can decide what to do, spending money or not. This is handled by business rules in their CRM system.

The participant explained that the problem the operator faces is not the prediction of who and why but turning the churn categories and related stories into retention strategies. The participant explained that the gap is not technical knowledge, but the ability to identify the right approaches to retain customers and that this is a skillset all larger telecommunications operators must work on.

The participant emphasis that how you action churn prediction results and what strategies you use to retain customers or build loyalty to keep them in the long run is the biggest business challenge.

The participant added that if you provide a good service, customers are willing to spend more and stay longer. A metric that can be used to verify if you are providing a good service is NPS. However, NPS is getting disproved as an accurate idea of customer sentiment.

The participant indicated that the next step would have been to run small pilot programs to experiment with retention strategies, using control groups. The provider's implementation of the CRM systems are not yet able to track such experiments.

The participant also mentioned general rules and issues the operator was facing into the process than the previous described status-quo:

- Wrong use of churn prediction scores: targeting the top 20 percentile of churners to try and retain them might not be useful, since they might already decide to leave and there is nothing you can do about it.
- Customer churn prediction boils down to identifying potential churners and determining what it takes to make them stay.
- A retention strategy does not need to make things cheaper, it just needs to add additional valuable
- Churn prediction is standard, but the retention strategy is the next thing to make it effective.
- Customer acquisition is much more expensive than retaining an existing customer, generally.
- It is important to drive the loyalty earlier in the contract period
- Australian market is facing a challenge, where the trend is moving away from post-paid to prepaid subscriptions.

Key information

From the interview the following key information is gathered:

a) The most important step in churn prediction is what you do once you have a churn score.
b) There is a gap between how operators interpret and action data.
c) Operators do not treat churn prediction and retention separately, which they should since churn prediction is the identification of a churner and retention is the prevention of churn.
d) The operator had already created a churn prediction model that could identify churn probability, which is expended by identification of why customers churn based on eight predefined churn categories.
e) The operator used to send standard retention packages to the top percentile churners, including discounts or any retention package was available at the time.
f) The operator has access to more than 140 data points on its customers, including: interaction sentiments, usage data, demographics, contract status, current handset and related variables.
g) The operator aggregated the available data points into 30 bigger data pieces to help identify which type of churner a customer is.
h) The operator identified eight different types of churners, which are used in the churn prediction model.
i) Not all available data is relevant and thus should be included into a model or analysis.
j) The operator uses the predefined types of churners to help the marketing team with developing retention strategies.
k) The operator's churn prediction model identifies the churn probability and most likely churn reason category with an accuracy score for every customer.
l) Identifying a potential churner as early as possible in the customer life cycle increases the chances of success.
m) The operator has business rules in their CRM system that can use the model output and customer related data to decide to retain a customer or not.
n) The challenge the Australian operator faces is the translation from the churner categories into retention strategies, indicating that there is a lack of ability to identify the right approach to retain customers.
o) The biggest business challenge the Australian operators face is how to action churn prediction results and what strategies to use to retain customers or build loyalty.
p) Building loyalty can help to keep customers in the long run
q) The next step would be to run pilot programs to experiment with retention strategies.
r) The operator's current implementation of CRM systems is not yet capable to track pilot programs performance.
s) Wrong use of churn prediction scores: targeting the top 20 percentile of churners to try and retain them might not be useful, since they might already decide to leave and there is nothing you can do about it.
t) A retention strategy does not need to make things cheaper, it just needs to add additional valuable
u) Customer acquisition is much more expensive than retaining an existing customer, generally.
v) Australian market is facing a challenge, where the trend is moving away from post-paid to prepaid subscriptions.
w) Providing a good service increases willingness to pay more and stay for longer.

United States – USA1

Interview churn prediction – US01

Participant R has multiple years of work experience in the United States telecommunications industry. Participant R has fulfilled many high-profile roles within US companies regarding data science, marketing and analytics and is currently data science lead at Accenture.

Participant explained that the business-to-consumer US telecommunications market is very competitive, and the operating enterprises are fighting each other with similar tactics.

The participant explained that US operators are facing issues regarding their data. The data is poorly integrated. This is due to a very siloed environment, a historical issue which occurred due to the mergers and acquisitions. Therefore, a returning problem they face is that their data is not in a useful format. Today's larger operators were growing with millions of customers, but they failed to keep up with the data preparation cycle further increasing the complexity. Due to this situation, operators have a hard time identifying customers and their products. The business systems are also siloed, so the billing system, which received its data directly from the switches, does not share information with other siloes e.g. marketing. The participant indicated that if you combine this information to a customer it will give a lot of information.

The participant indicated that the major operators have not been very good at developing profiles at a customer level. Their current profiles are based on some demographics, but (in some cases) half of their customer database has no appended information. The participant explained that this is an issue, since you have nowhere to start if there is no data at all. The participant explained that most operators do have segmentation models, which try to identify households based on size e.g. 2.2 children and 2 adults.

The participant added to that that in the participant's experience some of these models are created by manual identification of customers data. The participant explained that most telecommunications operators can tell the average spend on a customer level but have difficulties identifying what product is associated to that.

The participant explained that the churn models currently used take spending behavior and customer life time in consideration. The participant added that the churn prediction models are not mature and are mostly a rule-based system based on regression and decision tree analysis on a data environment. During these analyses the operators try to identify churn and churn drivers.

According to the participant the major operators are looking into churn more seriously, focusing on the b2b market. They do this because margins are generally higher in the b2b market compared to the b2c market. The participant added that losing a high value business customer can have major implications on an operator.

The participant explained that customer touch points are a strong indicator of churn. Customer touchpoints referring to the number of calls to a call center. This was especially true in the small business segment. The participant added that when there is no response to their request it is an indication that they are going to leave. Unfortunately, they are not keeping track of such customer touchpoints.

The participant explained that the data situation is not a regulatory issue. Most regulation describe that you cannot use individual personal information. However, if the data is anonymized it can be used without any problems. The participant added that many customers are willing to provide their personal information for a financial incentive. A pilot that provided customers a 5-dollar discount had an 80% positive response rate. The participant emphasized that it is not necessary to have data on a personal level, if you can identify groups of people.

The participant explained that most of the major operators are more concerned with acquisition than retention. Some of the operators have adapted their acquisition strategy to pay all transfer fees and pay everything a customer owes to the competitor.

The participant explained that providers are offering services without a contract, meaning a monthly cancelable contract with flat fees, in order to retain customers.

The participant added that most operators have a churn prevention call center as their retention strategy. Customers are transferred to these call centers if they indicate that they are going to churn. The churn prevention call center will propose the customer a retention offer in order to keep the customer. The participant added that this is not ideal, since the customer already left emotionally. Therefore, it works better when you prevent churn before it happens.

According the participant the ideal situation regarding customer churn prediction, is looking at customer related variables and identify if there are any churn drivers that give a red flag and pro-actively trying to retain a customer. A customer should not be calling an operator, but operators should be truly pro-active trying to reduce churn, because by doing so you also improve customer satisfaction, improve brand recognition and brand scoring. This makes your retention and acquisition more organic.

Key information

From the interview the following key information has been gathered:

a) The United States consumer market is very competitive and focused around customer acquisition.
b) Major operators have poorly integrated systems due to a siloed environment
c) Major operators have difficulties identifying customers and their products/services on a personal level, due to poorly integrated systems
d) Customer related data is incomplete in almost half of the cases
e) Customer information is poorly shared between departments
f) Customers are willing to opt-in when provided a financial incentive.
g) Operators create rule-based systems based on analysis of their data environment
h) Models take customer lifetime and spending as variables
i) Churn prediction models are immature
j) Churn analysis uses regression and decision trees to identify churn drivers.
k) Major operators are focusing more on retention in the business environment
l) Major operators use churn prevention call centers, that do a retention offer once the customer call to end their relationship. According to the participant this is ineffective, since the customer already left emotionally at this point.
m) Actively trying to reduce customer churn improves customer satisfaction, thus improves brand recognition and brand scoring.
n) The ideal situation would be: looking at customer related variables and identify if there are any churn drivers that give a red flag and pro-actively trying to retain a customer.
o) Us operators are shifting to providing monthly flat-rated subscription besides their standard 12-24-month offerings.

United States – USA2

Participant R has been working for Accenture applied intelligence for the past 8 years. During this period the participant focused on the comms, media and technology industries (CMT). Most of the participant's experience is in the telecommunications field, but the participant also did media and high-tech related projects. The participant's focus in the telecommunications industry has been on video analytics, television services and online streaming products. During the participant's career the participant observer the transformation from the linear television with a set-up box to IPTV and finally online streaming and the challenge of Netflix, YouTube and Hulu of which churn is a big part.

The participant explain that the US market consists of two groups of big players: Telecommunications operators e.g. AT&T and Verizon, and cable companies e.g. comcast and Charter.

Before the FCC regulation of 1996 there was no competition between the two groups of players. The regulation stated that cable companies can provide phone and internet services besides there cable television and telecommunications operators can provide television products. Currently, both types of players seem very similar providing a triple play offering. Triple play is the offering of a package with television, internet and phone. Telecommunications operators can offer an additional wireless service on top of triple play, which is called quadruple play. However, the participant stated that this is not very popular in the United States. The participant added that some cable companies are also expanding into providing wireless services (from now on both will be referred to as operators).

The participant explained that internet companies like YouTube are starting to compete directly with operators by providing services like YouTube TV and internet services in certain areas.

The participant explained that every operator has their own footprint, region of operation, since it does not make sense to operate everywhere due to the high costs of infrastructure. Therefore, rural areas can in most cases choose between two or three operators whereas in larger cities there is much more competition. The participant clarified that rural areas are not considered competitive by the FCC, since the definition is based on the number of options in an area. However, their marketing tactics are very aggressive, attacking each other continuously through promotions and commercials.

According to the participant the US market exists of two different markets: whereas the first market is of both the North-east and south-west and the second market is everything in between.

Regarding churn, the participant explained that there are two types of churn: customers that quit an operator completely and customers that stop using one of the operator's services. According to the participant customer churn is not very serious in the residential service area because in many cases as a customer you do not have much choice. However, there is a lot of customer churn in the wireless segment including aggressive marketing.

The participant explained that product churn is a bigger issue, especially the television product. In the united states product churn is increasing every year because Americans drop their television services.

According to the participant this is due to customers switching to online streaming services. Operators are actively trying to reduce this type of churn, by providing online television services (TVi) and more recently introducing their own online streaming platform. Currently almost every US operator has their own online streaming platform, that customers can use to stream any channel and title they are entitled to.

On the other side, the participant added, that operators introduced IPTV as a cost reduction solution. IPTV allows operators to use the same infrastructure for television as is used for phone and internet.

Therefore, from a cost perspective they have IPTV and from the customer perspective it allows for more freedom in watching television since you can now watch anywhere. Some operators even partner with Netflix to provide such services on top.

Another reason an operator decides to create its own content is the increasing costs content creators ask per viewer from the operator. Sometimes it can be more beneficial to drop certain channels and replace them with OTT subscriptions e.g. Netflix. These increasingly high costs push operators to become the content creators themselves. They do this by acquiring larger content creators like EOL and more recently Warner.

In the participant's opinion this switch form providing telecommunications services to content creation is the best course of action for operators regarding the current churn situation. The participant added that this strategy is only viable if it generates enough cashflow to create new and enough original content.

When asked about churn prediction the participant explained that most operators have, roughly, a churn prediction model. The participant added that for most operators, analytics plays an important role. Therefore, they have a data warehouse to support analytics and have their own data scientists that are building models. However, the participant added from our Accenture perspective there is a lot of room to grow.

The participant added that they have all kind of different issues from target coverage to data quality issues. According to the participant the biggest challenge is that their data and business teams are isolated, meaning both operate without guidance, resulting into fancy models that are not actionable by business. Therefore, there is a huge gap between technology and business.

The participant elaborated a bit more on this gap between technology and business. Data scientist do not understand what the final goal is, and which model is most suitable for that specific goal and the business cannot provide direction because they have no idea how the data and model should look like. Therefore, parties like Accenture can provide them guidance by figuring out the business priority and make the translation to an analytical model. The participant added that in most cases the data is available, but they do not know how to utilize it.

The participant mentioned that due to merger and acquisition. Operators used to have a lot of legacy systems of small cable companies that they acquired. All data was in different formats and therefore hard to integrate. However, most operators are aware that this issue exists and are doing something about it.

According to the participant the data gap has been closed in the past few years. The participant added that it most likely varies from provider to provider. The major operators had already successful projects integration data systems. The participant emphasized that the data gap is one of the easiest things to fix. The gap between data and business is really the challenge.

The participant explained that the data operators use consists of: demographics based on their own data and third-party data sources, customer usage, service data, billing data and finance data. The participant added that the quality of demographic and usage data is concerning. The other data sources are in better shape.

When asked how freely operators can use these types of data, the participant explained that the GDPR has a huge impact on the united states. California passed their own data protection regulations based on the GDPR and according to the participant other states will most likely follow. The participant explained that in the past they used a lot of different data, now they must remove personal identifiable data, and cannot use any usage data if a customer wishes to opt-out.

When asked about CRM systems, the participant explained that the operators do have their CRM systems in place and do a lot of campaigns. However, it is not well integrated with the models. The participant provided the example that most data scientists build a model that gives the churn probability and accuracy. The marketing team can do nothing but provide generic retention packages to those with a high churn probability. The marketing team needs a driver or root cause in order to send a targeted message. According to the participant this is the major gap. There are good churn models in place, but they do not allow for a good action plan.

The participant explained, when asked the question how retention marketing has changed because of churn prediction models, that the biggest change until now is the targeting of customers. The participant added that the next step is to personalize the offer. Currently, churners are presented a generic offer e.g. discount or credits. The next long-term goal would be providing better hardware if customers are experiencing bad quality or providing an additional service if there was an outage and similar personalized offers. This is currently not possible with the current models and scoring.

The participant also indicated that operators are starting to focus more on customer experience and customer engagement. Meaning, trying to improve customer experience before customers decide to churn, instead of just focusing on customers with a high churn probability. Thus, instead of a KPI on churn, there is an KPI on customer satisfaction. This can then be used to monitor the quality of the experience and can help operators to identify how to make it better. So instead of trying to reduce churn, operators are trying to improve their NPS. The NPS score is not a perfect metric, since it is slightly biased but can provide a direction. Identifying triggers that reduce NPS can be used as an early warning for operators to act accordingly.

Another change is the focus on cost reduction by automating certain aspects of the customer experience e.g. replacing a call center with a chatbot.

The participant concluded that churn is just one of the branches operators are looking into.

Key information

From the interview the following key information is gathered:

a) The US market is separated into rural areas and highly populated areas e.g. north-east and south-west coast. Rural areas often have no more than three players, while highly populated areas see much more competition.
b) Every operator in the US has their own footprint, area of operation, due to the large scale of the country and high costs of infrastructure.
c) US telecommunications players can be divided into two distinct groups: cable companies and telecommunications operators. Both types of players are competing on triple play products.
d) Telecommunications operators used to have an advantage over cable companies, due to the ability to sell wireless products and services.
e) In the united states, quad play is not as popular compared to triple play offerings.
f) Internet companies e.g. Google are starting to compete directly with operates with services such as YouTube TV and broadband internet services in certain areas.
g) Operators are using aggressive marketing tactics to convince customers to churn, including device acquisition and paying contract termination- /transfer fees. Even if operators share their footprint with just one or two other players.
h) Churn can be defined as leaving an operator completely, as well as dropping a operator's service while still using other services.
i) Full churn is a big concern in the US wireless industry, while being a less relevant compared to product churn in the triple play/residential offering.
j) Product churn is a yearly increasing problem in the US industry, especially the television product.
k) US customers are dropping television services in favor of online streaming services.
l) Operators are trying to combat television product churn by providing online television services as well as introducing their own online streaming platform.
m) US operators also have a financial incentive to create their own online streaming platforms and content, caused by the increasing costs content creators inquire per customer for their content. This is illustrated by the trend of acquiring content creation companies such as warner media group by operators.
n) US operators have basic churn prediction models as well as data warehouses and data scientists to support it. However, there is still a lot of room for improvement regarding data quality and actioning.
o) The biggest challenge is closing the gap between technology and business, which results in churn prediction models that are not actionable. This gap is caused by both parties not being able to communicate and understand each other.
p) Business is not able to action on the models, because basic churn prediction models do not provide any additional insights such as churn drivers besides churn probability and accuracy.
q) Retention marketing has changed due to churn prediction models, the biggest change is the targeting of customers with retention packages instead of sending out offers randomly.
r) The next longtime goal would be to target customers with a personalized offer based on the churn driver or root cause. Without insights into churn drivers marketing teams can only provide generic retention packages.
s) Operators are starting to focus more on customer experience, putting KPIs on metrics such as NPS instead of churn in order to improve a customer's experience and preventing customer churn one step earlier. Indicating that customer churn prediction and prevention is just one of the branches operators are looking into.
t) Another challenge in creating churn prediction models is that demographic and usage data is of concerning quality. However, operators are aware of this issue and actively trying to resolve it.

u) The European General Data Protection Regulation (GDPR) has huge impact on the US, California has passed a similar regulation and other states will most likely follow, further challenging the data availability of operators.

Norway – NOR1

Interview churn prediction 3.0

Participant M has 10 years of professional work experience at a major Norwegian telecommunications operator. The participant is currently a data scientist.

In Norway there are three major operators: Telenor, Telia and ICE. Of which the last once, ICE, is a relatively new and aggressive player also competing on price with virtual operators.

The participant is currently working for a low-cost segment subsidiary virtual operator. Virtual operators are in simple terms a brand that uses the physical network of another operator. The Norwegian virtual operator market is very saturated. The virtual operator the participant works for, offers simple products to cost-conscious customers e.g. sim-only subscriptions. Cost-conscious customers are customers that are not willing to pay for what they do not need and want to have full control over what they are paying.

The operator the participant works for does not have 12- or 24-months long subscription contracts but offer monthly subscriptions. The larger operators do provide 12- or 24-months contracts. The participant explained that as a low-cost operator you must cut somewhere, so either in their network or customer support.

The participant explained that the subsidiary virtual operators experiences more churn than its holding company, major operator, which is logical because of the contract lock-in. The participant explained that their customers aware of the market and switch whenever there is a better offer. Usually customers of the larger operators are less price-sensitive.

The participant also explained that switching is very easy in Norway. The digitalization of Norway allows people to fill in a simple form in order to switch from provider. In the case of a mobile subscription a sim-card is sent to you by post or can be picked up at a nearby pick-up point within 15 minutes and activated by a mobile application.

The participant indicates that his employer started churn prediction around two years ago, because the holding enterprise wanted to push a fact-based approach to its subsidiaries. The participant explained that at that time there was nothing and they had to start from scratch. Before the participant joined the company, around four years ago, there was no customer or marketing data available, just production data.

The participant indicated that they have their internal billing system, that can provide very detailed lines on their customers' usage and costs. However, this will not provide a 360-view on their customers. The participant explained that the use of a good identifier to link different tables and systems together is very important, this was a challenge they faced setting up their customer relationship management systems. The participant also elaborated on the team composition, explaining that their relatively small multi-disciplined team allowed for very fast paced changes and an agile way of working.

The participant explained that they had around 60-70 data points on their customers. The provider is also challenged by the GDPR but mitigates this by customer opt-in in their contracts.

The participant explained that supervised learning is used for their churn prediction models. The time-frame is important in churn prediction, because you want to know who to action when. Also, it is important to define who will be taken in consideration, if there is not enough data, for example. prepaid customers they are left out of the modeling.

The participant explained that currently they are identifying a churn probability and define a threshold to act. This was done by using a lot of pilots, testing out marketing approaches at different threshold levels and scores. These pilots existed of a test and control group without a specific treatment. The participant indicated that some treatments only work at specific thresholds, which helped identify who to target. The participant indicated that after the first development of churn prediction models and testing it was integrated in the CRM systems by business ruling. The participant explained that business ruling is based on triggers, based on customer related variables and output from the churn prediction models. These churn prediction models run once a month, because of the frequency of data updates. The participant indicated that one of the future steps could be to increase the frequency.

The actions are defined based on pilots and are split on in-bound and out-bound actions. In-bound, when the customer interacts with the provider through e.g. an app, are always on. Out-bound actions are used less frequent and are based on customer characteristics and model outputs. Out-bound actions include: sending of text messages and email.

The participant explained that out-bound actions with discounts generally don't work. What they found to be working is clear communication and informing customers about more fitting bundles based on their usage.

The participant explained that both in-bound and out-bound actions can be pro- as well as re-active. The monthly regression models run based on monthly data and are not as advanced or real-time. Therefore, model-based actions are more re-active and trigger-based actions are more pro-active.

The participant also explained that their customers are segmented into micro segments based on ad-hoc analysis. These analyses are combined with qualitative data to identify potential churn causes, which are mostly linked to competitor's actions and changes in the market.

The participant indicated, when asked what should be done in order to reduce churn, that it is important to innovate their product portfolio as well as relevant communication. Relevant communication refers to content, timing, channel and group. This is especially important because consumers are already bombarded with communications daily. The participant also indicated that it is important for churn prediction to combine analytics with business sense and a lot of testing to be effective. The participant added to that that you do not need the state-of-the-art algorithms, but it is about finding the right treatments, which is more difficult than creating a model.

Key information

From the interview the following key information is gathered:

a) The Norwegian market exists of three major players of which the newest is a very aggressive player competing in every segment. Additionally, there are multiple smaller virtual operators.
b) The Norwegian virtual network operator market is very saturated
c) The operator is a virtual network operator that focusses on cost conscious customers.
d) Low cost operators need to cut somewhere in order to offer low pricing e.g. customer service or network quality.
e) Due to Norway's digitalization, switching from provider is very easy.
f) The operator used to have no available customer or marketing data and is since the last two years working on churn prediction.
g) Currently the operator has a CRM system that can provide very detailed information on its customers. During this process integrating different data sources by suitable identifiers was the main challenge.
h) The operator has 60-70 data points on its customers.
i) The operator actively opt-in every newly acquired customer automatically in order to stay compliant with the GDPR.
j) The operator created a churn prediction model by using supervised learning.
k) The operator takes time-frame and available data in consideration when creating churn prediction models. Time-frame to indicate when in which period the customer is likely to churn e.g. 2-3 months and data availability to exclude customers groups that do not have enough data available to make a reliable prediction e.g. prepaid customer.
l) The operator uses churn probability to define thresholds to act.
m) The operators uses pilots to test retention strategies on multiple thresholds to identify the best strategy to use.
n) The operator connected the churn prediction models and retentions strategies by business ruling in their CRM system.
o) The operator's business rules are based on triggers. These triggers are based on customer related variables, that are found to be related to churn, and on the output of the churn prediction model that is run once per month, because CRM data is updated once a month.
p) The operator uses in-bound and out-bound actions. In-bound actions are more frequent and occur when a customer interacts with the provider themselves and include notifications and messages. Out-bound actions are based on model outputs and include text-messages and emails.
q) The operator out-bound actions can be pro- and reactive. Pro-active actions are based on triggers related to customer data and re-active/less pro-active actions are based on churn prediction models, because the model only runs once per month.
r) The operator has micro segmented its customers, which is combined with qualitative data to identify potential churn causes.
s) Innovation of the product portfolio can help to reduce churn.
t) To effectively use churn prediction, it is important to combine analytics with business sense and testing
u) To effectively use churn prediction, you do not need state-of-art algorithms, but finding effective treatments is wat matters the most.

Appendix 6: datamining algorithms and classifiers

This part of the appendix explains the most popular algorithms/classifiers used for churn prediction.

Artificial Neural Network

Artificial Neural Networks (ANNs) are a popular approach to address customer churn. ANNs are models based on a biological neural network e.g. the human brain. This neural network can be hardware-/ software-based. Hardware-based neural networks are represented by physical components and software-based networks are computer simulated models. Artificial neural networks are generally composed of arrangements of interconnected “neurons”, which can calculate values from inputs. This is done by applying weights to the different attributes of the inputs, which are used in the transfer function. The output of this transfer function is sent to the activation function which checks if the value is higher than the threshold value to activate the neuron and allows the information to pass to the next neuron. This is represented in Figure 21: representation of an ANN's neuron.

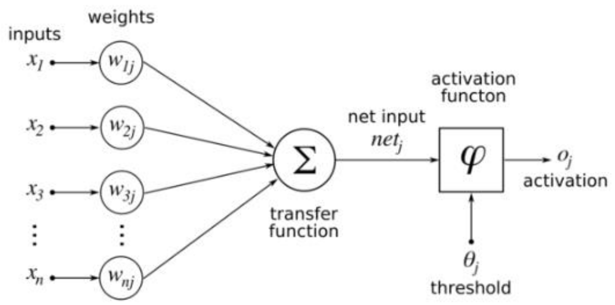


Figure 21: representation of an ANN's neuron

These neurons are part of a neural network, which contains at least an input layer, one hidden layer and an output layer as shown in Figure 22: representation of an Artificial Neural Network. However, more complex neural networks can have multiple hidden layers.

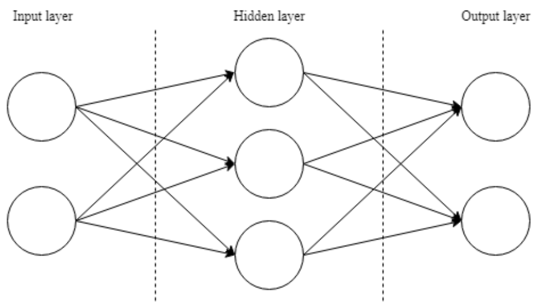


Figure 22: representation of an Artificial Neural Network

In short, the basic idea behind neural networks is that each attribute is associated with a weight. By combining the results of different neurons a combination of weighted attributes participate in the prediction task [19]. The weights of the attributes are constantly updating, therefore correcting the ‘effect’ an attribute has on the outcome. In the case of churn prediction, the neural network tries to calculate the probability that the customer is a potential churner as output with as input a customer data set and a set of predictor variables.

The advantage of a neural network is that they are very accurate, however they need a lot of data to be trained properly and take and a lot of time in to calculate an acceptable weightage for the predictor attributes [19]. Another major disadvantage of ANNs for CCP is that they scarcely uncover patterns in an easy to understand manner, thus hard to interpret for e.g. deciding on a next best action in the spirit of churn prediction [15].

Support Vector Machines

Support Vector Machines (SVMs), also known as Support Vector Networks, were introduced by Boser, Guyon, and Vapnik [61]. SVM's are supervised learning models with the associated learning algorithms that analyze data points and recognize patterns [40]. SVM's are used for classifications and regression analysis and can be grouped as regression-based methods.

Support vector machines are based on the Structural Risk Minimization principle from computational learning theory [62], The idea behind Structural Risk Minimization is to find a hypothesis h for which it is guaranteed to have the lowest true error. In SVMs this is achieved by mapping the data points so that examples of the separate categories are divided by the widest gap possible. New data points are then mapped into the same space and predicated to fit to a category based on which side of the gap they are placed. Figure 23: Linear Support Vector Machine (LSVM) is an example of a Linear Support Vector Machine. The LSVM divided the planes evenly by the hyperplane (red line). The margin in this example (D) is as large as it possibly can be to guarantee the lowest true error.

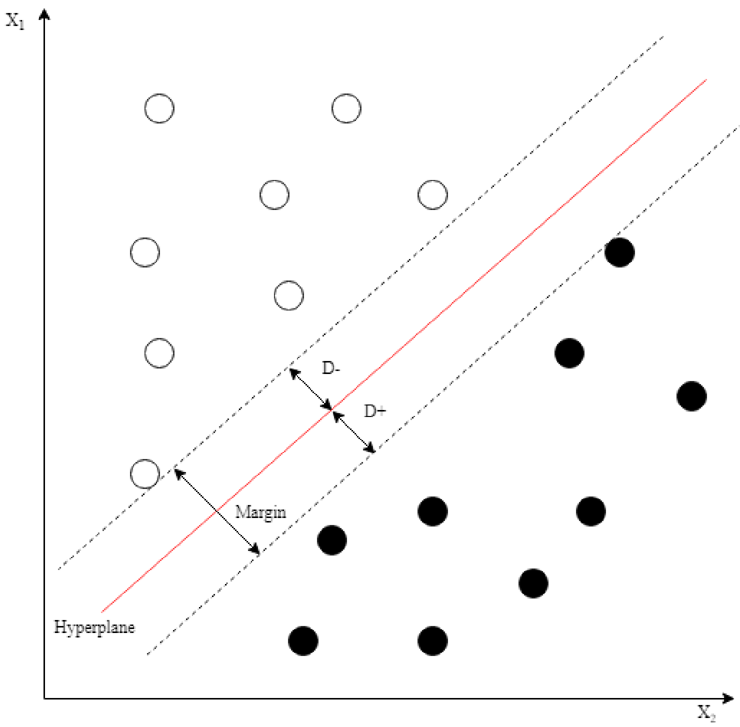


Figure 23: Linear Support Vector Machine (LSVM)

This LSVM example is based on the original maximum-margin hyperplane algorithm proposed by Vapnik in 1963, who constructed a linear classifier. However, later on Boser, Guyon and Vapnik suggested a way to create nonlinear classifiers by applying the kernel trick to maximum-margin hyperplanes [61]. This allowed for the algorithm to fit the hyperplane in a transformed feature space and can now be nonlinear. The transformed feature space can also be high-dimensional. In this higher dimensional space, the same rules apply as the Linear Support Vector Machine.

SVMs are universal learners. In their basic form, they learn with the linear threshold function as describes as shown in Figure 23: Linear Support Vector Machine (LSVM) . However, the kernel trick allows for (a) plug-in function(s), which allows SVMs to learn with polynomial classifiers, radical basic function networks, and three-layer sigmoid neural nets [62]. Research on selection the best kernels or combinations of kernels is still in progress [40]. In churn prediction problems, Support Vector Machines outperform Decision Trees and sometimes ANNs, depending on the type of data and data transformation that takes place [63] [60]. However, the biggest downside of SVMs is that they do not provide a probability estimate.

Decision Trees Learning

Decision trees (DTs) are the most commonly used tool for classification and prediction of churn prediction problems [13] and are created using two major steps: building and pruning [19]. During the building phase the data set is partitioned recursively until most of the records in each part contain identical values. During the pruning phase some branches which contain noisy data are removed. This is mostly based on the largest estimated error rate.

A well-known Decision Tree is a CART, a Classification and Regression Tree, which splits of an instance into subgroups until a specified criterion has been met. In the case of churn prediction, this criterion is if a customer is a churner or not. The tree grows until the impurity falls below a user-defined threshold [19].

Each node in the decision tree is a test condition and the branches are based on the value of the attribute that is tested. The tree is representing a collection of multiple rule sets. Building of a Decision Tree is done by evaluating a customer data and traversing though the tree until a leaf node is reached. A leaf node is the final node in the tree, in the case of churn prediction this is the churn status of the customer. During evaluation the target variable (churning) is assigned to the record. Figure 24: simplified version of a churn decision tree shows a simple telecommunication churning Decision Tree.

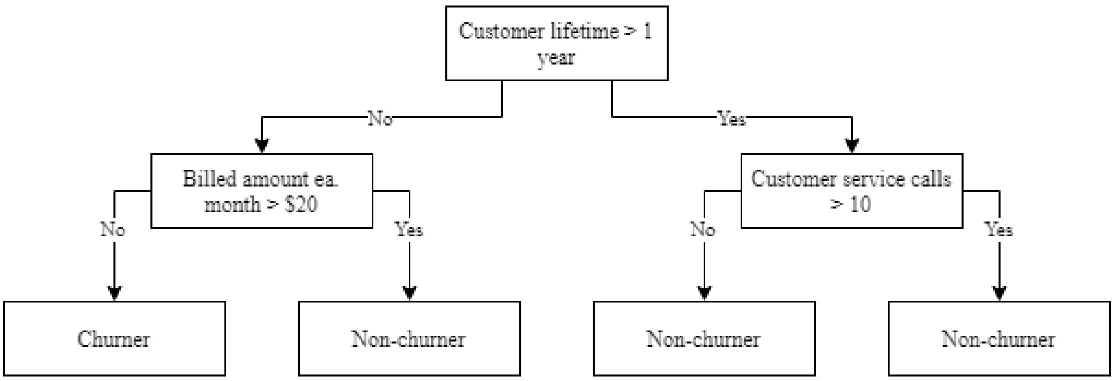


Figure 24: simplified version of a churn decision tree

Decision trees are criticized that they are not suitable for complex and non-linear relationships between the different attributes [19]. In contrast, research shows that the accuracy of decision trees and training data requirements are high [18] [64] [65]. However, higher accuracy can be achieved using other methods, like regression and ANNs. The main advantage of Decision Trees is that it is easy to understand the results, due to the tree structure and clear decision points [65]. The disadvantages of decision trees is that there are prone to overfitting [58].

Naïve Bayes

Naive Bayes is a supervised-learning module that contains examples of the input-target mapping which the model tries to learn. This input-target mapping is done by analyzing previous data by applying the mathematics of Bayes' Theorem as shown in Equation 9 with a strong independence assumption about the prediction features (naïve) [40]. In basic terms, a Naïve Bayes classifier assumes that the presence (or absence) of a data feature (i.e. customer churn) is unrelated to the presence of any other feature.

Equation 9: Bayes' theorem stated mathematically

$$P[A|B] = \frac{P[B|A]P[A]}{P[B]}$$

Bayes' Theorem (Equation 9) states that the probability of a predicted event: P[A|B], the likelihood of event A occurring given that B is true, is computed from three other probabilities:

1. The probability that event B occurs given that A is true.
2. The probability of observing A independently of B.
3. The probability of observing B independently of A.

If we look at customer churn we can think of a Bayes classifier that considers unsolved support tickets which results in the following: the probability of churn (C) given that a support ticket is not solved (S). Bayes' Theorem will state that the probability that a customer will churn given that a support ticket is not solved is equal to the probability that a support ticket is not solved given that the customer will churn, multiplied by the probability that a support ticket is not solved, both divided by the probability that a customer will churn.

This example classifier would be based on historical data and the model could use this classifier in combinations with other classifiers based on other features to calculate the probability that a customer will churn (or not).

The Naïve Bayes classifier achieved good results solving a churn prediction problem for the wireless telecommunications industry [66]. The biggest advantage of using Naïve Bayes is that it is very simple, thus requiring short computational time for training, and has good performance. Additionally, it improves the classification performance by removing the irrelevant features. The main disadvantages of NB is that it requires a very large number of training records to obtain good results and is less accurate compared to other classifiers on some datasets [58].

Regression analysis-logistic regression analysis

Regression analysis is a well-known type of analysis in statistics and the process of estimating the relationships between variables. It tries to find the correlation between the independent and dependent variables and can use a multitude of techniques [40]. However, regression analysis is not widely used because linear regression models are only useful for predicting continuous values. Therefore, in the case of churn prediction a logistic regression model makes more sense, since it is more suitable for binary attributes (churn being a binary attribute) [19]. A representation of a standard logistic regression is a logit function. An example of a logit function is a sigmoid function as shown in Equation 10.

Equation 10: Sigmoid function

$$S(x) = \frac{1}{1+e^{-x}}$$

In the case of customer churn this function can be used to estimate the probability of customer churn as shown in

Equation 11.

Equation 11: Logistic function to calculate the churn probability

$$P[churn] = \frac{1}{1+e^{-T}}$$

Where $\mathrm{T} = \mathrm{a} + \mathrm{BC}$. a is a constant term. X represents the predictor attribute vector and B is the coefficient vector for the predictor attribute.

The use of Logistic regression requires proper data transformation on the initial data, since it will not work well with noisy data. However, it has good performance [67] and can perform as well as Decision Trees [68].

Appendix 7: customer churn overview

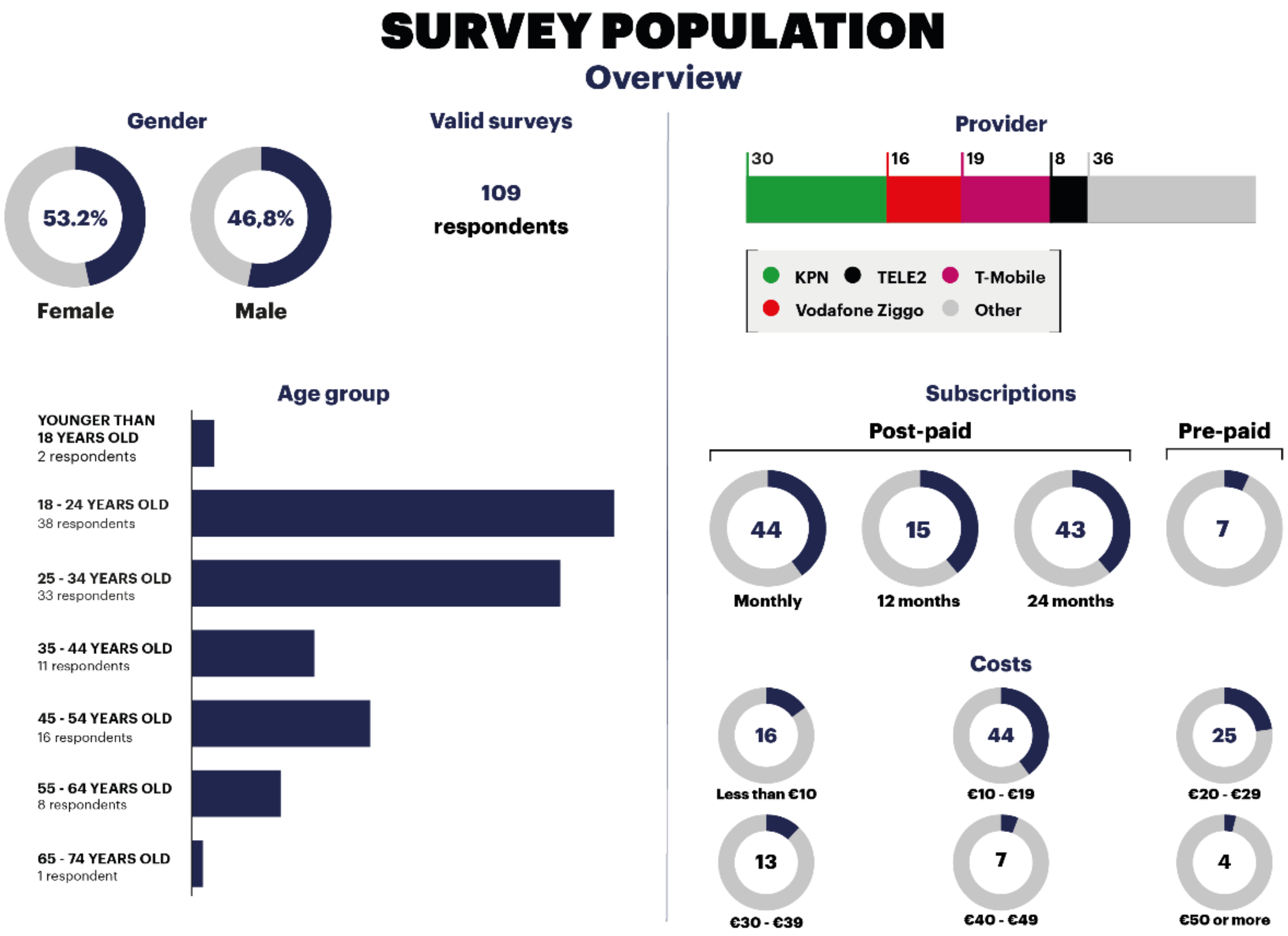
Table 22: complete customer churn overview - part 1

	Voluntary churn			Involuntary churn	
	Active/ deliberate churn				
	Economical	Technology	Quality	Passive churn	Non-voluntary churn
Rationale	The customer is not satisfied with the current services and products based on value and is actively pursuing to change to a competitor's service or product with a better value	The consumer is not satisfied with the current service and product offerings and is actively pursuing to change to a competitor's more advanced services and products	The customer is not satisfied with the quality of the services and products provided and is actively pursuing to change to a competitor's service or product	The consumer fails to update their billing information correctly, this might result in failing subscription charges, thus termination of the service agreement.	The provider revokes the service agreement, because it is no longer willing to provide the service to the customer.
Potential Cause	Competitively priced services by competitors, competitor promotions	Unavailable of new services by provider, advanced service and product offerings of competitor, lack of innovation	Poor customer service, Poor coverage, Poor call quality	Expiring credit/debit card, red flagged transactions, failed account renewal, failed account update	No longer providing the service, billing issues, fraud, bad debt, violation of service agreement

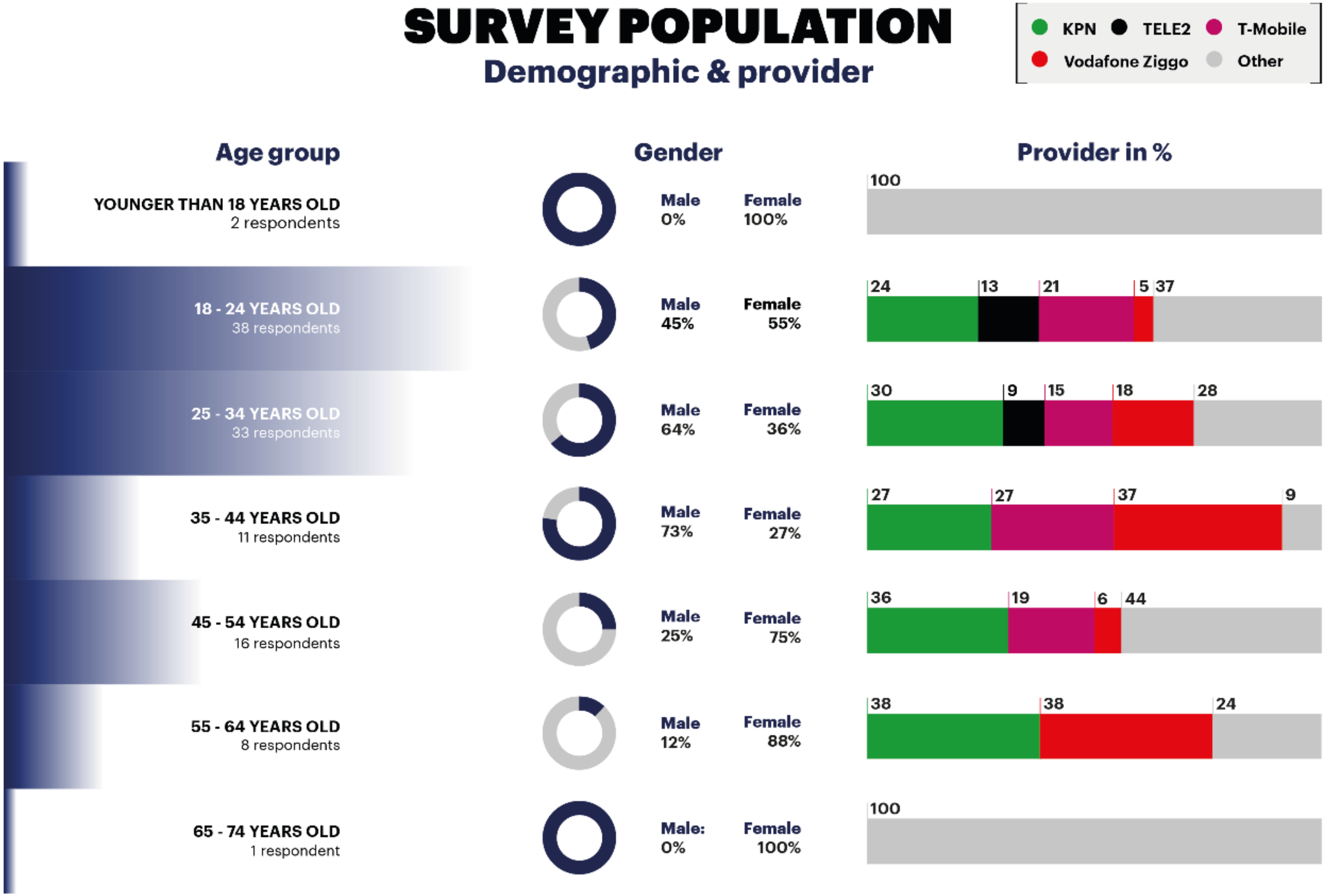
Table 23: complete customer churn overview - part 2

	Voluntary churn		
	Incidental / rational churn		
	Geographical change	**Financial change**	**Life change**
Rationale	The customer moves to a new area where the service provider is not able to provide the same services, thus the consumer if forced to switch service provider	Due to changes in the financial situation of a customer, he needs to cut costs and is forced to switch from service	Due to changes in the customer's life he or she no longer requires the provided services.
Potential cause	Unavailability of a service in certain regions	Consumer related financial issues	Consumer related life changing events, like: death of the consumer, parents that discontinue their children's service and other unforeseen variety of causes

Appendix 8: survey population



SURVEY POPULATION
Demographic & provider



SURVEY POPULATION
Subscription & Costs

Age group	Post-paid: Monthly plan	Post-paid: 12 months plan	Post-paid: 24 months plan	Prepaid
YOUNGER THAN 18 YEARS OLD 2 respondents	100% 2 respondents Avg. Spending Less than € 10			
18 - 24 YEARS OLD 38 respondents	45% 17 respondents Avg. Spending € 10 - €19	13% 5 respondents Avg. Spending € 10 - €19	39% 15 respondents Avg. Spending € 20 - €29	3% 1 respondent Avg. Spending € 20 - €29
25 - 34 YEARS OLD 33 respondents	37% 12 respondents Avg. Spending € 20 - €29	9% 3 respondents Avg. Spending € 20 - €29	42% 14 respondents Avg. Spending € 30 - €39	12% 4 respondents Avg. Spending € 20 - €29
35 - 44 YEARS OLD 11 respondents	36% 4 respondents Avg. Spending € 20 - €29	27% 3 respondents Avg. Spending € 10 - €19	27% 3 respondents Avg. Spending € 40 - €49	10% 1 respondent Avg. Spending Less than €10
45 - 54 YEARS OLD 16 respondents	44% 7 respondents Avg. Spending € 10 - €19	12% 2 respondents Avg. Spending € 20 - €29	44% 77 respondents Avg. Spending € 10 - €19	
55 - 64 YEARS OLD 8 respondents	29% 2 respondents Avg. Spending € 10 - €19	14% 1 respondent Avg. Spending € 10 - €19	43% 2 respondents Avg. Spending € 10 - €19	14% 1 respondent Avg. Spending Less than € 10
65 - 74 YEARS OLD 1 respondent			100% 1 respondent Avg. Spending € 10 - €19	

Glossary

BSS

Business support systems are components that telecommunications operators use to run its business processes.

Campaigning

A planned group of activities to reach a certain goal. For example in retention campaigning the goal is to retain customers by use of marketing activities.

Churn rate

customer churn is a basic unit of the telecommunications industry used to describe customer loss. It is defined as the gross rate of customer attrition during a given period. Customer churn assesses a telecommunications provider's customer retention efforts and provides insights into the growth or decline of the subscriber base.

Complaint management programs (CMP)

A complaint management system is a software system that allows companies to address customers' inquiries, deliver support and manage complaints in a timely manner.

Customer churn

The phenomenon that customers choose the competitor's services over your own company services, which results in customers leaving your business.

Double play

Refers to the selling/ delivery of phone and broadband internet services to a single customer by one provider.

ELT / ETL

A method of extracting data from a transactional system to an analytics environment. ELT is an acronym for Extract Load Transform.

FTC

The Federal Trade Commission (FTC) is an independent agency of the U.S. government that aims to protect consumers and ensure a competitive market by enforcing consumer protection and antitrust laws.

GDPR

General Data Protection Regulation (GDPR) is an European legal framework that sets guidelines for the collection and processing of personal identifiable data.

KPI

A key performance indicator (KPI) is a measurable value that indicates how effectively a company is achieving key business objectives.

Operator

An enterprise that provides telecommunications services to businesses and consumers. True operators own their own telecommunications infrastructure.

OTT

Over The Top, refers to content provided by third parties using the internet. Well known examples are Youtube, Netflix and Spotify.

Pilots

Running self-contained experiments to identify the performance of e.g. marketing activities.

Provider

Mostly used interchangeable with operators. Providers provide telecommunications services to business and consumers.

Quadruple play

Refers to the selling/delivery of triple play services and wireless services to a customer by one provider. Quadruple play is also referred to as quad play.

Residential services

Refer to the telecommunications services provided at home e.g. land-line, broadband internet & television.

Triple play

Refers to the selling/delivery of phone, broadband internet and television services to a customer by one provider.

Value-added services

Value-added services is a telecommunications industry term for non-core services, all services other than standard telecommunications services e.g. call, internet and television services.

Virtual operator (VO)

Virtual operators provide telecommunications services to businesses and consumers. However, virtual operators do not own telecommunications infrastructure and lease capacity from network operators.