APPLYING MACHINE LEARNING TO MARKETING: IMPLEMENTATION AND MANAGEMENT OF A NEXT BEST OFFER RECOMMENDATION MODEL IN THE FINANCIAL INDUSTRY

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ABSTRACT

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<tr><td colspan="2">This Master’s Thesis researches how a predictive analytics next best offer (NBO) recommendation model is developed, implemented and managed in a Finnish retail bank. This Thesis studies how the NBO model is strategically employed as a customer-oriented marketing communications tool in marketing, customer service and customer relationship management (CRM). The NBO model predicts the customers’ interest in the products and services the case bank offers and prioritizes the recommendations. Then, the recommendations are used to target marketing communications messages based on customers’ interest. With the help of the NBO model, the case bank has reached better conversion rates, optimized marketing budget, increased customer experience and increased sales.
The goal of this research is to study the successes and challenges in the implementation and management of the NBO model in the case bank located in Finland. Further, this Thesis studies the best practices and challenges in evaluating the NBO model performance. The research goal is achieved by thoroughly studying what kind of challenges and facilitators can emerge in the implementation and management of an NBO model. The key findings and the perceived benefits of an NBO model are presented.
The main theoretical background centers upon NBO as a customer-centric marketing tool, and adoption, implementation and management of predictive analytics and data-driven decision-making. The research findings are analyzed based on the themes derived from the theoretical background and research findings, including implementation, management, and NBO performance evaluation.
This research complements the existing research literature on predictive analytics implementation and management. This research found several consistencies with prior literature, including the importance of involving employees to the implementation, importance of clear communication and adequate training, and the significance of centralized cross-functional management. Further, this research completes the earlier research for example with the importance of documentation and significance of careful planning and continuous testing.</td></tr>
<tr><td colspan="2">Key words
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TIIVISTELMÄ

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Koneoppimisen hyödyntäminen markkinoinnissa: Next best offer -suosittelumallin käyttöönotto ja johtaminen rahoitusalalla

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Tämä Pro gradu -tutkielma tutkii kuinka ennustavaa analytiikkaa hyödyntävä next best offer (NBO) -suosittelumalli on kehitetty, otettu käyttöön ja johdettu suomalaisessa kuluttajapankissa. Tämä Pro gradu -tutkielma tutkii, kuinka NBO-malli on otettu käyttöön asiakaslähtöisen markkinointiviestinnän strategisena työkaluna niin markkinoinnissa, asiakaspalvelussa kuin asiakkuudenhallinnassa.

NBO-malli ennustaa asiakkaiden kiinnostusta pankin tarjoamia tuotteita ja palveluita kohtaan ja priorisoi ennustetut kiinnostuksenkohteet järjestykseen kiinnostavimmasta tuotteesta alkaen. Suositteluja käytetään pankissa markkinointiviestinnän kohdentamiseen asiakkaiden kiinnostukseen pohjautuen. NBO-mallin avulla pankki on saavuttanut paremman markkinointitoimenpiteiden konversioasteen, paremman asiakaskokemuksen, kasvattanut myyntiä, sekä pystynyt optimoimaan markkinointibudjettia.

Tämä Pro gradu -tutkielma tutkii, millaisia menestystekijöitä ja haasteita NBO-mallin käyttöönotossa ja johtamisessa Suomessa sijaitsevassa pankkialan yrityksessä on ilmennyt. Lisäksi tämä tutkielma pyrkii löytämään parhaita käytäntöjä NBO-mallin tulosten mittaamiseksi. Tutkielman tavoitteeseen pyritään löytämään vastaus tutkimalla millaisia haasteita ja parhaita käytäntöjä NBO-mallin käyttöönotossa ja johtamisessa sekä tulosten mittaamisessa voi esiintyä.

Teoreettinen viitekehys keskittyy NBO-mallin käyttöön asiakaskeskeisenä työkaluna markkinoinnissa. Lisäksi teoreettinen viitekehys keskittyy ennustavan analytiikan ja dataohjatun päätöksenteon omaksumiseen, käyttöönottoon ja johtamiseen yrityksessä.

Tutkielman tulokset on analysoitu pohjautuen teoreettisesta viitekehyksestä ja tutkielman tuloksista johdettuihin teemoihin sisältäen käyttöönoton, johtamisen ja NBO-mallin tulosten mittaamisen.

Tämä tutkielma lisää ymmärrystä aikaisempiin ennustavan analytiikan käyttöönottoon ja johtamiseen liittyviin tutkimuksiin. Tämä tutkielma löysi useita yhteneväisyyksiä aikaisempiin tutkimuksiin, kuten työntekijöiden sitouttamisen tärkeys, selkeän viestinnän ja riittävän koulutuksen tärkeys, sekä keskitetyn ja liiketoimintoja läpileikkaavan johtamisen merkitys. Lisäksi, tämä tutkielma täydentää aikaisempia tutkimuksia lisäämällä ymmärrystä huolellisen suunnittelun, jatkuvan testaamisen sekä dokumentaation tärkeällä roolilla käyttöönotossa ja johtamisessa.

Asiasanat
Ennustava analytiikka, koneoppiminen, suosittelumalli, next best offer, digitaalinen markkinointi

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CONTENTS

1 INTRODUCTION

In today's hyper-competitive business environment, organizations have a continuous need to react to the shifts in the market environment by updating and redefining their resources to create sustainable competitive edge (Erevelles, Fukawa & Swayne, 2016). Especially the digital transformation has generated whole new challenges for organizations in the past years – the internet is currently one of the major marketplaces, the channels have proliferated, and dealing with big data and analytics has become a norm (Leeflang, Verhoef, Dahlström & Freundt, 2014; Barton & Court, 2015). The complex, fast-paced environment enriched with big data volume, velocity and variety require faster decision making from organizations than ever before (Kiron, Shockley, Kruschwitz, Finch & Haydock, 2012; Firestein, 2012; Leeflang et al., 2014).

On the backdrop of the proliferation of digital technologies, channels and devices, customers' demand for more innovative and on-demand services has multiplied. As a result, customer engagement has become one of the major success factors for organizations (Clow & Baack, 2016). At the same time organizations, including the financial sector, are facing budget crunch and increase in regulations, thus, effective utilization of the limited resources has become an increasing challenge for the organizations (Deloitte MCS Limited, 2013; Goldenberg, 2017).

Due to digitalization, the current marketing transformation is increasingly technology-driven – the available marketing technologies, customer-centric strategies and obtainable customer data are continuously increasing and delivering business value (Sleep & Hulland, 2019). The most visible challenges businesses and marketers are currently facing relate to the ability to analyze data, produce and leverage deep customer insight and measure digital marketing performance (Leeflang et al., 2014). Kiron et al. (2012) state, that battling with increasing uncertainty and competition leaves organizations in trouble unless they apply analytics broadly to inform decision-making and understand their customers. However, organizations do not always know how to use big data to make complex decisions and gain business advantage (Mithas, Lee, Earley, Murugesan & Djavanshir, 2013).

Due to an endless number of advertisers and messages, digital marketing amongst customer service is drifting towards precisely targeted messages and optimizing the marketing budget and ad spend. Thus, many traditional targeting methods are getting outdated. (Clow & Baack, 2016.) Especially financial sector organizations have big number of transactions and thus, are able to capture great amounts of customer data and representatively benefit greatly from data-driven customer insights (Manyika, Chui, Brown, Bughin, Dobbs, Roxburgh & Byers, 2011; Leeflang et al. 2014). Big data provides extensive possibilities for organizations to follow customer journeys across all channels, from awareness to loyalty, which is consequential in terms of understanding customers better and optimizing marketing campaigns and budgets. This enables organizations to deliver the right content to the customers at the right time. (Leeflang et. al. 2014; Stone & Woodcock, 2014.) Ability to turn customer information into insight and implement it to engage customers across their purchase journey, from sales to loyalty, is becoming a characteristic of successful marketing (Hartman, 2014).

Here, recommendation models such as next best offer (NBO) are providing a novel solution to marketing and budgetary challenges. The recommendation models predict customer's preferences and actively make relevant suggestions for them by simultaneously simplifying the exploration of obtainable alternatives (Adomavicius & Kwon, 2007; Jugovac, Jannach & Lerche, 2017). NBO recommendation model allows more precise targeting method to organizations, which can lead to better customer experience, higher return on investment, increase in customer life-span and reduced marketing costs (Ginovsky, 2010; Goldernberg, 2017).

1.1 Justification of the research

Machine learning and AI are currently prevailing and widely interesting themes in business and marketing discussions. As Sleep, Hulland and Gooner (2019) state, the ongoing development of marketing towards more customer-centric models emphasizing data-driven decision-making and technological advancements, as well as marketing practitioners' access to fast increasing amount and variety of customer data, also known as big data, are currently shaping the corporate strategies. As particularly financial industry organizations have a large amount of customer and transaction data, the organizations operating in the financial sector are in the precedence to implement data-driven decision-making strategies. Thus, the research topic is highly relevant for many businesses innovating in today's competitive business environment, especially in the financial industry, where big data are continuously shaping the strategies and exponentially producing unstructured information about the customers.

In the research literature, machine learning, artificial intelligence (AI) and prediction models in business context are rather new themes, however widely studied themes in general. Nevertheless, the majority of the studies are made by researchers in computer science and information technology (IT). Thus, most of them focus on the technical perspective of the topics. The research concerning machine learning in marketing context from a business perspective is nevertheless relatively scarce. However, there are a few noteworthy studies concerning the topic. In recent literature, Campbell, Sands, Ferraro, Tsao and Mavrommatis (2019) have widely studied the various possibilities of how marketeers can leverage AI and machine learning in marketing strategy and activities. Further, implementing big data analytics to marketing is researched for example by Erevelles, Fukawa and Swayne (2016), Mithas et al. (2013) and Bose (2008).

Various different predictive analytics recommendation models are widely researched in literature, particularly in e-commerce business context. However, the research of recommendation models is scarce in financial industry. Particularly NBO or next best action (NBA) recommendation models are rather little researched based on searches from various scientific databases with key terms 'next best offer', 'NBO model', 'next best action' and 'NBA model'. Hence why, this research provides a novel perspective on implementing and managing NBO recommendation model in marketing. Further, this research provides topical insight on utilizing NBO recommendation model effectively in multichannel marketing and communications.

The concept of implementation and management of a predictive analytics recommendation model in marketing is meager in literature. Many studies concerning the topic focus on predictive analytics adoption and implementation drivers and impediments. For example, the research by Sleep, Hulland and Gooner (2019) studies the factors influencing the adoption and implementation of data-driven decision-making focusing on capabilities, drivers and challenges in adoption and implementation. However, the existing studies fail to form a comprehensive view of the process from planning and adoption to implementation and continuous management of predictive analytics in business. Thus, this research provides an opportunity to form a holistic picture of the implementation and management of a predictive analytics model in marketing. Further, this research propounds factors leading to success or failure in the implementation and management of a predictive analytics model. It is interesting to study how the identified drivers and challenges in implementation and management in existing literature are manifested in this case study research.

Hartman (2014) has recognized how the digital revolution is reshaping the field of marketing and bringing chief marketing officers (CMOs) and chief information officers (CIOs) closer together. Also, Sleep and Hulland (2019) have studied how big data drive the CMO and CIO relationship and cooperation in organizations, and how the evolving relationship can create competitive advantage for businesses. The recently emerging number of research literature regarding the emerging relationship of marketing and IT indicates, that the topic is timely and relevant for today's businesses who are moving towards adopting and implementing novel analytics solutions to their marketing and searching for best practices to manage the implementation and development. This research comprises the timely topic of CMO and CIO relationship and how it manifests itself in the implementation and management of predictive analytics.

Customer-oriented business strategies is a widely researched and timely topic, which is studied extensively also in the marketing context. A substantial amount of the research studies the organizational change from a product-centric strategy to a customer-centric strategy. Further, many studies research the potential implications of transforming to customer-oriented strategy. This research complements the existing literature by providing further insight into how predictive analytics leverages customer-oriented business strategy and how an NBO model can be used as a tool to transform marketing communications customer-centric.

According to Malthora, Birks and Wills (2012) it is important to interact and discuss directly with the key decision-makers in the early stage of the research to identify a marketing problem and define the research objective. Adams, Raeside and Khan (2014) further state, that it is important to also understand what is important to the stakeholders and who are the key actors regarding the topic to define the research. As the authors suggest, the research topic was first extensively discussed with the data scientist and marketing director of the case company. The discussions concerned a brief history of the topic and the identified challenges in implementation and management of the NBO model in the case company. Based on the discussions, the research topic was defined.

The case company is a Finnish retail bank which provides loan, investment and daily transaction services for its customers. Thus, the scope of this research is in B2C business, in a retail bank. The financial industry is an interesting study subject, as retail banks generally have big amounts of customer data. Thus, employing the data to gain added value for marketing, business and customers is highly relevant for many companies. As many organizations struggle with how to utilize the enormous amount of customer data, this research provides one standpoint and proposition on how to take advantage of the data. Furthermore, especially the financial industry companies are continuously facing new challenges with new market entrants constantly tightening the competition and creating new demands of action for the traditional retail banks to win the customers. Incessant innovation and increasing customer knowledge are required to successfully compete with the technology-driven start-ups entering the market. Further, the threat of 'big giants' as Google, Apple and Amazon, are creating additional threats and challenges for local retail banks. Thereby, researching new ways to innovate and win customers is highly interesting.

The case company was selected, as the author worked there during the implementation of the NBO model. The author was responsible for product and brand marketing activities. The development of the prediction models originally began before the author started working in the case company, but the author took part in the implementation and development of the NBO model during her employment.

1.2 Key concepts

The key concepts of this research encompass machine learning, predictive analytics, and recommendation models including NBO and customer centricity. To begin with, machine learning refers to automated discovering of meaningful patterns in large data sets; it has become a common method to extract information from data and perform optimization tasks with minimum human interposition

(Shalev-Shwartz & Ben-David, 2014; Cui, Wong & Lui, 2006). Machine learning comprehend computer programs that simulate human learning behaviour – learning by experience (Natarajan, 1991). Silver, Yang and Li (2013) further state, that the aim of a machine learning program is to consecutively maintain the learned information and shift that knowledge when new task is learned to develop more exact hypotheses and procedures. Machine learning provides an opportunity to gain insight on consumer behaviour and improve marketing performance and management decision-making for example by modelling consumer choice and predicting loan default (Cui, Wong and Lui, 2006).

Predictive analytics is based on machine learning. Kiron et al. (2012, p. 3) define analytics as "*the use of data and related insights developed through applied analytics disciplines (for example, statistical, contextual, quantitative, predictive, cognitive and other models) to drive fact-based planning, decisions, execution, management, measurement and learning. Analytics may be descriptive, predictive or prescriptive.*" Analytics is used to understand customers and their needs and engage with them in more personalized ways (Kiron et. al., 2012). The businesses with predictive analytics capabilities can collect raw data from customer interactions and behaviour and utilize the data to inform the business of critical issues and target offers based on customer data. Further, predictive analytics capabilities allow companies relevancy in communication and personalized customer service while engaging with customers throughout the buying cycle. The strategy also enables driving growth and improving cross-selling rates through exploiting the customer insight in promotions and campaigns. (Teerlink & Haydock, 2012; Woodcock & Stone, 2012.)

Personalized customer insights help target marketing actions precisely – NBO amongst many other marketing analytics allow this to organizations (Goldernberg, 2017). Recommendation models including NBO model drive customer-oriented marketing communications by allowing personalized communication and recommendations for customers in multiple channels (Deloitte MSC Limited 2013). For example, product, transaction, enquiry and web-data can be analysed real time to predict the needs and propose a next best offer for the customers (Woodcock & Stone, 2012). NBO is commonly used for personalising product or service offers for individual customers based on customer insights, enabling businesses to shift from a product-centric view to customer-centric focus (Deloitte MSC Limited 2013).

Lamberti (2013) notes, that customer-centricity has been one of the most debated marketing concepts in recent years. It is often referred to as the opposite of product-centricity. While product-centric companies focus their resources and competences to developing products and services and selling those to customers, customer-centric companies focus on developing solutions to customers' needs. Customer-centric companies focus on generating customer insight to support personalized marketing activities, involving customers in marketing and innovation and moving the focus from products and services to customer experience. Joiner (2012) states, that customer-centric marketing can be seen as meaning-based marketing where data-analysis is utilized to understand customers and provide optimized customer experience across channels. For example, software that enable pattern-matching provide better customer knowledge for marketeers and the ability to predict what is going to attract the customers next.

1.3 Research objective and research questions

This research has three objectives. The first objective of this research is to increase the comprehension of the NBO recommendation model implementation and management. The second objective is to study the successes and challenges in the implementation and management, when the NBO model is used simultaneously by many teams. The third objective is to form a comprehensive view on how the NBO model performance should be measured to evaluate its performance and further develop the model and its usage.

Based on the research objectives, the research questions are:

RQ1: What are the drivers and impediments for implementing predictive analytics in a financial organization?

RQ2: How to manage the usage and development of a predictive analytics model which is used simultaneously by multiple business units and managers?

RQ3: How should the NBO model's performance be measured and evaluated in a financial organization?

1.3.1 Introduction to the research method

In this research, a qualitative research approach was used to answer the research questions. The primary data collection method was semi-structured, in-depth face-to-face interviews. Semi-structured interviews were adopted, as they enable leaving space for open discussion to discover unforeseen information influencing the implementation and management, which could otherwise be unnoticed (Mann, 2016; Hair and Page, 2015).

In total, six of the case company's managers and specialists from marketing, CRM, customer service and analytics departments were interviewed face-to-face for this case study research. These participants were chosen, as they were closely involved with the NBO model implementation and management in the case company. Consequently, all managers involved with NBO were interviewed. Each interviewee had a different role in the case company, which enabled gaining a comprehensive view of the topic from different perspectives. The data were collected during 2019, when the first interview was arranged in May 2019, while rest of the interviews were arranged in November 2019. In addition to the interviews, documentation provided by the case organization was used as data for this case study research.

1.4 Structure of the research

This research comprises seven main chapters, which are introduction, two theoretical background chapters, methodology, results and analysis and lastly, conclusions. Further, this research includes references and appendixes.

The theoretical background for this research is gathered to compound a comprehensive view of the current studies and research of the topic. The theoretical background combines academic publications and researches compiled from various scientific databases. First part of the theoretical background, chapter 2, focuses on predictive analytics as a customer-centric marketing tool. The chapter discusses about how customer-centric marketing can create added value for businesses, marketing and customers, how predictive analytics can be used as a customer-centric marketing tool, and how marketing activities' and recommendation models' performance can be measured and evaluated. Chapter 3, the second theoretical background chapter focuses on adoption, implementation and management of a predictive analytics model.

In chapter 4, the research method is described. First, the case organization and the sampling method and the interviewees and their roles in the case organization are presented. Next, the data collection method is presented including the interview guide. Then, the data analysis methods are described.

In chapter 5, the data and the results are presented, and the key findings are summarized.

In chapter 6, the research is concluded. The results are analysed based on the theoretical background and then, the managerial implications are derived from the research findings and analysis. Further, the validity and reliability of this research are evaluated, and lastly, further research topics are suggested.

2 NEXT BEST OFFER RECOMMENDATION MODEL AS A CUSTOMER-CENTRIC MARKETING COMMUNICATION TOOL

In recent academic literature, customer-centricity has been a salient theme (e.g. Lee, Sridhar, Henderson & Palmatier, 2012; Verhoef & Lemon, 2013; Peltier, Zahay & Lehmann, 2013; Goldenberg, 2017). That is a consequence of today's noisy business environment, where customer engagement has become one of the major success factors for businesses (Goldenberg, 2017). Therefore, many organizations have come aware of the imperative need to move towards customer-centric strategies to gain valuable competitive advantage (Lamberti, 2013). Lamberti (2013, p. 594) compounds three major customer-centric capabilities for organizations: "*(1) generate customer intelligence, gathering and processing data and information to build comprehensive data repositories about the interactions between the customer and the firm, to support customized marketing activities; (2) actively involve customers in marketing and innovation processes, cocreating value with them; (3) move the focus from the product/service offered to the whole customer experience to create value in a way that is intimately related to the individual self of the customer*".

Today, majority of customer interactions take place in digital channels, continuously generating significant amounts of data which enable businesses to gain better customer insight and integrate that to engage customers throughout their purchase journey (Hartman, 2014). Data of consumer phenomena and of individual customers can be captured real-time with the help of modern technologies, which have turned consumers into a constant generator of traditional, structured, transactional and behavioral data. Marketing can then turn the consumer behavior data into insights by combining the collected data with human perception to make it effective, which could eventually generate market advantage. (Galvin, 2013; Erevelles, Fukawa & Swayne, 2016.)

As a result of the change in the business environment and changed customer demands, organizations are investing in customer databases which enable understanding, monitoring and influencing customer behaviour. Furthermore, new technologies that enable attracting new customers, reducing customer management costs and cross- and upsell to existing customers have become more prevalent tools to increase the value of customer relationships. (Verhoef &

Lemon, 2013.) Organizations that can understand their customers' needs through creating a single view of the customer by collecting data from various sources, can engage with their customers for example through a predictive analytics next best offer strategy (Deloitte MCS Limited, 2013, Sleep & Hulland, 2019).

2.1 Customer-centric marketing

Today, consumers expect personalized solutions to their service and product needs (Clow and Baack, 2016). Due to the consumers' increased ease of switching and higher customer demands, retaining high-value customers is predicted to become highly important, especially in the financial industry (Deloitte MCS Limited, 2013). Hence, improving and enriching the long-term customer experience has become essential for organizations (Goldenberg, 2017).

The current uncertain economic environment and changing customer demands require marketing amongst customer service to drift towards personalized customer experience and precisely targeted messages. At the same time, cost-effective customer management and optimizing the marketing budget and ad spend have become rising themes in organizations. (Deloitte MCS Limited, 2013; Clow and Baack, 2016.) Thus, cost-efficient growth strategies resulting in increased customer satisfaction and effective customer-analytics strategy turning insights into sales growth are required (Teerlink & Haydock, 2012; Sleep & Hulland, 2019).

According to Sleep & Hulland (2019) one of the biggest challenges marketing is currently facing is trying to implement customer-centric strategies while simultaneously dealing with big data. Evidently, many organizations have an excessive amount of customer data available from an increasing number of various sources including CRM systems, transactions, social media, online purchases and face-to-face interaction (Teerlink & Haydock, 2012; Sleep & Hulland, 2019). However, organizations that are able to harness the data and turn it into customer insights, can achieve greater customer knowledge and improved service response and as a result, can build competitive advantage (Manyika et al. 2011; Schroeck, Shockley, Smart, Romero-Morales & Tufan, 2012). Goldenberg (2017) states, that the key to getting enhanced and more productive long-term customer relationships is engaging with customers and continuously learning from each engagement. Thus, the customer analytics that aim for generating recommended offers for customers based on their behaviour is required to go forward.

As stated, data and analytics activities are expected to build competitive advantage and improve customer experience. Hence, developing and implementing data-driven strategies will become an increasingly important business asset (Barton & Court, 2012; Brown & Gottlieb, 2016). According to the research by McAfee and Brynjolfsson (2012), data-driven organizations are five percent more productive and six percent more profitable than other organizations. Those organizations that understand their existing stage of data-driven decision making, the value of big data, and their internal capabilities that support the implementation of a higher level of data-driven decision making, are capable of providing value to both customer and the organization itself (Sleep, Hulland & Gooner, 2019).

Organizations need to utilize customer insights gained from big data to continuously improve marketing activities and eventually, innovate and design new ways to utilize big data (Tellis, Prabhu & Chandy, 2009; Story, O'Malley & Hart, 2011; Erevelles, Fukawa & Swayne, 2016). Systematic data analysis and data-driven decision-making enable organizations to shift from business-centric to customer-centric marketing strategy, which is likely to result in stronger customer relationships, higher customer value and better customer satisfaction (Lee et al. 2012; Deloitte MSC Limited, 2013; Leeflang et al., 2014). Further, the alliance of marketing and technological tools drives smarter decision-making and productivity and enhances profitability (Manyika et al. 2011; Schroeck et al., 2012).

Analytics and deriving a deep understanding of customer behavior is necessitated to deliver efficient, relevant, personalized and engaging customer experience and eventually, increased return on marketing investment. Further, increased growth and customer satisfaction can be achieved while simultaneously decreasing unnecessary costs. Moreover, increased customer satisfaction and loyalty positively contribute to customer retention and revenue. (Ginovsky, 2010; Teerlink & Haydock, 2012.) Also, Woodcock & Stone (2012) state, that regular customer interactions and introducing renewal or additional offers are likely to reduce the value decay of existing customers.

A seamless multichannel marketing strategy can help further to increase customer loyalty and conversions and provide ease of use and convenience for customers through consistent customer experience across all channels (Teerlink & Haydock, 2012). Accordingly, businesses should aim for an omnichannel always-on marketing approach where marketing communication is delivered to customers when it is most relevant to them an in the channels the customers want to use, instead of a blanket campaign marketing approach. Thus, marketing should move from using channels in silos to a model where one channel is informing or triggering the communication in another channel. (Deloitte MSC Review 2013; Stone & Woodcock, 2014.)

The success to move from product-centric to customer-centric marketing strategy depends on the organization's ability to know its customers through proactive, real-time analysis – who the customers are, what devices they use, what content they want to see and when, or if they resist the attempts to build a relationship (Woodcock & Stone, 2012; Stone & Woodcock, 2014; Sleep, Hulland & Gooner, 2019). Woodcock and Stone (2012) emphasise the importance of integrating marketing, sales, service and operative silos to develop a customer management process and ensure the customer experience and interaction is efficient and coherent throughout the customer journey. Creating a coherent customer experience resulting in personal, long-term customer relationships requires close cooperation, especially between marketing and IT (Sleep & Hulland, 2019). Furthermore, the transparency between the business operations is likely to lead also to reduced customer management costs (Woodcock & Stone, 2012). To conclude, successful transition requires aligning the organizational structure, performance metrics, internal processes (particularly customer-facing activities), and organizational culture to be focused on fact-based marketing to satisfy customer needs and requirements (Shah et al. 2006; Teerlink & Haydock, 2012).

Figure 1 summarizes the external demands, components, organizational capabilities and potential outcomes of customer-centric marketing derived from the research literature. The external demands to execute customer-centric marketing strategy come from both customers and the competitive environment. The components of executing customer-centric marketing activities are listed on the left. The organizational capabilities and requirements in order to successfully implement and manage the customer-centric marketing strategy are named below. Finally, the potential outcomes and benefits from a customer-centric marketing strategy are listed on the right.

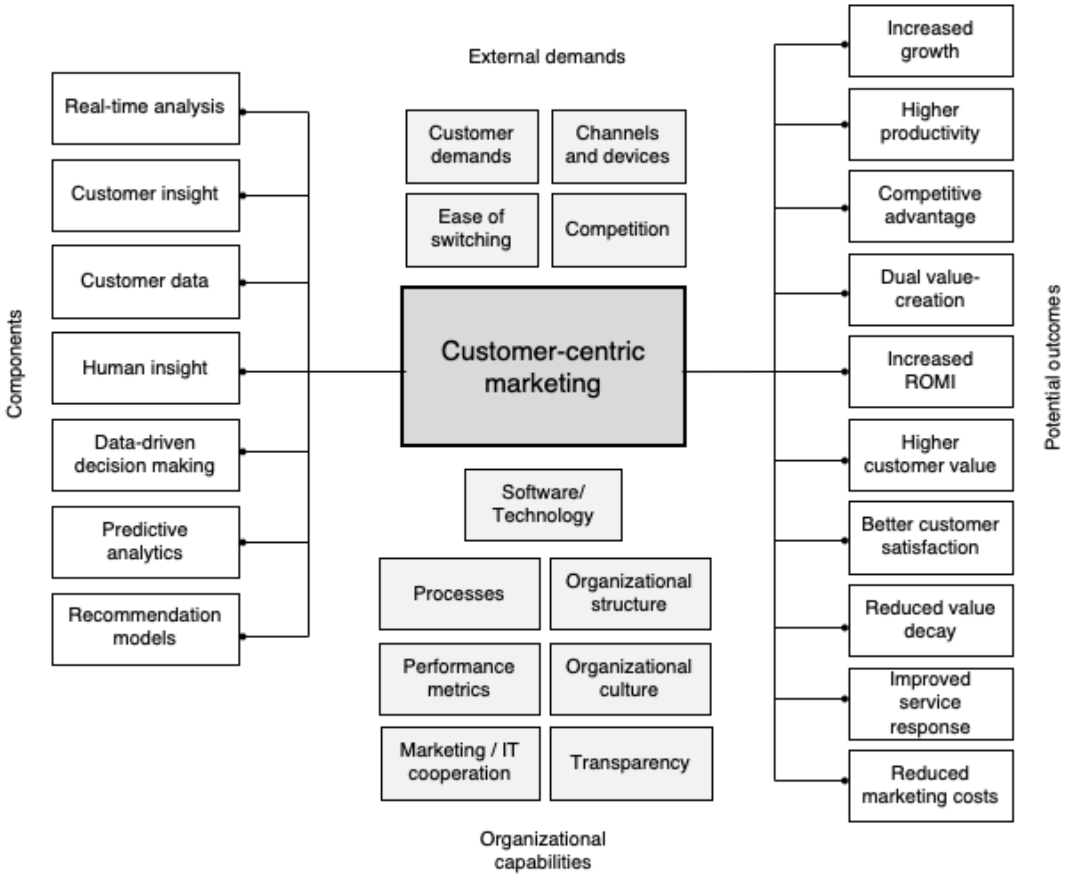

FIGURE 1 Customer centric marketing demands, components, capabilities and potential outcomes (adapted from e.g. Teerlink & Haydock, 2012; Stone & Woodcock, 2014; Brown & Gottlieb, 2016; Sleep, Hulland & Gooner, 2019)

2.2 Next best offer recommendation model

Modern technological advances are enabling marketers to catch rich customer data with greater volume, velocity and variety than ever before (Firestein, 2012). With the help of big data, consumer behavior can be proactively predicted, and as a result, organizational decision-making can be improved (Erevelles, Fukawa & Swayne, 2016). Various personalization techniques including the recently popular recommendation models have brought relief to the continuous battle of consumer attention (Adomavicius & Kwon, 2007). The developing technologies help organizations predict what to offer for whom and when (Jugovac, Jannach & Lerche, 2017). At the same time, the recommendations assist consumers in decision-making and decrease the consumers' information overload (Ginovsky, 2010; Said & Bellogín 2014).

Leeflang et al. (2014) state that efficient tracking of customer journeys is a consequential success factor for organizations in terms of optimizing marketing activities and budget. Recommendation models help organizations identify which products or services could match their customers' wishes and needs. An in-depth understanding of the decision-making strategies of the customers' needs to be developed to create successful recommendations. (van Capelleveen et al., 2019; Amrit, Yazan, & Zijm, 2019.)

All customers have several touchpoints with organizations through transactions, social media and various other online activities, which continuously generate customer behaviour data (Sleep & Hulland, 2019). The gathered product, transaction, enquiry and web-data can then be analysed to predict the needs of the customers and to target offers in all channels based on customer behaviour (Woodcock & Stone, 2012). Analysing customer behaviour patterns and building scoring models to predict future purchase patterns and customer preferences can be further used to optimize customer-centric marketing communication through all channels. As a result, organizations can increase the financial outcomes (Teerlink & Haydock, 2012). Based on the analysis of Teerlink and Haydock (2012), the organizations using predictive analytics and executing multi-channel marketing strategy can drive top-line growth even five times more than less-advanced businesses. Additionally, predictive modelling such as next best offer can improve the organization's cross-selling rates (Woodcock and Stone 2012). The appropriateness and timeliness in the next best offer models achieved through deep customer understanding are the keys to successfulness also in building customer relationships (Ginovsky, 2010).

NBO is a predictive analytics recommendation model for tailoring product or service offers for individual customers across all communication channels to increase customer value (Deloitte MSC Limited, 2013). NBO model additionally enables generating real-time recommendations for customers and allows multi-channel customer monitoring (Teerlink & Haydock, 2012). Robbins, Palan, Mui and Tao (2019) determine NBO as a follow-up offer to an identified or potential customer, based on customer data collected from various sources, including marketing database and third-party data. NBO is commonly used for marketing purposes, such as targeting marketing messages based on known or identified information and customer identity (Robbins et al., 2014). The purpose of NBO is to find solutions to customers' needs rather than find a target group for a campaign. Accordingly, NBO enables targeting personalized offers for individual customers instead of costly mass-media advertising campaigns. (Deloitte MSC Limited, 2013.)

In addition to marketing, NBO is often used also in customer service as a sales tool. Ginovsky (2010) states, that the customer service representatives (CSRs) should have the information and intelligence of the NBO model at disposal to make relevant product or service recommendations for the customers. This capability should be automated in the sales system the CSRs use, so that they do not have to analyse the customer information themselves and deduce what product or service should be offered to each customer. This enables the CSRs to focus on interacting with the customer and building the customer relationship, rather than working with the computer.

Individual customer's NBO can be predicted by analysing trends and patterns in data and using various modelling techniques to predict and anticipate the individual customer's needs and preferences (Kiron et al., 2012). The data are collected from various sources, including internal sources such as transaction data and external sources (van Capelleveen et al., 2019). More accurate NBO predictions allow more precise targeting, a bigger increase in sales and larger cost reduction, as marketing investments are not used for activities that get ignored by the target group. In addition, understanding the causes behind customer churn and analysing which customers are of the highest value and most important to retain and at what cost, has become highly important, especially for banks. (Deloitte MCS Limited, 2013.)

NBO models also encompass challenges and limitations. Ginovsky (2010) states, that catching the remarkably large amount of customer data at the precise moment when the customers are likely to acquire their next product or service can be challenging. Additionally, aging of the data and challenges in structuring the data generate additional challenges to predict the NBO reliably. Bringing the data and knowledge derived from data together on a real-time basis to engage with the customer requires a set of infrastructures that enable collecting information on a real-time basis and only when it is needed. Further, calculating the profitability of a single customer is an identified challenge regarding the NBO models.

2.3 Marketing performance measurement

Increased demand for demonstrating positive returns on marketing investments, and the global, hypercompetitive business environment are shaping marketing departments' jobs and driving marketing analytics deployment (Germann, Lilien & Rangaswamy, 2013). Fortunately, novel analytics tools and technologies provide marketing practitioners a fast-increasing amount of objective, standardized and quantitative data, which is simple to communicate to senior management. (Järvinen & Karjaluoto, 2015). Insights and customer understanding derived from that data further enable marketeers to measure and improve the effectiveness of existing marketing activities and digital advertising, which potentially results in gradual innovation (Erevelles, Fukawa & Swayne, 2016). Moreover, deploying marketing analytics can deliver positive outcomes for organizations including improved decision consistency, wider decision options and the ability to assess the impacts of decision variables (Germann, Lilien & Rangaswamy, 2013).

Järvinen and Karjaluoto (2015) state, that the use of web analytics is important in the digital marketing environment to achieve measurable marketing. Web analytics means collecting, measuring, analyzing and reporting web data for understanding and optimizing web usage. It can be used to collect clickstream data, navigation paths and website behavior to understand online behavior, measure responses to digital marketing activities and optimize digital marketing actions and elements. Various marketing studies have found that when marketing decisions are supported by marketing performance measurement data, it generates positive performance implications. (Järvinen & Karjaluoto, 2015.) To create a successful metrics system, the web analytics metrics ought to be aligned with the organization's strategy, business objectives, key performance indicators and digital marketing strategy (Järvinen & Karjaluoto, 2015; Chaffey & Patron, 2012).

Even though the positive results of deploying marketing analytics has been widely recognized (e.g. Germann, Lilien & Rangaswamy, 2013; Erevelles, Fukawa & Swayne, 2016), for a long period, measuring marketing performance has been a major concern in literature and a central issue in organizations (Lamberti & Noci, 2010). One of the biggest issues regarding data is measuring the impact and return on marketing investment (ROMI) (Woodcock & Stone, 2014). According to Stewart (2009) marketing activities can have either long-term or short-term financial effects. Nevertheless, it is challenging to measure the long-term effects – marketing practitioners are most successful in measuring the short-term effects such as responses to direct marketing campaigns or incremental sales during a promotion. However, marketing should adopt a long-term perspective which permits long-run gains instead of optimizing only short-term results. (Seggie, Cavusgil & Phelan, 2007; Stewart, 2009.) Woodcock and Stone (2012) state, the in addition to measuring ROMI, organizations should understand the reasons behind customers that did not buy from the company. To increase the quality of acquired customers, organizations should perform a thorough analysis of where and how the best customers were acquired and utilize the results to acquire new customers with the same strategy.

Another issue in measuring marketing activities according to Seggie, Cavusgil and Phelan (2007) is that many organizations manage marketing by historical performance data, such as revenue and gross margin. However, historical data does not provide insight to the future performance and changes in the business environment. Thus, organizations should focus on developing forward-looking metrics instead of measuring past performance. Leeflang et. al. (2014) further note, that measuring marketing performance reliably is difficult, as many organizations advertise in multiple overlapping online and offline channels. Specifying the contribution of a specific marketing activity or advertisement in each channel is difficult, and many organizations tend to measure the performance of individual channels using the last-click method. Nonetheless, the method ignores the individual customer journeys with multiple touchpoints and overvalues the efficiency of the final step on the customer journey. Thus, organizations tend to emphasize the power of the channels that seem to actuate the sale. (Leeflang et. al. 2014.)

According to Järvinen and Karjaluoto (2015), organizations are overall more motivated to invest in digital channels, as the results of digital marketing activities are easier to measure than the results of traditional marketing activities. Further, the changing customer behavior and the lower costs in digital marketing channels reinforce the behavior. Leeflang et. al. (2014) also note, that organizations tend to compare offline and online media performance to each other when measuring marketing performance. However, offline channels are typically used to mass advertising to reach large audiences and to create awareness in the early phase of the customer journey. On contrary, for example search engine advertising is more likely to yield direct sales as it is used by customers in a later phase on the purchase journey. (Leeflang et. al., 2014.) Aiming to develop a single view of the customer and combining these online and offline data sources is an ongoing issue which marketing professionals need to tackle (Sleep, Hulland & Gooner, 2019). As a solution, Leeflang et. al. (2014) present that organizations should focus on analysing data on a more aggregate level using econometric models, that link marketing costs to multiple online and offline media and channels.

When it comes to measuring recommendation models as NBO, measuring the quality of the recommendations provides insight of the performance of the recommendation model. Optimizing the model requires improving the algorithms by adapting the parameters of the model to eventually improve the performance of the model. Common metrics for evaluating the measurable goals set for the recommendation model include accuracy metrics, such as precision and recall, error metrics and user experience research, such as surveys and interviews. (van Capelleveen et. al. 2019.)

In addition, customer satisfaction is one of the key measures of a successful NBO programme, as measuring and evaluating customer experience informs the strategy and enables more customer-centric decision-making. Understanding what drives satisfaction and what are the causes behind customer churn and negative experiences helps to identify pain points and find practises to reduce unsatisfaction. For instance, NPS (net promoter score) can be used as a metric. (Deloitte MCS Limited, 2013.) Further, click through rates of NBO advertisements and site dwell time amongst NBO target audience can be used to measure the success of the recommendations (Yi, Hong, Zhong, Liu & Rajan, 2014). Said and Bellegino (2014) argue, that the evaluation and presentation of the results regarding NBO model performance should be delivered in extensive detail to assure a reliable comparison to the original model and algorithms used.

3 NEXT BEST OFFER IMPLEMENTATION AND MANAGEMENT

3.1 Adoption

When a new technological innovation appears, organizations make a decision if they want to adopt it and at what level. Adoption drivers can be divided into external and internal drivers. According to Sleep, Hulland & Gooner (2019) the external drivers typically concern market characteristic and competitive environment, whereas internal drivers concern executive commitment, dynamics between departments, organizational characteristics and organizational complexity. The external drivers often influence the interest towards the technical innovation, whereas the internal drivers are more likely to influence the level of adoption.

Strict competition and changing customer preferences are more likely to drive the adoption of a new technological innovation than a stable business environment. Adopting data-driven strategies enable understanding the customers and the competitive environment better, which is likely to be a remarkable driver for marketing practitioners to adopt a new innovation. (Germann, Lilien & Rangaswamy, 2013; Sleep, Hulland & Gooner, 2019.) After the external drivers have motivated the organization to adopt the technological innovation, internal drivers influence the level of adoption based on beliefs about what kind of impact the technological innovation will have for the business, and existing capacity and skills to implement the technology across the organization (Sleep, Hulland & Gooner, 2019).

According to Teerlink and Haydock (2012), a top-down approach where managers lead with example and foster gaining new skills amongst relying on fact-based decision-making is likely to lead to successful adoption of a new tool. Executive commitment to data-driven decision-making is predominantly driven by senior executives and CEO (Fosso Wamba, Akter, Edwards, Chopin & Gnanzou, 2015; Sleep, Hulland & Gooner, 2019). They have a prominent impact on the adoption by communicating and strengthening the benefits of the technological innovation for the business. If data-driven decision-making is supported by executives, it more likely becomes rooted in the organizational culture. In turn, executive resistance can also be an impediment for the adoption. (Sleep, Hulland & Gooner, 2019.)

Integration between marketing and data functions such as IT, business intelligence and finance, is seen as a substantial factor to provide strategic insights and thus, another significant internal adoption driver for technological innovations. Corporate strategy built around data and customers, leading to improved business performance and creating a single view of the customer, need a collective support from marketing and IT. (Sleep & Hulland, 2019; Wade & Hulland, 2004.) Teerlink and Haydock (2012) emphasize that understanding both sides and uncovering the difficulties, inconsistencies and issues in the adoption process between marketing and data functions is important.

Another factor influencing the adoption is the complexity of the organization and dynamics between various business departments (Sleep, Hulland and Gooner, 2019; Lee et al., 2012). Sleep, Hulland and Gooner (2019) state, that separate, siloed business units can entail challenges in identifying data sources, overlap in data usage and issues with coordinating consistent and usable data across the organization. Additionally, getting an organization wide perspective on obtainable information gets more challenging in more complex organizations, whereas organizations with more simple structure are able to manage data better.

Further, Sleep, Hulland and Gooner (2019) state, that product-centric organizations tend to focus on product innovation and market environment instead of customers. Additionally, they tend to use historical data if each product line is siloed and holds information sharing across business units. On contrary, organizations with a customer-centric strategy more often tend to adopt a single strategy in terms of customer data collection and cooperation between business units.

If an organization is satisfied with their existing solutions and feels that the solutions serve the organization's business needs well enough, the organization is less likely to adopt a new perspective or technology. Furthermore, if the organization lacks the expertise to implement the innovation, is trapped with existing competencies, or focuses on the problems instead of positive outcomes, it is less likely to adopt a new technology. (Sleep, Hulland & Gooner, 2019.)

The drivers and impediments identified from the research literature for adopting a new technology are summarized in table 1.

TABLE 1 Technological innovation adoption drivers and impediments

Adoption drivers	Adoption impediments
Strict competitive environment (Sleep, Hulland & Gooner 2019)	Stable business environment (Sleep, Hulland & Gooner 2019)
Changed customer preferences (Germann, Lilien & Rangaswamy, 2013)	Executive resistance (Sleep, Hulland & Gooner 2019)
Better understanding of customers and competitive environment (Sleep, Hulland & Gooner, 2019)	Complex organizational structure (Lee et al. 2012)
Executive support and commitment (Teerlink & Haydock 2012)	Product-centric, siloed business units (Sleep, Hulland & Gooner 2019)
Marketing & IT/BI cooperation (Wade & Hulland 2004)	Satisfaction to existing solutions (Sleep, Hulland & Gooner, 2019)
Customer-centric organizational structure (Sleep, Hulland & Gooner, 2019)	Lack of expertise and competence to implement new technologies (Sleep, Hulland & Gooner, 2019)
	Focus on problems instead of solutions (Sleep, Hulland & Gooner, 2019)

3.2 Implementation

Leeflang et. al. (2014) propose in their study that complementing existing business models with digital tools or technologies is a successful strategy to react to the changes that digitalization creates to existing business models. To succeed, it is critical to have a realistic business case whenever considering a new big data related project (Mithas et al., 2013). The most effective strategies to build a prediction model according to Barton and Court (2012) begin from identifying business opportunities and predicting possible performance improvements the model can deliver instead of starting solely with data. Even though data are essential, it is the analytic models that enable predicting and optimizing the outcomes, and eventually enable increased performance and competitive advantage.

In their study, Sleep, Hulland and Gooner (2019) present a conceptual model of four stages, where organizations can exist regarding their data-driven decision-making strategy:

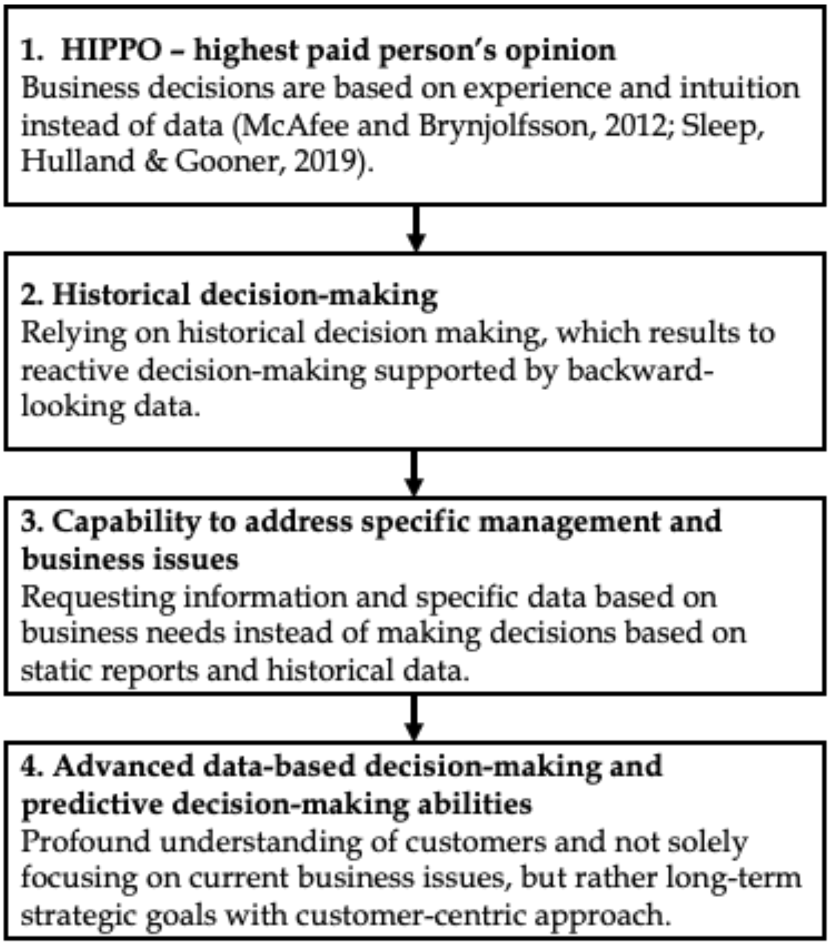

FIGURE 2 Four stages of data-driven decision-making strategy (adapted from Sleep, Hulland & Gooner, 2019)

Rust, Moorman and Bhalla (2010) have recognized, that the organizations on the third stage are still highly focused on product- and brand-centric strategies instead of customer-centric approach. Sleep, Hullad and Gooner (2019) then propose four key transitional capabilities needed in order to move to fourth stage, customer-centric predictive decision-making strategy: (1) providing consolidated and accessible data for entire organization; (2) appropriate analytical tools with machine learning capabilities; (3) technology knowledge; (4) collaborative environment. Further, other structural, technological and organizational changes may need to be performed (Rust, Moorman & Bhalla, 2010; Henke, Bughin, Chui, Manyika, Saleh, Wiseman & Sethupathy, 2016).

Grönroos (2015) further states, that the customers should be in the forefront of thinking when planning and implementing activities leading to customer-focused performance throughout the organization. Additionally, accessible and usable data providing a single view of the customer, implemented across the organization, is the foundation for data-driven decision-making, as it enables improved decision-making and reduced internal power struggle over data ownership (Sleep, Hulland & Gooner, 2019). Further, developing a culture of always-on, fact-based marketing approach, system capabilities and internal process change are needed to efficiently improve the analytical sophistication (Teerlink and Haydock, 2012; Deloitte MSC Review, 2013; Stone & Woodcock, 2014). To interpret predictive analytics, analytic tools need to be implemented (Court, 2015). In addition to fulfilling the functional requirements, the managers need to understand the value of the analytic tools and make sure the users master and are willing to use the tools, and trust and understand the analytic outcomes (Court, 2015; Lam, Sleep, Hennig-Thurau, Sridhar & Saboo, 2017; Sleep, Hulland & Gooner, 2019).

According to McKinsey Global Survey (Brown & Gottlieb, 2016), senior executive involvement and the right organizational structure are pivotal, and more important factors than technical capabilities and tools, when it comes to how successful the organization's analytics efforts are. Further, Germann, Lilien and Rangaswamy (2019) argue, that successful implementation of a new tool requires organizational change that goes beyond technical implementation process. An organizational culture, that supports marketing analytics is critical for effective deployment. Involving employees in the development and implementation of data-driven decision making, as well as executive support, focus on change management and equivalent resources is required to successfully implement data-driven decision-making (Brown & Gottlieb 2016).

Nonetheless, Grönroos (2015) states, that the management should not be directly involved in operational decision-making on a daily basis as management can be quite far from customers and service encounters. Instead of participating in operational decision-making, the top management should give the strategic guidelines and resources to achieve the customer-centric strategic goals. However, the important role of management support should not to be forgotten, as managers are in the key role of maintaining the values of service-oriented, customer-conscious organizational culture.

When implementing a new perspective and technological innovation, the change has to be distinctly communicated to employees – why the implementation is necessary and what kind of positive impacts can be expected (Sleep, Hulland & Gooner, 2019). To get the full value out of the NBO, it has to be implemented to the organisational culture and everyday processes throughout the organization. The role of analytics and prediction models should be clearly qualified and integrated to the customer strategy to allow value-adding, actionable and measurable insights. (Deloitte MCS Limited, 2013.) Furthermore, Grönroos (2015) argues, that the performance measurement and reward systems of employees should be aligned with building and maintaining customer relationships. Both planning and implementing the customer-influencing activities and performance measurement systems ought to be aligned to the total marketing process covering the whole organization.

van Capelleveen et al. (2019) state, that a typical starting point for developing a recommendation model is defining the recommendation goals, shared amongst all stakeholders and which are commonly divided into user and organizational goals. Traditionally, the goal is to support customers' purchase decision, which then further supports organizational goals, such as profit growth resulting from the increased sales. The desired goals and effects of a recommendation model ought to be defined in collaboration with the engineers and other main stakeholders in the development phase. Van Capelleveen et al. (2019) note, that the goals should be translated into practical use-cases to clarify the expected actions and behaviours associated with the goals, for example, by creating scenarios based on stakeholder input and expectations. The goals should be prioritised and defined carefully to further guide the measuring of the model's results.

Implementing NBO enables marketing, operations and customer service to gain customer analytics and information to deliver better customer experiences. However, to get the full value out of NBO, it has to be implemented to the organisational culture and everyday processes throughout the organization. (Deloitte MSC Review, 2013.) Sleep, Hulland and Gooner (2019) note, that the entire organization needs to be convinced to implement the solution and get the positive business impact. Various business departments should work together to guarantee collaborative environment and information sharing with a single view of the customer across teams. Further, the role of analytics and prediction models should be clearly qualified and integrated to the customer strategy to allow value-adding, actionable and measurable insights (Deloitte MCS Limited, 2013).

Implementing a high stage of data-driven decision-making can also entail challenges. Joshi (1991) presents, that inadequate change management, conflicts among users, user acceptance and changing work environment can cause implementation challenges. Different strategic and performance objectives between business units, as well as resistance to change, new responsibilities and processes can also cause challenges. A recognized issue in the implementation phase is the level of cooperation and conflicts between marketing and IT – the priorities of IT can cause disagreement, as in addition to marketing they support also other business functions. Further, cultural differences leading to frustration can appear between marketing and IT, as marketing teams are typically used to work in a collaborative environment, continuously working with variety of functions gathering customer information, whereas IT is more often used to gather requirements and deliver a solution. (Sleep, Hulland & Gooner, 2019; Sleep & Hulland, 2019.)

Further, Court (2015) states, that lack of immediate return on investment or lack of understanding of how analytics guide decision-making might lead to challenges. In addition, lack of leadership support and communication, understanding and trust towards big data projects can also cause challenges. Organizational structure that does not support the analytics program and having troubles finding right people with right competence, and retain them, can also cause challenges. (Barton & Court, 2012; Brown & Gottlieb, 2016.)

Sleep, Hulland and Gooner (2019) Further state, that if the employees do not understand the value of the new analytic tools and do not utilize them, or if marketing and IT departments do not speak the same language, it is difficult to adopt and implement new, more sophisticated analytic capabilities. Additionally, if the organization believes their existing capabilities are adequate and implementing predictive analytics will not provide added value, the organization is unlikely to implement the predictive approach. As an example, a large retailer company faced a challenge in the implementation, as the frontline marketing professionals did not use the implemented model, because they did not understand how the model worked and did not believe the results (Barton & Court, 2012).

When success criteria are technically and formally described and measured, and the implementation is likely to have an improved outcome and project resources can be preferably utilized (Sleep, Hulland & Gooner, 2019). According to Fernández and Thomas (2008), the success can be divided into three categories; technical development, deployment to the users of the system and how the system is able to deliver business benefits. The primary success measure ought to be the net impact that the project delivers. It can be seen as successful if the stakeholders perceive it as successful – the perception is dependent on the expectations of the stakeholders. Thereafter, the success of the project surpasses the technical implementation and can be measured by user satisfaction and the business benefits it generates.

3.3 Management

Sleep and Hulland (2019) emphasize the importance of developing an integrated approach between marketing and IT around data management and data analysis. As customer-centric strategies, data-driven decision-making and big data are currently increasingly important topics, the relationship and cooperation between chief marketing officer (CMO) and chief information officer (CIO) is becoming significantly important. According to Harvard Business Review (2015) new technology innovations are progressively moving from IT to marketing. However, marketing is not necessarily knowledgeable about how to deliver technological IT projects, thus, close cooperation between the two is required in order to successfully manage the new technology innovations.

The cooperation between marketing and IT is likely to drive creating a seamless customer experience (CMO Council, 2010; Sleep & Hulland, 2019). Interactive marketing, meaning marketing efforts that are targeted and personalized through customer behaviour analysis, is strongly dependent on effective business intelligence (BI) operations and the marketing practitioners' knowledge to execute marketing analytics (Germann, Lilien & Rangaswamy, 2013; Stone & Woodcock, 2014). As Accenture's research has shown, the marketing-technology alignment is one of the top priorities for many organizations, as the cooperation evidently enables becoming relevant to consumers across all customer touch points (Hartman, 2014).

Hartman (2014) states, that the collaboration of marketing and IT is a prerequisite for designing successful customer-experiences. By aligning the insights and business intelligence that IT is able to provide to the brand knowledge marketing has, they are able to provide valuable customer experiences. The capability to address business intelligence needs and implementing them is a crucial part of connecting and developing the relationship between IT and marketing (Stone & Woodcock, 2014). Sleep, Hulland and Gooner (2019) further emphasize, that defined roles and responsibilities between marketing and IT regarding new solutions is necessitated, as communication between IT and marketing can be inconvenient and hard if the departments do not speak the same language and do not have an interpreter. Therefore, a role that links the technology and marketing knowledge with the right skillset is required to go forward.

Stone & Woodcock (2014) defines business intelligence (BI) as a business function that transforms data into useful insights that support business. BI can be either a separate function or part of IT function in organizations. Marketing commonly utilizes BI especially for reporting, online analytics, past and predictive analytics such as NBO or NBA modelling, as well as data and text mining. Stone & Woodcock (2014) propose three key points, that are particularly important in regards of connecting BI and marketing: (1) Developing a strong data culture; (2) Connecting BI to marketing, sales and customer service; (3) Management of BI development and use.

Sleep, Hulland and Gooner (2019) state, that a collaborative organizational environment with integrated customer-oriented strategy and a single view of the customer, instead of siloed functions, are described as key capabilities for firms evolving to data-oriented culture and decision-making strategy. Further, German, Lilien and Rangaswamy (2013) argue in their study, that high marketing analytics skills have a positive influence on marketing analytics deployment, which can also indirectly positively impact to organizational analytics culture and analytics deployment. Thereafter, marketing teams need to gain modern technology skills in order to become more data oriented. The skill to understand both technology and business side of decision-making and translate the business needs to data scientists and then interpret analytics to marketing managers is required to go forward. (Sleep, Hulland & Gooner, 2019.) The combination enables common language, deducts disagreements with other business departments and creates a valuable link between technology, insights and marketing (Henke et al. 2016).

As BI supports users with tools and data, it has to be appointed who makes sure the data are understood, adopted and used correctly (Stone & Woodcock, 2014). Stone and Woodcock (2014) state, that misunderstandings and limited communication can lead to a situation where BI is demanded to develop new analysis, models and reports only to support the marketing results. The issue can be solved only by the partnership between BI and the users by clearly stating the roles of users, managers and BI.

To sum up, Stone and Woodcock (2014) propose a strategy where central team manage how the data and tools are used, with BI having a control over the content of the dataset. The team should maintain a clear focus on the strategies that require support from BI and ensure, that higher management has a clear view of how BI benefits the whole organization. Thus, the marketing strategies that need BI support have to be clearly defined and prioritized.

Thereafter, it is of high importance that the link between marketing and BI is strong. The role of linking the two together should understand both marketing issues and opportunities and data science, as this operational model assures the validity of the results across organization. Stone and Woodcock (2014) suggest that a strong focus should be kept on the marketing and customer strategies that guide the BI needs to support marketing. When strategy leads the BI needs, it helps avoiding a problem, where the users of BI tools determine BI needs to support marketing without clear focus on strategy, leading to long planning and delivery times and unavailing information. The operational management model is presented in figure 3 which is derived from the article by Stone & Woodcock (2014).

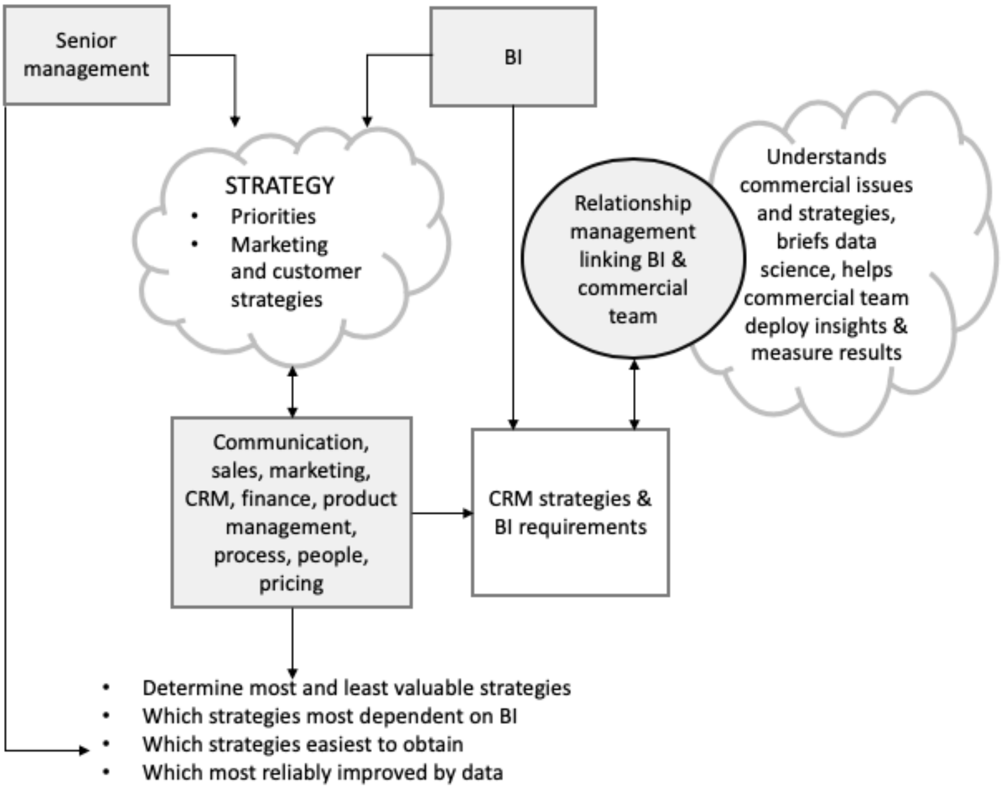

FIGURE 3 The proposed strategy to manage the BI requirements based on the article by Stone and Woodcock (2014).

4 DATA AND METHODOLOGY

In this chapter the case company is first briefly described, and after that the research method, sampling method and the methodologies for collecting and analysing data are described.

4.1 Case company description

The case company is a middle-sized Finnish retail bank, that operates in Finland. The case bank offers investment, loaning, credit and daily transaction services to its customers. The headquarters of the bank are located in Helsinki, Finland, and additionally the bank has several customer service offices located around the country. The case bank serves the customers through multiple channels and touchpoints including website, mobile application, online bank, call centre and various social media channels, such as Facebook, Instagram, Twitter and YouTube. The case company uses customer service and online channels to sell its products. Customer service channels include call centre, customer service offices and specialized customer service offices for mortgage loan and investment services. The online channels include online banking service and mobile application.

The case company started to develop the NBO model in 2016 after which it has been implemented to marketing, customer relationship management (CRM) and customer service. Even though the implementation can be seen as a phase or a project, it was soon noticed in the case company, that the implementation proceeded to management and development of the NBO model without a clear frontier and can be seen more like an ongoing process or strategy.

The author worked at the case company from 2016 to 2019 in marketing and participated to the implementation of the NBO model. The author worked closely together with other key employees in the implementation process including marketing, CRM, sales and analytics teams and managers.

4.2 Research method

This research was conducted as a case study research using a qualitative research method. A case study research can be defined as an in-depth study of a phenomenon in its real-life context, which provides an insight or understanding to the study subject (Farquhar, 2013; Yin, 2014). Dul and Hak (2008) further stress, that a case study is a research of one single instance, which is the case, or a few instances of the object of the research. Schramm (1971, p. 6) states, that the essence and central tendency amongst case studies is *"…that it tries to illuminate a decision or a set of decisions: why they were taken, how they were implemented, and with what result"*. The research objective of this research is the implementation and management of the next best offer model. Thus, this research focuses on a single case, implementation and management, in its real-life context, which is the case company.

Case study research has been advocated as a valid research strategy in marketing studies by Bonoma (1985) and Dul and Hak (2008). According to Dul and Hak (2008) case study is a suggested research method in marketing topics such as marketing strategy development and implementation, customer service and business reengineering. Further, in operations the dynamics of technology implementation is suggested as an interesting topic for case study research. According to Yin (2014), case study is a preferred method when the central research questions begin with "how" and "why", when the researcher has little control over behavioural occurrence and when the research focuses on a contemporary phenomenon. Further, Farquhar (2013) infers, that in a business context a case study research focuses on collecting information of the phenomenon where it is taking place, such as in a company, with questions how, why and who - hence, case studies tend to contribute to decision-making and policies rather than science. The motivation for this research is to understand why certain decisions were made in the implementation, management and development of the NBO model in the case company, how the model was implemented and managed and with what result.

Dul and Hak (2008) state, that case studies can be divided into two groups – practise and theory-oriented studies. A theory-oriented research aims to contribute to theory building, and a practise-oriented study aims to solve or clarify a problem and tries to contribute to the knowledge of a practitioner such as a manger or an organization. This research is a practise-oriented case study research, as the aim is to contribute to the practitioners' knowledge in the case company, other practitioners interested in this topic and practitioners working in a company that is about to or have already implemented a predictive analytics or a next best offer model.

A qualitative research approach was used to answer the research questions. Berg (2009) defines, that a qualitative research focuses on collecting qualitative data innovatively in natural settings and then analysing the information. Gillham (2000) states, that qualitative research enables investigating situations where only little is known about what is going on and what can be found, and to get a closer look to an organization and find out what really happens. Further, qualitative research enables longer, more detailed and variable content that enables understanding the phenomenon as seen by the interviewees (Patton, 2002). A qualitative research approach was a suitable choice for this research, as the objective was to find out the factors leading to success and failure in implementation and management. Thus, qualitative research enables getting a close look at the underlying factors and situations in the organization and understanding what has happened and why.

Adams, Raeside & Khan (2014) state, that the aim of qualitative research is to examine also social relations and describe the phenomenon as it is experienced by the interviewees. Nachimas and Worth-Nachimas (2008) argue, that the role of the qualitative researcher is to understand behaviours and institutions by familiarizing him or herself with the involved stakeholders, their values, rituals, symbols, beliefs and emotions. Accordingly, this research aims to find out the underlying experiences from each interviewees' point of view and to inspect the cooperation and communication in the case company.

Patton (2002) states that qualitative research is a powerful source of theory that accumulates from interviews and observations from a real-world scene rather than in laboratory setting. Qualitative research generally develops knowledge for those who are interested in the phenomenon, as other researchers and policymakers. Respectively, this research contributes to the knowledge of practitioners interested in this topic through developing an understanding of a real-life phenomenon by interviewing the employees involved with the implementation and management in the case company.

4.3 Data collection method

Patton (2002) states, that qualitative research has three data collection methods: In-depth interviews, observation and written documents. Interviews are a widely used method to gather information from participants in qualitative research (Goodman, 2011). Hair & Page (2015) specify, that interviews are an appropriate data collection method when the aim is to understand why something happens, whereas observation is used when examining behaviour. The main purposes of conducting a qualitative interview as gathering unique information or interpretations from the interviewee, collecting a compilation of information from a group of interviewees and gaining knowledge of something that would not have been found out otherwise (Stake, 2010). Mann (2016) states, that interviews are generally used to understand the phenomenon from the subject's point of view.

The data collection methods in this research were one-to-one in-depth semi-structured interviews and written documents provided by the interviewees. According to Patton (2002) interviews provide information especially about peoples' knowledge, experiences, opinions and feelings, whereas document analysis yield knowledge through extracts, quotations or organizational records and official publications, for example. In-depth interviews can be described as purposeful conversations combining both structure and flexibility (Ritchie & Lewis, 2003). Interviews allow the researcher to enter to the interviewees' perspective and understand what is in or on the interviewee's mind. Further, open-ended questions allow interviewees to answer freely without pre-determined questionnaire categories (Patton, 2002). Hair & Page (2015) specify, that qualitative interviews should focus on describing the phenomenon and asking why, how, when, where and who questions.

Interviews can be either highly unstructured or highly structured (Hair & Page, 2015). Berg (2009) classifies the interview structures to three groups – standardized, semi-structured and unstructured. The interviews in this research were semi-structured. The benefit of semi-structured interviews is that they provide an interview structure without sticking to a pre-determined script, they leave room for discussion and expanding the answers of the interviewee, thus, enable gaining unforeseen information increasing the findings (Hair and Page, 2015; Mann, 2016). Combining a conversational theme-based interview and standardized interview by forming certain questions exactly and leaving space for conversational topics offers the possibility to explore some topics in greater depth and ask additional questions (Patton, 2002). In consequence, semi-structured interview structure was seen appropriate, as it allowed asking related additional questions and gaining deeper, unexpected information. As the author was not aware of all factors and phases in the implementation and management, semi-structured interviews enabled the interviewees share unanticipated information enhancing the findings.

The interview structures and questions needed to be covered during the interviews were planned and prepared beforehand (see Appendix 1). According to Malthora, Birks and Wills (2012), open ended questions allow the interviewees to express attitudes, opinions and views that they found important. Thus, the questionnaire included open ended, unstructured questions, that the interviewees answered by using their own words to allow free responses. However, the disadvantage of open-ended questions is that the data analysis is more time consuming as the data is unstructured, and they might give more weight to more talkative interviewees (Malthora, Birks and Wills, 2012). According to Baur (2014) it is important to ensure that each interviewee answers to the same questions using the same themes in the same interview situation. Thus, the interview themes, questions and structure were carefully prepared beforehand based on the theoretical background and the research objectives of this research. The interview questions were sent to the interviewees by email two days before the interview took place to give the interviewees a possibility to familiarize themselves with the questions.

According to Gillham (2000) qualitative research should take place in the context where the people operate to understand their behaviour, thoughts and feelings in the right context. Thus, the interviews were performed in the case organizations office, where all the interviewees worked. The interviews were arranged during a two-week period in November 2019, except the interview with the data scientist, which was arranged in May 2019 because he left the company in June 2019. Arranging the interviews in limited time window ensured that the data was collected in the same phase of the implementation and big changes did not take place between the interviews. The length of the interviews varied between 30 minutes to 80 minutes. The length of the interview varied, as some interviewees could not allocate as much time as others, and additionally some interviewees more talkative and willing to share more information than others. In addition, some interviewees were more involved with the implementation and management than others. The interviews were conducted in Finnish, as it was the author's and the interviewees' mother tongue and main working language. All six interviews were recorded with authorization of the interviewees and transcribed afterwards to make the analyzing easier. In addition, some of the interviewees provided documentation about the implementation and management of the next best offer model. Therefore, the documentation was also used as data.

4.3.1 Sampling method

Hair and Page (2015) state, that interviewees, a sample, for in-depth, one-to-one interviews are generally selected due to their experience or knowledge in a specific topic, that will give the researcher relevant insight. A sample is a small subset of population, which can be selected by either probability or nonprobability sampling procedure. Nonprobability sampling is more commonly used in qualitative research, as judgement is involved in choosing the sample, whereas in probability sampling, which is typically used for quantitative researches, a random procedure is used to objectively select a representative sample. (Hair & Page, 2015.)

To collect relevant information, it is important to select people who know about a particular topic. Hair & Page (2015) state, that in nonprobability sampling the researcher subjectively selects the sample by using his or her own experience, judgement or convenience to select the sample. This way the researcher is able to make informed judgements, and thus, gain usable information. However, the limitation of this sampling method is, that nonprobability sampling is not representative of the population and the findings cannot be generalized.

The non-probability sampling method used in this research was purposeful sampling, also known as judgement sampling. In purposeful sampling the researcher uses his or her own judgement to select the sample. Purposeful sampling can be used for example for selecting a group of experts with knowledge of a specific topic. (Hair & Page, 2015.) The sample for this research was selected from the case company based on who have the most knowledge of the topic. As a result, six experts from different teams in the case company were selected, as they were most involved with the implementation and management and had most knowledge of the topic. Thus, all key managers in the case company involved with the topic were interviewed for this research. Further, they worked in different roles and represented different viewpoints, which enabled getting more comprehensive findings. It was not seen relevant to interview more employees, as other employees in the case company were not as involved with the implementation and management, thus, did not have deep knowledge of the topic. The main reason for selecting the interviewees was, that they have been part of the implementation and management of NBO, and it was seen likely that these employees could give comprehensive and substantive information. As the research objective was to conduct a manager level understanding of the adoption and implementation, only manager and senior level employees were interviewed. One interviewee was selected from each business unit closely related to the NBO model to get different perspectives on the topic. The interviewees can be seen in table 2.

TABLE 2 The interviewees

Title	**Major role and responsibilities in the position**	**Years in the company**	**Interview date**
Digital sales manager	Responsible for digital sales, targeted advertising, marketing technologies and website development. Responsible for the group developing and managing predictive analytics models.	Four years	October 31st 2019
Marketing and communications director	Responsible for marketing and communications strategies, reputation management, social media, and developing and supporting customer communications in the case company. Marketing and communications team leader.	Four years	November 4th 2019
CRM and digital sales director	Responsible for digital sales and managing and developing customer relationships on organizational level. CRM and digital sales team leader.	Six years	November 4th 2019

Analyst	Responsible for predictive analytics models, their development and management.	Eight years	November 5th 2019
Customer service director	Responsible for customer service and contact center operations and sales support for all customer service channels.	Two years	November 14th 2019
Data scientist	Responsible for designing and developing predictive analytics models.	Four years	May 29th 2019

4.3.2 Interview Guide

Next, the interview guide including the reasoning for the chosen themes and questions is described to explain why the specific questions were asked from the interviewees and how the chosen questions are related to the theoretical background and the research objectives of this research. Patton (2002) states that the interview guide ensures that all interviews follow the same structure by providing themes and specified questions to guide the interview. It guarantees the interview is carefully planned and the process is systematic and comprehensive. Concurrently, the guide allows the interviewer to ask questions more freely to clarify the topic, make a conversation and word questions spontaneously with focus on predetermined themes.

At the beginning of the interview, the interviewee was offered a written copy of the privacy notice that outlined how their personal data is processed in this research (see Appendix 3). Then, the researcher briefly described the topic and themes of the interview, and the purpose and objectives of the research to each interviewee to channel the focus to the topic. Additionally, confidentiality of the interview and the research, and the rights of the interviewee were shortly discussed.

A first, the role and key responsibilities of each interviewee in the case company were discussed. Additionally, the main priorities and key performance indicators (KPIs) of the interviewee and the interviewee's team were asked (see Appendix 1). These questions were asked, as it was seen relevant to know the background of each interviewee and to understand the interviewee's position and responsibilities in the organization.

After this, the interviewee was asked to briefly describe what the NBO model is and how it is used in the interviewee's team. The questions were asked to gain information whether the interviewees' understandings of the NBO model were aligned and discover how each team utilizes the model in practice. Next, the interviewee's role regarding the implementation and management of the NBO model were discussed, since it was relevant to understand each interviewee's role and how much they were involved with it. Further, the identified challenges and success factors regarding the implementation and management were discussed to gain an in-depth understanding of each interviewee's perception, experience and opinion.

The next topic discussed was each interviewee's relationship to other employees using the NBO model. Since the theoretical background strongly emphasized the importance of aligning the objectives and actions of each business unit, and the cooperation between IT, BI functions and marketing, it was seen relevant to discuss this topic. Next, the interviewee was asked to describe how the NBO model was managed and developed, and which business units or teams used the model. These questions were asked to understand the management of the NBO model from each interviewee's perception and gain a comprehensive understanding of the management.

The next topic discussed was measuring the performance of the NBO model. The interviewees were asked about the metrics they used to measure the performance, the results they had achieved with the NBO model and how the results were utilized. The author saw it relevant to understand the metrics used to measure the results and how the results were utilized, as the theoretical background supports continuous measurement of the NBO performance and using the results to develop the model. Additionally, some interviewees were asked if they were measuring CLV, as CLV was seen as one of the most important metrics to measure customer engagement in a customer-oriented organization in theoretical background.

Lastly, the development and management of the NBO model were discussed in more depth. The researcher asked about the current state of the model's management and development and the future development plans for the model. The author saw it highly relevant to discuss the development needs and opportunities, as management and development of the model were identified as critical issues by the case organization. Further, the theoretical background supported the need for continuous development of predictive analytics.

As it was stated before, the interviews were conducted in Finnish. The researcher's and the interviewees' native language was Finnish, so it was justified to use the native language. As the thesis is conducted in English, a backtranslation method, often used by academics and marketing research companies, was used to translate the interview questions to ensure the translation quality and equivalence, which is required when collecting cross-cultural data (Craig & Douglas, 2005; Taylor, 2011; Curtarelli & van Houten, 2018). Taylor (2011) states, that it can be seen as a flaw if a study does not use the back-translation method. As Curtarelli and van Houlten (2018) suggest, the interview questions were translated from Finnish to English and then back-translated to Finnish by another bilingual translator. Then, the back-translated questions were compared to the original ones to ensure the translation quality. The interview form is included in attachments in both languages.

4.4 Data analysis method

Malthora, Birks and Wills (2012) state, that recording the interviews and verbatim transcription of the interviews are important especially when the questions are unstructured, as it minimizes the potential bias of the researcher. The interviews were recorded by the permission of the interviewees and then after the interviews the recordings were transcribed. The transcriptions were conducted word-to-word, as it was seen relevant to retain the significance and purpose of the answers. However, pauses and filling words were not included in the transcriptions, as they were not relevant.

After transcribing the data, the data analysis started with reading the data many times through to get familiar with it. Reading the data through before starting the analysis is important to get into the lives and experiences of the interviewees (Corbin and Strauss, 2008). After getting familiar with the data, the predetermined and supplementary themes from the data were identified. Next, as the researcher had gotten familiar with the data and identified the relevant themes, data-reduction was conducted due to the large amount of data, of which all were not relevant for this research. Data-reduction is suggested to organize and structure the data (Malhotra, Birks & Wills, 2012).

The analysis of a qualitative case study is a process, where the aim is to collect comprehensive, systematic and thorough understanding of each case of interest – which results in a case study. Data analysis can be divided into the inductive and deductive analysis. Inductive analysis means finding patterns and themes from the data where the findings of the study emerge. Inductive analysis is typically used in qualitative studies. In turn, in deductive analysis the data is analysed based on an existing framework. (Patton, 2002.) This research is primarily analysed with an inductive approach. However, Strauss and Corbin (2008) state, that research is often both inductive and deductive process, as every time the researcher derives interpretations and hypotheses from data, it is a deductive process. Thus, deductive analysis is also used to confirm the analysed data and examine the findings to the theoretical framework (Patton, 2002).

The primary data analysis method used in this research was theme-based analysis, as the interviews were theme-based, thus, it was a logical choice. Themes can be considered as higher-level concepts of the data (Corbin & Strauss, 2008). Patton (2002) suggests using theme-based, or content analysis in qualitative and case research to reduce and to make sense of the large amount of data. Theme-based analysis helps to identify patterns and themes from the data and bringing together a comprehensive picture of the experiences of the interviewees. Further, theme-based analysis enables creating an understandable narrative of the case that can be utilized by decision-makers.

5 RESEARCH FINDINGS

In this chapter, the research findings are presented. As stated in the previous chapter, the data was collected through six semi-structured in-depth interviews in the case company. The research findings are presented following the theme-based interview guide derived from the theoretical background and research questions. At first, the roles and responsibilities of the expert interviewees are presented. Next, the NBO-model and its utilization in different teams and organizational functions are described. After this, the adoption, implementation, management of the NBO model in the case company are discussed. Then, it is described how the case company evaluates the NBO model performance and what are the development needs and opportunities.

5.1 Roles and responsibilities of the interviewees

The first interview with the data scientist was performed in June 2019. The data scientist was interviewed earlier than others, as he left the case company in July 2019. However, it was highly valuable for the researcher to interview the data scientist already in an earlier phase of the research, as he assisted in defining the topic of the research and provided a thorough representation of the NBO model, its development, utilization and management in the case company. The data scientist was responsible for developing the predictive analytics capabilities in the case company and had designed and developed the NBO model.

The rest of the interviews were arranged in November 2019 in a two-week time period. The first interview in November was carried out with the digital sales manager. He had worked for the case company for over four years in various analytics positions focusing on digital sales and web analytics. His main responsibility was managing the digital sales to get the customers to convert better in the digital channels by developing and optimizing the paths to purchase. Further, he was responsible for website development and marketing technologies in the case company including tools for personalizing and targeting marketing communications messages in digital channels and advertising. In addition, he was responsible for leading the group that managed and developed the NBO model.

The digital sales manager stated, that his main priorities and KPI's were strongly aligned with the case company's sales targets, which were then derived into product level and customer segment targets.

Next, the CRM director was interviewed. She had worked for the case company for nearly six years in various marketing and CRM positions. Her major responsibility was leading the customer relationship and digital sales team. She further explained, that the team was responsible for the customer relationships on an organizational level, including the development of the customer base so, that the customers progress to more active and profitable customers for the case company. The main KPI's of the CRM director and her team were fostering customer experience including NPS and user experience in different channels, segment-based sales targets derived from organizational level sales targets, and activating passive customers by helping the customers to take certain services in use to support sales.

Next, the marketing director was interviewed. He had worked for the case company for almost four years. His major responsibility was leading marketing and communications on an organizational level. His team was responsible for promoting sales, brand management, reputation management and contributing to encouraging the customer-centric culture in the case company. More specifically, marketing was responsible for traditional marketing tasks including marketing strategy and planning, marketing budget management and advertising in digital and traditional channels. In marketing the main KPI's were sales targets and activating various services. He further stated, that in some cases the quality of the customer relationships is measured and used as KPI, such as the number of customers that have activated from passive to profitable customers.

Next the analyst was interviewed. She had worked in the case company for eight years in various positions in the analytics team. Her primary responsibilities were managing, maintaining and developing the predictive analytics models including the NBO model. In addition, she also provided reports and analysis for the business's various needs. She said, that the analytics team worked as a centralized function serving all business units.

Lastly, the customer service director was interviewed. She had worked for the case company for two years. Her main responsibility was leading the customer service function including contact center and customer-interface support function, which was a sales support team for all customer service representatives around the organization. The KPI's of the customer service function incorporated efficiency, customer experience, sales and employee satisfaction. She pointed out, that customer experience including the quality of the customer service and NPS was an important KPI for them. Lastly, sales and customer activation were strategy led KPIs, which depended of the case company's prevailing sales targets.

5.2 NBO model in the case company

In this chapter, the background and motivation behind developing a predictive analytics NBO recommendation model in the case company are first presented. Then, the NBO model's functionality and limitations are discussed and lastly, the use cases and perceived benefits and results of the NBO model in the case company are presented.

5.2.1 Background for developing the NBO model

The motivation for developing the NBO model in the case company was to clarify the marketing team's responsibilities and to reinforce customer-centricity in marketing. The data scientist explained, that in the case company's marketing team each marketing manager was responsible for a single product or product group. It resulted in working in product silos without full transparency to the overall image of marketing, and what marketing activities other marketing managers were doing and when.

"The original idea was, that one person responsible for a specific product, doesn't use all customer potential to that product's marketing, if it is more favorable to advertise some other product to some of the customers. So NBO is the tool to support how our marketing and business is organized." **Data scientist**

Before the NBO model was implemented, there were situations when marketing managers were doing the same marketing actions at the same time. They then ended up targeting their marketing activities to the widest possible customer base to meet their own sales goal. This resulted in a situation, where one manager targeted most of the potential customers leaving only small target groups for others to their marketing actions. Another lousy option was, that the customers were approached too frequently, as the managers targeted the same customers. As this operative model was highly business-centric, the NBO model was developed to move towards a more customer-oriented approach. The goal was to keep the customers in the central of the thinking so that they get relevant messages in different channels.

"The idea behind this kind of centralized model is, that we can control for example how many messages a customer gets and about which product. When the development of the NBO model began, the marketing managers competed of the same target group with each other. They then ended up stealing target groups from each other for their own marketing activities. The target groups were intentionally made larger by the managers, but it is the customers who suffer, when they get many different messages. That is a good reason for developing an NBO model." **Digital sales manager**

Further, before the prediction models were used in marketing, the marketing managers made the target groups by hand picking. The target groups were based on demographic and customer data, such as age, geographic area and products and services in use. However, this method generated only rough estimates, as a human is not able to observe as many variables as a computer and analyze which action to take based on the data. The prediction models are able to simultaneously observe hundreds of background variables and predict which customers could actually be interested of the product.

"It is also kind of modeling, when you research who have applied for a loan before, whose application has been accepted, what age they are and other background variables, and based on that start picking the target group. That is kind of the same, but the predictive model then adds mathematical models to the background." **Digital sales manager**

5.2.2 The functionality of the NBO model

The NBO model is a probability and prioritization model, that can be utilized to guide sales and marketing investments to most likely converting and realizing product and service sales. It consists of several different prediction models, that are combined into one bundle, NBO model. The NBO model prioritizes the product recommendations for each customer.

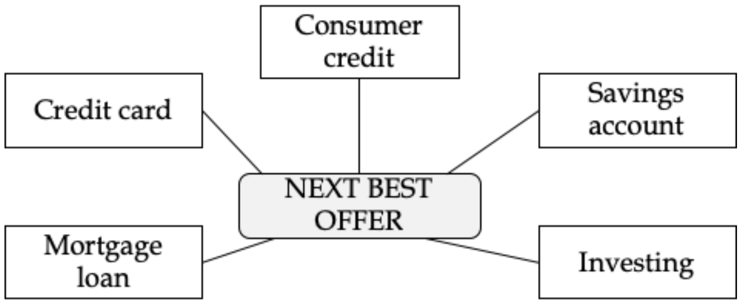

FIGURE 4 Illustration of the NBO model components

"The NBO model is a product recommendation model, a frame, which consists of several different, independent prediction models. It is used to recommend products and services for customers and to optimize marketing activities." **Analyst**

"With NBO model we aim to find the most interesting service for each customer. On the background there is modelling and calculations about how interested each customer is about each service and what is the most interesting one for the customer." **Digital sales manager**

The NBO model predictions include customers' predicted interest towards the products and additionally, predicted acceptance rate of loan products. The interest prediction indicates, which product should be advertised for the customer and the acceptance model indicates, whether the customer's loan application will be accepted or not. As a result, the model recommends each customer a product or service, that they are most likely to take in use or purchase in the following two-month time frame.

"The two-month time frame makes the recommendations comparable to each other and enables that the recommended products can be arranged to most likely, second likely and so on. With the help of the model, each marketing manager can target the marketing actions to the customers that are most likely to be interested of the product they are advertising, without using the best customer potential of other products." **Data scientist**

The technical functionality of the model is however more complicated, as the NBO is a so-called black box machine learning model.

"The models are quite technical and hard to explain. So, it works as it works and generates the results, but it is not easy to explain what the model actually includes." **Analyst**

The data scientist stated, that the NBO model predictions were based on customer data from the previous 12 months from the moment the prediction is made. The model utilizes 700 background variables including for example demographic data, postal code area data, behavioral data and transaction data, of which the model selects the best variables to explain each customer's interest. As a result, each customer gets an interest rate for all the products in the NBO model.

The NBO model includes specific interest limits for each product, which is a calculation based on machine learning. All customers whose interest rate is the same or above the NBO limit, would then be in the target group of that specific product. The NBO model then prioritizes the recommendations based on the customer's interest rate. The NBO recommendation prioritization is illustrated in figure 4.

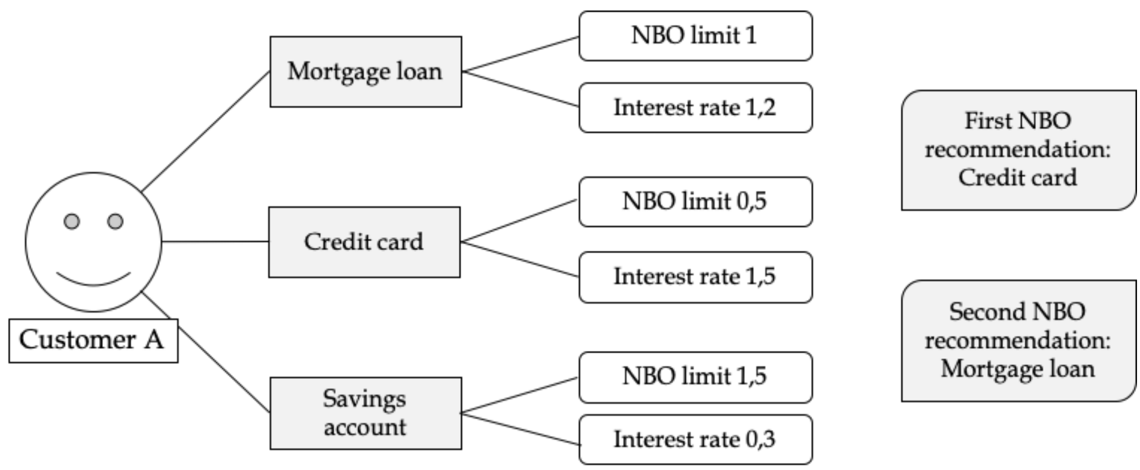

FIGURE 4 The NBO model limits and interest rates generate the recommendations for each customer

The data scientist stated, that the optimal NBO limit is found through testing different limits in marketing activities. The limits can be adjusted for different channels separately, for example digital marketing and customer service, depending on each channel's characteristics. The data scientist stated, that choosing the limits also include lots of business logic and decisions about how big target groups are pursued. Determining the limits is balancing between the quality and the quantity of, for example, loan applications. If the NBO limit is lower, the bigger target group can be reached, but the conversion rate will be lower. On the contrary, with high NBO limit a smaller target group will be reached, but the quality is better, thus, the conversion rate is higher. The digital sales manager acknowledged, that they also sometimes adjusted the NBO limits to achieve sales goals.

"We have sales goals and if we are reaching one goal, and we know, that that product has a big target group potential in NBO which we don't need in advertising, we can advertise some other product which sales are lagging behind the target, for those customers. Then we get a larger target audience for that product's marketing and we test what is the impact." **Digital sales manager**

The marketing director pondered which should be prioritized – business goals or the NBO model.

"I think business goals should come first, but how we get to the goals, there we should primarily follow the NBO model. Business goals should start from setting a profit goal and then think about the different options how we get to the set goal. In the best case, the NBO model could guide us about how many customers from our customer base could get different products in use. It could help inform the sales goals – what sales distribution and customer relationship development gets us to the desired profit goal." **Marketing director**

5.2.3 Use cases

The NBO model was used in marketing, CRM, digital sales and customer service to target sales and marketing activities. According to the marketing director the NBO model was used both in online and offline channels including emails, direct mail, digital advertising and personalizing online bank and website content.

"Advertising in digital channels and direct marketing are the most important from our area of responsibility. In the future, also mobile application communication should be based on the NBO model. NBO model is used in other teams as well and my job is to make sure that the same recommendation is shown consistently in all customer touchpoints for a customer – the same message that the customer service representative says to the customer, reaches the customer in direct mail as well, for example." **Marketing director**

The marketing director said, that more could be however done in marketing, as in some product groups the utilization of the NBO model was more coherent than in others. The NBO model was however not used in traditional communications. The marketing director thought, that NBO is not directly relevant for communications activities.

The CRM director stated, that they used the NBO model consistently in all customer communication, as they were targeting all marketing and communications based on customer behavior to avoid spamming. The messages were coherently targeted for customers who had made some action themselves and thus, could be interpreted as interested, or to customers that were highly interested about some product based on the NBO model.

"The NBO model is on the background of each customer contact we make. Our aim is to never make a cold contact and always take the NBO pool as the basis, as we say." **CRM director**

The CRM director mentioned, that they were starting to be in a good phase with how consistently the NBO model was used in the case company as a whole. Most recently the NBO model was implemented to display advertising, where it was used as a targeting method in 30 % of the advertising in total.

In customer service the NBO recommendation was shown to the customer service representatives (CSRs) in the software they used in the customer service situation both on phone and in customer service offices. The idea was, that the CSR recommends the product to the customer during the customer contact. The customer service director stated, that the NBO model also benefits the CSRs, as they do not have to think what they should sell to each customer. The customer service director said, that the CSRs had been instructed to handle the NBO recommendation in each customer contact and they had been told why it is important and how it benefits them.

"Our goal is that all sales and customer activation that we do is done through the NBO recommendations. When the CSRs make the NBO recommendations, it leads to the sales targets expected from us." **Customer service director**

5.2.4 Limitations of the NBO model

There appeared also some limitations in the NBO model and its utilization during the interviews. As the NBO model is a very targeted method, only the customers of whom the company had enough data of, could be reached with the NBO. The digital sales manager said, that as the NBO model is a predictive analytics model, it requires large amounts of data to be able to make the predictions. However, the case company had enough data only from the minority of their customers in order to make the predictions.

"We are not able to use only NBO model as a targeting method. It is quite targeted. You reach only a certain target audience based on the background variables. We also need to get new customers interested about the products and the model does not necessarily find those customers, as you need quite a big amount of data to make the predictions." **Digital sales manager**

"We might have hundreds of thousands of customers who are interested of our loan, but we don't know it, because we don't have the data. So, the NBO model is not the solution to everything." **Marketing director**

The digital sales manager noted that also other targeting methods were needed to get new customers and introduce new products which were not yet implemented to the NBO model, both to existing and new customers. Particularly passive customers did not generate enough data, as they did not use the services actively, which made predicting the NBO difficult for them.

The marketing director further pointed out the challenge of providing a cohesive recommendation for the customers in all different digital channels and customer service. The marketing director believed, that in the worst case they might lose sales and the customer might think, that the bank does not understand the needs and requirements of the customer. He considered the issue is hard to solve and did not know what could exactly be done.

"For example, if a customer has authenticated on a web browser on laptop, we can make the NBO recommendations to the customer there. But when the customer uses for example his mobile device and goes to our website, the customer isn't authenticated there. The

customer might have our mobile application in use where the customer is authenticated, but if he hasn't logged in on the browser on his mobile device, he doesn't get the NBO recommendations there. He might end up getting a general recommendation, such as 'download the mobile app' or 'have you lost your log in information' or something like that. And the customer might already have all those services in use." **Marketing director**

The data scientist stated, that it is also important to understand that NBO model predictions are not exact facts.

"The models predict probabilities, so nothing is sure. We can make wrong predictions to any customer and we are doing that all the time. The predictions are not facts, but the results show the prediction models are however more useful than other targeting methods. The models are not perfect and won't be, it is good to remember that." **Data scientist**

The customer service director stated, that also the CSRs had expressed, that the customers were not always interested in the recommended product despite it had been the NBO recommendation. She said it had weathered the CSRs' trust towards the NBO model.

5.2.5 Benefits of the NBO model

The NBO model provides a possibility for multi-channel recommendations based on the customer lifecycle. In addition, the model prevents product groups from cannibalizing other product groups' visibility in marketing communications and customer touchpoints. The model also prevents different channels optimizing their performance at the expense of other channels.

"The NBO model is a tool to provide just the right service for the customers on the right time. I think it creates us a possibility to do personalized communication, marketing and customer service." **Marketing director**

Further, the NBO model enabled centralized operative model in the case company, and streamlining the resources in sales and marketing, as the investments could be directed to activities that create most value and ROI. The NBO model also improved the customer experience, as targeted product recommendations were more relevant for customers.

"NBO has multiplied our sales. And also enhanced the customer experience, as customers get more relevant communications and not kind of cold sales. Plus, it has remarkably decreased our costs. If we look at the marketing spend, now that we can advertise more targeted, we of course, need to send direct mail to smaller target groups. That is a direct effect. Actually, our budget has decreased to third in three years and part of that is because of the NBO." **CRM director**

A common theme in the interviewees' answers was, that the marketing activities where the NBO model was used as a targeting method generated better results than with other targeting methods. The marketing director specified that the results and benefits were received through systematic testing.

"Test results show, that NBO is more efficient than other targeting methods. The data collected so far shows, that in advertising the output is twice as good than with other targeting methods. In marketing and advertising this means, that we save money." **Marketing director**

"We just checked, that if you for example buy target groups from Google based on customer interest, our NBO target groups still convert two times better. Clearly we can get better target groups with our own data." **CRM director**

On a general level, the NBO model had generated two to three times higher conversions in digital channels, including email and digital advertising, compared to other targeting methods. In customer service, the sales conversions had been even 11 times better. Further, the NBO recommendations had increased the percentage of approved credit applications and increased return on marketing investment (ROMI). In addition, it was seen that the NBO model promoted customer-centricity in marketing.

"I think customer-centricity is built into the NBO model, when it used, so you don't have to think about it separately on top of NBO. It guides the actions to the right direction. However, someone could say it is just a more effective spamming machine, where there is prediction model on the background." **CRM director**

The customer service director said, that despite the results the benefits had still been quite meager for the customer service, as the degree of actually making the recommendations was still low. However, she said they trusted to what the analysts had said – making the recommendation leads three times more likely to the wanted end result. Further, the NBO supports the CSRs work, as they can trust the recommendation, which indicates that the customer is interested in the product or service, which then leads to better success.

"I think the change towards data-oriented culture is somehow a very good thing, because the data is right a lot more likely than a single person deducing cases. I feel, that if we can utilize it and tell about it to our employees, why it is important and how it benefits them, it creates a huge advantage for us." **Customer service director**

5.3 Implementation of the NBO model

5.3.1 Adoption

According to the digital sales manager, in the beginning the fact that the business environment was continuously changing encouraged the adoption of the NBO model in the case company. As also other companies started using predictive analytics, it brought the conversations inside the case company as well and boosted the adoption.

The data scientist stated, that the primary adoption driver however was the organizational structure especially in marketing. As the structure was highly product-centric and focused on optimizing the marketing and sales actions from one product's perspective, the NBO enabled a holistic approach and better customer experience.

The marketing director stated, that he felt that they had higher management support for developing the models already from the beginning. He said, that harnessing the company's significant amount of customer data had been the case company's goal for several years, which encouraged the adoption. Further, he said that the middle-management's united vision about the NBO boosted the adoption. Everyone had the same vision, that NBO would be used as a primary recommendation model and targeting method.

Nevertheless, the CRM director stated, that even though they had higher management support, she felt that sometimes the higher management needed an external entity to persuade them about new innovations.

"It is easier here in middle-management level to prove things, where people are closer to practice. On a higher management-level it is more difficult. However, they were not an impediment either." **CRM director**

Further, she thought that the organizational culture encouraged the adoption.

"I think the organizational culture we have has had a huge impact, that if someone has a good idea and it can be proved, it's often adopted. People like to make changes, but of course, there are always also challenges. But we don't have a culture of stepping on toes or anything, that because of it an idea wouldn't go through. So as long as the work pays off." **CRM director**

5.3.2 Implementation

The group who originally started developing the prediction models consisted of the data scientist, the digital sales manager and a previous marketing manager. The digital sales manager said, that getting all three to participate was essential.

The digital sales manager pointed out that it is very important to begin with a business need when developing prediction models. The case company had developed a lot of different models over time, but some of the models were not used as they did not have an actual business need for them. Thus, it is important to align the goals, the needs and the actions.

"Some of the models might be useful, but it makes the implementation more difficult if the business need is not clearly defined, and what the model can actually be utilized for. For example, together with marketing and BI." **Digital sales manager**

The digital sales manager stated, that in order to implement a centralized NBO model, also technical capabilities and systems were required to the background. However, developing the capabilities took quite a lot of time. They thought that the process would have been faster, and the NBO model would have been up and running more quickly.

The development of the NBO model started from developing separate prediction models for single products and testing how well the models performed compared to the previous method – human-made target groups. Through testing the model, it was demonstrated that the prediction model generated better results than other targeting methods. After the first tests, the development team was able to make a business case and show the calculations to higher management.

"Everything started from seeing and understanding the results. We saw, that the prediction model target group performed better than a manually created target group. Then we started developing prediction models to other products as well. Then we had many separate prediction models and finally those were combined to a one single bundle, the NBO model." **Digital sales manager**

In order to implement the NBO model organization-wide, many tests needed to be made and results needed to be presented for various stakeholders. Through the evidence, it was nevertheless easy to show the benefits of the model.

"If you want to implement the model in the organization, it requires presenting results. It is quite hard to sell it to others internally, if you say that you developed a model and it didn't work. It can be even a small benefit which you find, which then raises interest." **Digital sales manager**

Further, he stated that proceeding with small steps was an important success factor in the implementation – getting results from smaller actions first, then presenting those to higher management and then scaling the model up. The support from higher management was earned through presenting the calculations.

"It requires starting from small and in the beginning, it is possible to try wider experiments with the prediction model, but then, the NBO should be centralized. No one wants to get too many messages." **Digital sales manager**

When the case company first started to test and use the model in practice, the NBO model was introduced to the analysts who created the target groups. However, finding time to learn a new way to work was somewhat challenging. The analysts needed to continue their original time-consuming way to create the target groups and at the same time learn the new way of utilizing NBO model. Nonetheless, the digital sales manager said, that after some difficulties in the beginning it had been easier.

The CRM director stated, that her role in the implementation was to determine needs and requirements for the NBO model, and then together with analytics analyze how the model worked and did it deliver the desired results. She further said, that as the results of the NBO model had been so good and the NBO model created a remarkable business case, the actual implementation and cultural change had been relatively easy.

"After we saw the model worked, the operative responsibility shifted to us. Then we started thinking where we utilize the prediction model." **CRM director**

The marketing director thought, that they had been particularly successful in creating an omnichannel experience for the customers throughout the channels by implementing the NBO model to all touch points in marketing and customer service at the same time. That enabled making the same recommendation for customers in customer service and in advertising.

"The change has been easier in digital channels and marketing. It has been easy to change the practices. It looks like the change has been more difficult in customer service, especially in physical customer service channels." **Marketing director**

In customer service, the most remarkable drivers in the implementation according to the customer service director had been telling about the benefits of the NBO model and what results can be expected when making the recommendations. The most remarkable learning was, that the implementation and communication required a lot of attention. The customer service director emphasized, that the implementation takes time and especially repetition is highly important when changing the behavior.

"I have noticed, that anything you want to implement requires at least seven times repetition, repetition, repetition, before it starts to get into peoples' heads and especially in their behavior. It is the same thing in all management, but it is clear in this case as well, that nothing happens by itself unless you rationalize everything a lot. You have to make them work in the daily business and justify the benefits enough. That has had a big emphasis in our case especially." **Customer service director**

However, she stated that it is enough for the CSRs to understand why the NBO model is important and how to recommend the products and services for the customers. She thought, that it is not important for them to understand the details of the model, as they have many other things to remember and it is significant, that the CSRs maintain the focus on the customer.

"We have many models in this house and if I expected everyone to understand them, I would be unrealistic. It is important to understand the essential things regarding everyone's own work and that is enough." **Customer service director**

The CRM director also felt that the CSRs do not need to thoroughly understand the NBO model logic.

"I think, that sometimes we could explain a little less. I hope that we could also move to a practice that if there is an NBO recommendation in the tool, it is recommended to the customer and everyone don't have to understand the NBO in detail. It just requires conceptualization and systematic leadership. But there are different opinions to this. But of course, we have presented the results of the NBO to the CSR's so that they can see the benefit." **CRM director**

The customer service director further stated, that they had also made examples for the CSRs' to encourage them to make the recommendations.

"We created kind of example sentences for our CSRs if they feel that it is difficult to make the recommendations, so that they can utilize the phrases and try if one of them feels natural. This at least helps to start the discussion. Now we have also filmed videos about how to do the recommendations, and we use those in the implementation." **Customer service director**

All in all, the case company did not set any specific goals to the NBO model implementation, as they did not know how it would perform. However, most of the interviewees said that they felt the NBO implementation had been successful, as the model delivered such good results and was used in all customer touch points.

"I am very happy about that everyone has been working with this and thought how the NBO could be utilized in their own are of responsibility. I think this is a success story." **CRM director**

5.3.3 Challenges in the implementation

The marketing director thought that all departments that used the NBO model should have been included in the implementation process in an earlier stage to enhance their understanding of why the NBO model was developed and why it should be used systematically.

"Customer encounters happen mostly in personal selling channels, in phone and especially in customer service offices, so especially in there it would be very important to maintain the systematic approach." **Marketing director**

The marketing director believed, that the organizational change required by the implementation would have been faster, if higher management would have understood the NBO model better. He thought that the model should have been more fundamentally explained to them and what was the vision and the target where the model was meant to be used.

The marketing director also believed that the CSRs did not understand what the recommendation model is thoroughly enough, and thus, they did not make the recommendations, even though they had been trained.

"If some other firm wants to learn something about this, more extensive engagement from top management to CSRs already in the beginning could fix the issue." **Marketing director**

The customer service director acknowledged that they had identified the same issue. The CSRs had been given instructions to make the NBO recommendations to customers and they had been told why it was important, but still the recommendation rate was low. In addition, the customer service director said, that the technical capabilities did not support the work.

"It has been kind of an extra thing to do for the CSRs. To begin with, on the customer service software display, the NBO recommendation is not shown on the first view when the CSR is serving the customer. They have to go to another view. The technical tools haven't supported [the implementation] in the best possible way." **Customer service director**

They had experienced some challenges also in spreading the understanding of the benefits of the NBO model and why the recommendations should be made. In addition, the CSRs' trust towards the NBO model had weathered, because all customers were not interested in the recommended product. When a CSR experienced a few unsuccessful recommendations, it led to a situation that they did not want to make the NBO recommendations anymore. The customer service director believed, that putting more effort into communication and creating understanding in the implementation phase would have made the implementation more successful. She said, that if that is done poorly, good results cannot be expected either.

The data scientist stated, that the narrow understanding of the NBO model and its functionality in the teams and business departments that utilized the model had also entailed challenges.

"The basic idea of the model is that each customer has a first recommendation, second recommendation, third recommendation and so on. The second or third recommendation should not be primarily recommended to the customer. However, the employees who use the model do not fully understand the logic of it. Target groups currently include also customers who have the advertised product as their second or third recommendation. Nonetheless, even though the customers would be interested of the product according to the model's prediction, some other product is predicted to be more interesting for that customer and the marketing activities should be targeted accordingly." **Data scientist**

Thus, according to the data scientist, the target groups should always be created with an employee who fully understands how the model works. This method would most likely generate optimal results.

"However, sometimes the target groups are picked with a strict timetable and all aspects are not considered every time. The method currently used might lead to well performing marketing actions and great results, but do not serve the overall strategy with the best possible way. To conclude, the working methods should be polished." **Data scientist**

The analyst had also noticed a knowledge gap between analytics team and the users of the model. She emphasized the importance of spreading knowledge inside the organization and stated, that there is no use making advanced models if no one understands what they do and why.

"Maybe they don't understand the logic behind the NBO model well enough and what the NBO model includes. Maybe that is something that could have been done better. It would be easier to use the models, if the understanding was better." **Analyst**

Further, she thought that the documentation should have been better in the implementation phase. The documentation was scarce, which also resulted in lack of understanding. However, she had tried to improve the documentation and fix the issue by educating some employees.

The digital sales manager and CRM director also thought that the documentation could have been better to be able to proceed more quickly, especially when people had changed. The digital sales manager stated, that as particularly data scientists were in high demand and there is a constant risk of them leaving, the documentation is very important.

"You also have to give time for the new people to learn. Especially analysts have their own style of working, and when the next one comes in, it is very hard for the new one to figure out things, maybe there has been some documentation issues… Sometimes it feels, that it would be easier to start from the beginning than make changes to the existing one. It has been quite surprising for me." **CRM director**

The data scientist noted, that an additional challenge appeared, as no one thoroughly knew how the model was used and modified in different teams, as there were so many technical pieces in the puzzle.

"For instance, if a customer service representative recommends a product to a customer, and the customer clearly indicates that he or she is not interested of the product, how is it prevented that the marketing department does not send the customer a marketing message about the same product? Or is it only the representative's interpretation of the customer's words? The customer might for example be in a hurry and say that he is not interested, but does that mean the customer is not interested or that he is in a hurry?" **Data scientist**

The CRM director said, the implementation took too much time also as they thought that they had to get the multi-channel customer experience working already in the beginning.

"I wouldn't say we have had very big challenges, except in the beginning when everything was more vague and it was more difficult to understand the NBO model and how it should be used. We could have made the implementation faster. However, when it is done piece by piece, it gets easier over time and part of daily business. We maybe should have taken a bit less holistic approach in the beginning and do things in smaller pieces and learn on the way. If I started from the beginning, that is what I would change." **CRM director**

The CRM director acknowledged that they had challenges with balancing sales and customer-centricity. She stated, that as the case company is continuously trying to get as many sales in as possible, it made shifting from product-centric to customer-centric strategy challenging. She further said, that they first had to ensure the sales, and after that they could focus on other things. The marketing director also thought, that the long traditions in product-centric sales made the change slower.

"When the resources are small, it drives us to make quick short-term sales. Then the customer relationship goals, and customer-centricity is forgotten. That has been quite a chal-

lenge, but maybe it has to be thought in smaller pieces as well and not try to make everything ready at once. We need to try to get the sales in and also have time to make something else too." **CRM director**

Another hindrance in the implementation was, that in the beginning the NBO model was managed by the executive team of the case company. The digital sales manager stated, that the management model slowed the implementation and scaling of the model, as it took a lot of time to get approval for every test from the executive team. The management model in the case company is presented more thoroughly in the following chapter.

5.4 Management of the NBO model

The case company had founded a cross-functional team to oversee and manage the NBO model and centrally coordinate its use and development on organizational level. However, before the NBO management team was established, the NBO management took a side-step. According to the data scientist, after the NBO model was taken in use, the case company started piloting where the decisions regarding the models should be made.

The decision was made, that the executive team would be responsible for the model development and management. However, according to the data scientist the management model did not work as intended to, as the executive team operated too far from the practical use of the model.

"The only way to optimize the NBO model is testing the model in practice. Optimal limits can only be found via continuous testing. If each modification and test need a permission from business executive team, it is a slow and difficult way to operate." **Data scientist**

Thus, the main issue was that it was stiff and slow to test the model and the management was found inefficient.

"At first the management went to a bit too centralized model. On the other hand, through that step the NBO model was introduced in detail to the executive team. Secondly, now they know that this is important. For some time, they looked at it, and kind of understood

it, and then we were able to move to a more agile way of working." **Digital sales manager**

"The earlier management model affected directly to our results, as we couldn't test the NBO model smoothly and we needed to wait for some decision for months. They are not closely working with the NBO in practice and how it works, so... Now that only the big changes go to executive team, it is ok." **CRM director**

The reason for establishing a centralized NBO management team was to oversee how the model was used in different teams and what recommendations were used in different channels. The sales manager said, that he has found the new management model more agile. The group, managed by the digital sales manager, was responsible for guiding the NBO activities to avoid working in siloes, determining the NBO limits, manage what kind of variables and rules were included in the model and presenting significant changes and findings for executive team, who then approved the bigger changes to the model.

"The team's responsibility is to implement the NBO to all channels including customer service and coordinate the use. I have the responsibility, that we can make even better targeting in digital channels, so the marketing technology side. So that we can measure the results better in display advertising." **Digital sales manager**

The core members of the NBO team were CRM director, CRM manager, digital sales director and analyst. Occasionally other stakeholders were participating in the meetings if the topic of the meeting was relevant to them. However, the customer service representative or the marketing director was not part of the NBO management team. The management team was intentionally small and compact to enable agile work. The analyst said, that one key benefit of the team was, that the key users are physically closer to each other and thus, able to share knowledge better.

"Once in a month, sometimes more often if necessary, we meet and check what needs we have and what changes we need to make to the NBO. We have the responsibility and right to test the models, but when we want to make bigger changes, the executive team approves

those. But in the NBO team we can otherwise be quite agile. That has worked quite well at the moment." **CRM director**

"The idea of this centralized team is to prevent people starting to do their own things. Then no one would know what happens where, and what kind of adjustments are made to the prediction models and how the NBO model is used… now the target groups go through our lens." **Digital sales manager**

Figure 5 illustrates the management model in the cases company. The management process started from defining the business needs and based on those, developing the models with predictive analytics capabilities. Then, the management and decisions regarding the NBO model, its limits and how it was used were made. At this stage, each customer got their NBO recommendations that could then be used in marketing and customer service. After that, the NBO model was taken to the campaign management system, where the target groups for different channels and campaigns were created. Next, the target groups were defined specifically for each channel and each marketing and sales activity. Lastly, the activities' results were measured, and those results were used to optimize the NBO model and develop it further. The digital sales manager said, the development can include also bringing new data to the models and testing whether that affects to the prediction accuracy.

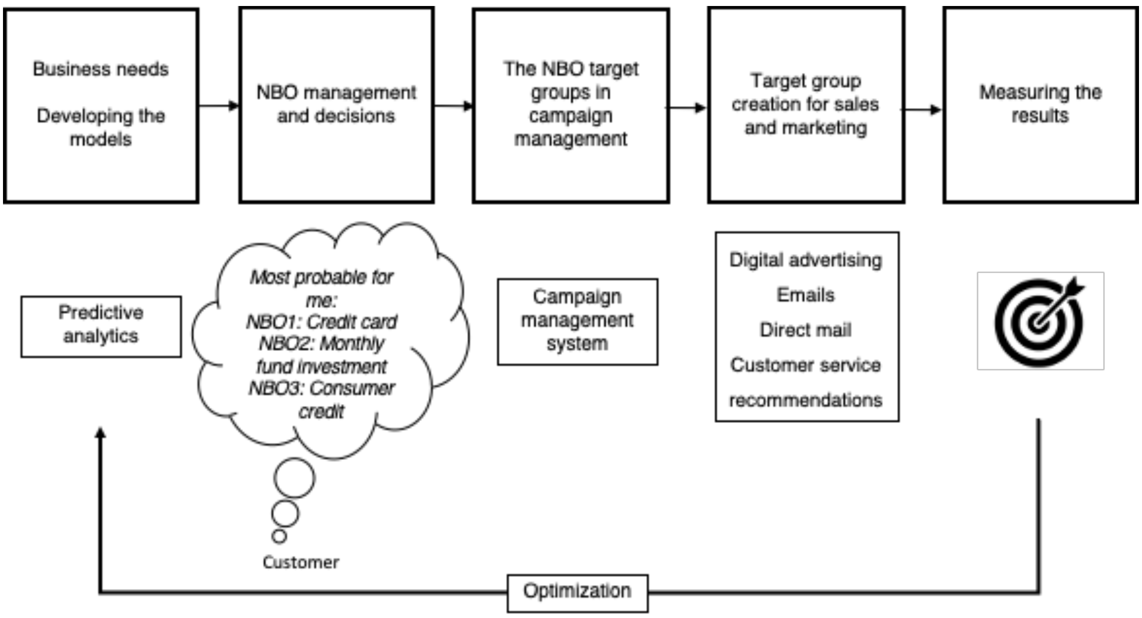

FIGURE 5 The NBO model management process in the case company

The marketing director also thought, the management model had been working well. From his experience, an important success factor had been that the discussions with the NBO management team had been relatively easy. His role in the NBO management was to be a contributor and user of the NBO model by innovating new ways to use the model, extend the use in marketing and pointing out challenges in the NBO model from the user perspective. In marketing the primary focus was on testing the NBO model's performance in different channels compared to other targeting methods and then analyzing the results.

"I think what is coherent is how we test the model through comparing its performance to control groups. In that sense, we have coherently been testing the model by targeting simultaneously the same activity to two target groups; NBO and some other." **Marketing director**

All of the interviewees thought, that the cooperation between marketing, CRM, sales, analytics and customer service worked well and they understood each other well. However, the marketing director thought that the cross-functional cooperation and alignment regarding the NBO model had been a bigger issue. The NBO model does not take sides – it utilizes all customer data and makes independent recommendations to customers. Thus, aligning the cross-functional goals and objectives was seen challenging.

"The CRM director runs the meetings where the business executives are present. We will see, if we can make it work. I hope so. That has been the challenge so far." **Marketing director**

The marketing director further thought, that the cooperation between analytics and marketing worked well. The marketing managers who were responsible for managing the marketing activities where the NBO model was used as a targeting method, worked closely together with the analysts. They for example discussed together about how the target groups should be designed for each marketing activity. He emphasized, that it is important to have a basic understanding of the NBO model in marketing. When the analysts and marketing managers first started working closer in cooperation, they noticed there had been some misunderstanding in marketing about how the model worked

"They [marketing managers] have also familiarized themselves to the NBO model and what variables it includes with the analyst who is responsible for the model…through working together, we have noticed that it has been very useful." **Marketing director**

The analyst said, that even though marketing is not part of the NBO management team, they have had chances to work together in other meetings, where they have discussed marketing's needs regarding the prediction models in general.

The customer service director said, the cooperation between them and the other key stakeholders regarding the NBO model had been scarce, as it had not been a priority for them and remained in the background as they have had many things to do. She pointed out, that she does not have a clear view of how, for example, marketing utilizes the NBO model and thought that it would be beneficial to understand the big picture better. The customer service director pondered that maybe they had not discussed enough why customer service had not made the NBO recommendations and what they could do together to fix the issue. Nevertheless, she said they were moving towards closer cooperation.

"Maybe it has lately become more significant…We just had a meeting with the CRM director, and we checked the recommendations we currently have and agreed, that they will make calculations whether we can achieve our sales goals only through making the NBO recommendations. We still have quite many tasks to do in cooperation and it is getting better." **Customer service director**

5.4.1 Resources

The analyst and the digital sales manager felt that they had enough time for managing the NBO model. Further, the customer service director said, that they had always had their needs fulfilled by other stakeholders, for example in analysis matters. However, the CRM director, analyst and marketing director thought they lacked resources especially in the development and optimization. The analyst said that it would be beneficial to get more resources especially in reporting and analyzing. The marketing director also thought, that there were some bottlenecks in the deployment of the model and executing the activities, which were more difficult to solve.

"For example, we are not able to test the model and make pilots and run data about how the model performs as much as we would like…the issue is, how do we get enough analyst resources and time to test the different actions." **Marketing director**

In addition, the marketing director thought, that they lacked especially technical resources to be able to develop the model and also marketing technology, website development and CRM know-how to implement the model in all touchpoints.

"We should have more resources. It is an obvious bottleneck. These things are very complicated and require both developing the model and driving data back to the model. Data should be collected from all customer touchpoints – customer service, advertisements, emails and everywhere." **Marketing director**

The marketing director also thought, they would need more highly skilled technical professionals with the right skillset both to develop the models and to the implementation to all touchpoints.

"So, time and money. This is probably easier for bigger organizations, but as a middle-sized organization I think we have a bottleneck in the deployment. We could do more with better resources." **Marketing director**

In addition, the data scientist noted, that due to limited resources thorough analyzation of NBO marketing activities had not been done. Thus, the optimization had not been done as well as it could have had been.

"As the results are not thoroughly analyzed, it is not possible to know which direction to take in optimizing the model." **Data scientist**

5.5 Evaluating the NBO model performance

The marketing director said, they measured the results by doing the same marketing action at the same time for different target groups, the NBO based target group and some other target group, and then compared the results.

"We test and then we look at the results. We check what is the end result with the chosen metrics, such as conversions, and whether the NBO model works better than other targeting methods. If we see that it works better, we extend the use and start using it as a default targeting method. Then we don't test it anymore." **Marketing director**

He gave an example of how they had tested the NBO model in display advertising.

"We see it clearly in display advertising, when have taken NBO model to the testing palette. We have had 3, or 5 different targeting methods. NBO, some other older target group based on the company's own data, some paid external target group, such as Google's target audience, and general non-targeted advertisement. Then we have consistently compared them and noticed, that NBO performs better than the others." **Marketing director**

The marketing director explained, that they mostly used conversions, impressions, sales, clicks and traffic as metrics when measuring marketing performance.

"If we could reliably measure the impressions of ads and then the realized sales from those who have seen the ad, it would of course be great. At least we can measure the click and the sales through the clicks. In direct mails measuring the results is a bit easier, because we are able to isolate the effect better in there." **Marketing director**

However, the marketing director stated, that the attribution was a persistent problem for them when measuring the performance of marketing activities. The challenge was to decide what weight should be given to each channel and advertisement when analyzing the realized sales – should it be from the last click and how much weight should be given to all impressions and direct advertising before the sales.

"That must be the biggest challenge, not only in NBO but measuring marketing performance in general. If I wanted to understand what has been NBO's actual effectiveness for example for ROMI, I couldn't calculate that. But what I can calculate is, that how much it improves the conversions in certain actions." **Marketing director**

The marketing director pointed out, that they were not able to measure everything also partially because of their capabilities and partially because of the industry-specific regulations. However, he thought that click-based measurement and conversions were good enough metrics to approximate the performance of the NBO model. He emphasized, that it is important that there is enough data points and volume in advertising to get reliable results and to be able to compare the effectiveness of different ads and target groups.

When the different target groups were compared in advertising and the results were analyzed, they continued doing the actions and targeting methods that generated the best results based on the chosen metrics.

"We stop the worst performing and continue and scale bigger the best performing ones. For example, all of our direct mail is now NBO-based in two product groups. Then we have expanded the use to other channels, such as search engine advertising." **Marketing director**

The marketing director said, that an important learning for him had been the significance of testing and the importance of planning. It is important to carefully plan the pilots and make sure there is always an adequate control group for the NBO target group to fully understand the impact of the recommendation model.

"The target groups have to be originally built so that afterwards it can be reliably analyzed, that the same product was advertised in same circumstances for same kind of audience, and with NBO targeting it performed this well with this metric, and for the control group this well with the same metric. The conclusion should be clear." **Marketing director**

The digital sales manager said, that in digital marketing the overlap effect brought additional challenges in measuring the NBO performance.

"In digital channels the NBO messages are not the only ones that are shown, there are many other targeting methods and channels, too. It is difficult to measure whether the conversion has happened as a result of one targeting method or as a combination of all of those that are running. Of course, we can evaluate, that in NBO targeting the conversion

is this good, and in the other targeting method this good, but it doesn't tell how much there is overlap." **Digital sales manager**

The CRM director told, that one important metric they also followed was the acceptance rate of loan and credit applications.

"It is not nice for the customer if we first advertise loan for him and then he won't get the loan. It is very important, that we maintain the level that as many people get the loan, if we advertise it. So, we use the results to optimize this kind of things." **CRM director**

The customer service director stated, that they measured conversions and sales from the NBO recommendations also in customer service. In addition, they measured the number of recommendations made by the CSRs. However, the customer service director mentioned that they could not use that reliably as the only metric, as the CSRs were able to tick the box even though they did not really make the NBO recommendation. Thus, they also measured on customer service level, how many CSRs actually made the recommendations, which was the most important metric for them.

"We are thinking about taking the NBO recommendations to our CSRs performance reward system. That is the way to get the focus to the NBO, when it is integrated to the performance measurement and reward system." **Customer service director**

The analyst stated that her role in measuring the NBO model's performance was to make sure that the predictions of the model held true and that the model in itself performed as it should perform. Her role was to use the results to optimize the model's predictions.

"If we see from the reports, that something is not working as it should be, we look for a reason and see if there have been changes in some processes that affect to the predictions." **Analyst**

Further, both the marketing director and CRM director said they measured customer lifetime value (CLV), but they were not systematically following the metrics, nor analyzed the value of the NBO for CLV. However, they had made some estimates about how different actions affect to CLV. The marketing director thought that calculating the effect of different actions to CLV could be useful information but stated, that they either had not had time or capabilities to calculate those yet.

"Probably there would be a lot to do in how the NBO could be measured. For example, if a customer makes a certain action, such as sends a loan application or makes a fund investment, how much the customer's CLV grows in 3 years for example. Or how much a recommendation made in customer service affects to CLV. At least I haven't seen this kind of numbers." **Marketing director**

However, the data scientist stated, that regarding the NBO the results from single campaigns and activities were measured, but the overall image was not achieved with the prevailing measuring and analyzing methods and resources in the case company.

"To optimize the model in digital marketing channels and marketing activities, the measuring and analyzing should be initially put in order. After this, modifying the limits and optimizing marketing actions could be performed. In digital channels, there are possibly many possibilities to optimization. Without full transparency and fact-based results, optimizing can't take place. This is the most significant challenge in digital marketing channels regarding the use of the NBO model." **Data scientist**

In addition, the data scientist said that long-term profitability impact should be calculated for each product and service which should be used as the base rate for prioritizing the NBO model recommendations. He stated, that the NBO model's prioritizations were based on gut-feeling and short-term profitability calculations, which ignored the long-term profitability of the NBO recommendations.

5.6 Development of the NBO model

The marketing director thought, that at first, they needed to solve the bottlenecks in their execution capabilities. He said, they should have more time to test and make pilots and analyze the results of the NBO, which would require resources and proficiency from both analytics and marketing.

"When we analyze the results, we should not look only transactions. We should be interested about how the customer relationships evolve as a consequence of using the recommendation model. Not only, that did the customer submit a loan application, but what started happening in the following six months." **Marketing director**

Further, the CRM director thought, that it would be very important to implement also other predictions to the NBO model in addition to the product recommendations. That would enable focusing on activating the customer relationships by also introducing other services to the customers, and not only selling single products.

"My personal opinion is, that soon we don't have any sales, if we don't do anything else. We are trying to sell more and more to a small group of people, so at some point we'll meet the limit if we don't foster the customer relationships." **CRM director**

In addition, one issue to solve in the future according to the marketing director was to resolve how the model could get the information if a customer is not interested about the product or service, that the model recommends to the customer.

"The NBO model doesn't receive reliable information if the customer doesn't act based on the recommendation, and then we end up faithfully promoting the same product for the customer." **Marketing director**

The analyst implied, that as the business environment is in continuous change, the development should be an ongoing process, which requires continuous monitoring and making necessary changes if they are required. She said, that one of the next steps should be to enhance the understanding inside the organization and also find the potential new use cases.

"I feel like the NBO model is not currently used in everywhere where it could be used. Maybe better documentation and understanding about the benefits and functionality of the model would encourage better utilization." **Analyst**

The digital sales manager thought the model should be scaled to a larger customer base, but that would require more data. He also said new prediction models should be developed for new products to find potential customers for those and improve the capabilities to make real-time recommendations. Additionally, one of the next steps was to tackle the challenge of CSR's not making recommendations to customers coherently. The customer service director told that they were putting more effort to the communication and believed that the issue would be fixed.

"We will clarify the customer service model so, that there are four things to complete when a customer makes a contact, and one of those is to handle the NBO recommendation." **Customer service director**

The data scientist stated that optimizing the NBO recommendations channel specifically should be further developed to optimize ROMI and budget allocation. He suggested, that marketing channels with high cost could be used for marketing the products with the largest budget and on the contrary, low-cost channels could be utilized to market the products that have a small budget. Thereafter, the services that do not have marketing budget could still be recommended for customers. He also said, that the NBO limits could be optimized so that they are higher in channels that have a high CPA to optimize conversions, and low in those channels that have minimal CPA to target a wider audience.

"However, this has a lot to do with improving measuring marketing performance and how conversions can be measured. Currently the conversions can be measured only from some products and campaigns. The conversions are the defining factor to optimize NBO for various marketing channels. If each action could be analyzed thoroughly, better decisions could be made, and the limits could be optimized." **Data scientist**

Next, the key research findings are presented and discussed in the following chapter.

5.7 Discussion of the research findings

The main objective of this research was to increase the comprehension of successful NBO recommendation model implementation and management and study the successes and challenges. The success factors and challenges in implementation and management found in this research are summarized in table 4 and table 5. Further, the table 6 summarizes the found best practices and challenges in measuring NBO model performance.

5.7.1 Implementation

The implementation of the NBO model was all in all found as successful in the case company, as they managed to implement the NBO model to all customer touchpoints and had achieved overall good results. It was found, that engaging the right, cross-functional team in the beginning to develop the model and starting with a clear business need were important factors in order to develop a usable and useful model. The case company had developed also some other models before without a clear business need, which were not used. Thus, a business need should be defined in the beginning.

It was also found, that testing the model performance in the beginning, getting measurable and good results, and then creating a business case was significant for success. Showing the good results to higher management enabled getting their support to implement the NBO model and scale it up. It also created interest in the whole organization, as they were able to see the benefit of the NBO model. Another success that came up was creating an omnichannel customer experience by implementing the NBO model to all customer touch points – customer service, digital marketing, direct marketing and CRM. In customer service, the implementation was more challenging – however, clear communication, repetition, and assisting examples encouraged the implementation.

Even though the implementation was overall successful, there were also several challenges which slowed the implementation. In the beginning, getting the necessary technical capabilities took more time than expected. Also finding time to learn the new way of working was a challenge, as at the same time the employees needed to continue their time-consuming old way to create target groups and learn to utilize and test the NBO model. It was also found, that the case company should have put more effort to involving employees from higher management to CSR's already in the beginning. That would have created deeper understanding of why the NBO model was important and how it benefitted the company. Further, communication, training and documentation were scarce throughout the implementation, which caused a lack of understanding, knowledge gaps, misuse of the NBO model and slower implementation.

It was found, that the case company's traditions in product-centric sales made the implementation more challenging and it was still a challenge for the case company. As the NBO is a customer-focused model, the product-centric business goals did not fully encourage the use of the NBO model. At the same time, NBO optimized customer-centric communication and the misaligned product-centric sales goals needed to be achieved.

It was also found, that in the beginning no one in the case company had full transparency of how the NBO was implemented and used in different business departments and teams. That made coordinating and aligning different team's actions challenging. Further, the implementation would have been faster and more successful, if it would have been made in smaller pieces and not try to implement the model to all channels at the same time. It was also found, that the implementation was more challenging in customer service than in marketing and CRM, as the CSRs' were not motivated enough to make the recommendations. Additionally, their tool was not optimal and their trust towards the NBO model had weathered because of some unsuccessful recommendations.

TABLE 4 The successes and challenges in the NBO model implementation

Implementation	
Successes	**Challenges**
• Right team to develop the NBO model • Starting with a business need • Showing the benefit through making tests • Making a business case and getting higher management support • Creating an omnichannel customer experience by implementing NBO to all channels • Making examples for CSR's about how to make the recommendations • Repetition and clear communication • All in all achieving good results with NBO	• Obtaining technical capabilities took more time than expected • Finding time to learn new way of working • Low employee involvement throughout organization • Lack of communication and understanding caused misuse of the model • Lack of documentation • Traditions in product-centric sales, product-centric sales goals • No one had full transparency of how NBO was used in different business departments • Trying to make everything ready at once • Getting CSRs' to make the recommendations • CSRs' tool did not support the implementation

5.7.2 Management

The NBO model was managed in the case company by a centralized cross-functional team, that coordinated the usage and development on an organizational level. However, before the case company got to this point, they had few challenges. In the beginning, the NBO model was managed by the executive team, who were too far from practical use of the NBO model and thus, did not fully understand it. The management model slowed the implementation and scaling of the model, as each test and change to the model required the executive team approval. It also negatively affected the results, as the users were not able to test the model and develop it smoothly. However, the benefit from this was, that the executive team understood that the NBO model is important.

It was found, that after the management was moved to the centralized team, only big changes were approved by the executive team which was experienced as a good practice. The cross-functional team further enabled full transparency of the NBO model across organization and allowed agile and continuous testing and optimization of the NBO model. A small and compact team was experienced as more agile, which enabled faster decision-making. It was also found, that as the management team was physically closer together, it allowed fast knowledge sharing and smooth cooperation.

There were also some challenges in the management. It was found, that even though the cooperation worked well, aligning the cross-functional goals and objectives with business executives was found challenging. Further, some knowledge gaps were still identified between different business departments, as they did not know how the model was used in other departments and teams. Thus, only the management team had full transparency to the NBO usage. Further, there were also some challenges due to lack of resources in developing and optimizing the NBO model. It was found, that especially technical skills and knowledge were important in NBO model development, and the case company would have needed more resources to that.

TABLE 5 Successes and challenges in NBO management

Management	
Successes	**Challenges**

• NBO got visibility in executive team
• Centralized, cross-functional management team
• Only big changes to NBO model go to executive team
• Full transparency in management team of how NBO is used and developed in different business departments
• Enabled agile, continuous testing and optimization
• Compact team enabled agile and fast work
• Management team physically closer together allows knowledge sharing
• Smooth cooperation and easy discussions between marketing, CRM, customer service and analyst
	• Executive team responsible of NBO management at first
	    • Too centralized model
	    • Far from practical use of the model
	    • Slow testing and development
	    • Slowed the implementation and scaling of the model
	    • Negatively affected to the results
	• Aligning cross-functional goals and objectives
	• Lack of knowledge about NBO model usage between business departments
	• Lack of resources in development and optimization

5.7.3 Evaluating the NBO model performance

It was found, that evaluating the NBO model performance was highly important in order to optimize the model and its usage in different channels. The case company measured the NBO model performance by testing the model continuously by comparing the NBO model activities and target groups to other target groups, and then using the results to optimize the activities and develop the model. It was found, that especially planning the tests carefully beforehand and ensuring large enough target groups and enough data points to get reliable and measurable results was seen important. Measuring the quality of the recommendations by for example analyzing approved credit applications and conversion percentage was useful in evaluating the NBO recommendations' quality and developing the model. Further, the case company measured CLV, NPS and the recommendation rate of the CSRs'.

Measuring the results also included challenges. It was found, that the case company had lack of resources in analyzing the results. Further, the case company was struggling with getting a holistic view of the NBO model performance, as single activities were measured, but the results were not coherently analyzed. Thus, only single activities were optimized, but holistic optimization was not performed. It was also found, that isolating the overlapping effect of different marketing channels and different target audiences was challenging, especially in digital channels. However, the case company thought that the prevailing metrics were good enough to evaluate the NBO model performance. It was also found, that measuring ROMI, long-term profitability and evaluating CLV from NBO activities were challenging. The case company did not have resources, time or skills to measure them, even though they were found as valuable metrics.

TABLE 6 Best practices and challenges in measuring NBO model performance

Evaluating NBO model performance	
Best practices	Challenges
• Carefully planning the tests • Testing the model continuously and using the results to optimization • Comparing the NBO model target group and activities to other target groups • Conversions and clicks as metrics • Ensuring enough data points • Measuring the quality of the recommendations • NPS • CLV • Recommendation rate in customer service	• Lack of resources in analysing the results • No holistic view of the NBO model performance • Overlapping effect of different channels and target groups • Lack of long-term profitability measurement • Measuring ROMI • Reliability of customer service metrics • Integrating measuring CLV to NBO

In conclusion, the findings showed, that it is important to begin with a business need when implementing an NBO model and ensure that the technical capabilities support the implementation. Further, the findings emphasized importance of communication and organization-wide involvement to the implementation. Furthermore, a centralized cross-functional team to continuously develop and coordinate the NBO model use was found consequential in order to manage the model while it was simultaneously used by many teams.

6 CONCLUSIONS

The goal of this research was to increase the understanding of successful NBO recommendation model implementation and management in a middle-sized retail bank. The research objective was supported by research questions with the aim to study the factors leading to successes and failures in implementation and management and examining how NBO model performance should be measured. This research found several success factors and impediments, as well as management and evaluation practices and development opportunities. In this chapter, the conclusions made from the research findings are divided into theoretical contributions and managerial implications. Thereafter, the limitations and reliability of this research are assessed and finally, the ideas for further research are discussed.

6.1 Theoretical contributions

Starting with the first research question of this research, *'What are the drivers and impediments for implementing predictive analytics in marketing?'*, the major drivers identified in the theoretical background were the growing need to understand customer behaviour due to increased competition and customer demands, and utilizing the data to support customer-centric marketing strategy. The findings of this research complement the earlier research, as reinforcing customer-centricity and responding to continuously changing business environment were drivers for implementing the NBO model also in the case company. It was found, that another major driver for the case company to implement NBO was to clarify the product-centric, siloed marketing team's responsibilities. As stated, siloed business units can experience overlap in data usage, and issues in coordinating consistent data and obtaining organization-wide perspective. The same issues were identified in the case company. Thus, NBO was implemented to function as a centralized prioritization model to coordinate marketing activities and cultivating customer-oriented marketing approach throughout organization. Thereby, another organization struggling with the same issue could also benefit from centralized customer-centric model, such as NBO.

According to earlier research, also the need to optimize marketing investments and finding innovative, cost-efficient growth strategies drive the adoption and implementation of data-driven marketing strategies. The research findings showed, that the NBO model improved ROMI, decreased marketing costs, multiplied the case company's sales, enhanced customer experience and improved conversions in marketing, CRM and customer service. Thus, the NBO model provided a novel solution to these needs recognized in the literature.

In the theoretical background, involving employees in the development and implementation, and distinct communication were identified as important success factors in implementing data-driven strategies. The research findings confirm that communication and employee involvement are indeed important. It was found, that involving employees from higher management to CSR's already in the beginning would have made the implementation more successful in the case company. Clear communication and repetition were seen highly important already in the early phase of implementation, as the case company had challenges, especially in implementing the NBO to customer service. Lack of communication and documentation, and a narrow understanding of the model had also caused a knowledge-gap between the developers and end-users of the NBO model, which led to errors in utilizing the model in the beginning. This finding shows that it is highly important to ensure communication, documentation and involving employees from all levels when implementing data-driven strategy.

It was identified in the theoretical background, that consolidated data for the entire organization, machine learning capabilities, technology knowledge and collaborative environment were seen as key capabilities for organizations implementing predictive decision-making strategy. The research findings were aligned with the theory, as all four capabilities realized in the case company. It was further stated, that also the managers need to understand the value of the tool and also the end-users have to trust the outcomes and be willing to use the tool. As the research findings showed, as soon as the higher management saw the results and the value of the NBO model, they supported the implementation. However, as the understanding, trust and willingness to use the NBO model in customer service were low, it was seen in the low recommendation rate. It was also stated, that aligning performance measurement and reward systems of employees with building and maintaining of customer relationships are important. The research findings showed, that the case company had acknowledged that their performance metrics did not support making NBO recommendations in customer service, and thus, they were aiming to fix the issue. Hence, another organization implementing recommendation models should pay attention to aligning the performance metrics with desirable action.

The theoretical background showed, that for example executive resistance, failing to show the benefit of analytics, product-centricity and lack of expertise and competence were identified as impediments for adoption and implementation. However, the case company had managed to solve these impediments by hiring a data scientist with the right expertise to develop an NBO model and gaining executive support through proving the benefits of the model by showing measurable results. However, the research findings confirm that moving from product-centricity to customer-centricity can be challenging, as there was still an inconsistency between product-centric business goals and customer-centric NBO strategy in the case company. Thus, it can be reasoned, that aligning business goals with the right strategy is pivotal in reinforcing customer-centricity and to ensure successful transition.

The second research question was '*How to manage the overall usage and development of a predictive analytics model which is used simultaneously by multiple business units and managers?*'. The theoretical background emphasized, that integrating marketing and IT and close cooperation with the two is highly important in managing technological innovations and implementation, as customer behaviour-based marketing activities are highly dependent on business intelligence. It was found, that in the case company marketing, analytics and data scientist together developed the NBO model, which was seen pivotal for succeeding in the case company. However, the marketing director was not closely involved with the management of the NBO model as it was managed by analyst, digital sales manager and CRM director. However, the results showed that it was not a remarkable issue in the case company as they felt that the cooperation still worked well. Thus, each organization implementing data-drives strategies should define a suitable cooperation level between the departments. However, as the theoretical background showed, higher-level data-driven strategy requires higher-level cooperation.

Further, strong data culture, collaboration between business intelligence, marketing, sales and customer service, and management of BI development and use were identified in the theoretical background as particularly important in connecting marketing and IT functions. The research findings showed that all three key points were identified in the case company and were considered in managing the NBO model. However, the research showed also some knowledge gaps between marketing, customer service, CRM and IT. Stronger and more consistent collaboration between these departments, as also suggested in the theoretical background, could narrow the gap and improve the cooperation.

The theoretical background suggested implementing a centralized team to manage how data and tools are used with a strong focus on marketing and customer strategies. The research showed, that the case company had implemented this approach by grounding a cross-functional NBO management team. The findings confirmed, that the management model worked well in the case company. The case company had also unsuccessfully tried a different management model where NBO was managed by higher management. The theoretical background also recommended that higher management ought not to be involved with operational decision-making. Thus, a centralized management team consisting of employees who closely work with the technology could be a suitable management model also for other organizations.

The third research question was *'How should the NBO model's performance be measured and evaluated?'*. According to the theoretical background, marketing analytics can improve decision-consistency, enable assessing the impacts and communicating the impacts to higher management. The findings showed, that the case company had benefitted greatly from analysing the NBO results, as they enabled showing the benefits of the NBO to higher management and thereafter, gaining management support. Comparing the NBO model activities to other marketing activities using various metrics, the case company was able to achieve better results in marketing, CRM and customer service, and make more informed decisions. Further, the theoretical background suggests, that also user experience research, precision, recall and customer satisfaction should be used to evaluate NBO. Thus, these metrics could provide deeper knowledge in evaluating NBO performance.

However, as the theoretical background already showed, deploying marketing analytics has also many challenges, for example measuring ROMI, long-term effects and overlapping effects of different channels. The same challenges were confirmed in this research. Especially measuring overlapping effects of different target groups and marketing channels were recognized as challenging and almost impossible. Further, the case company struggled in finding time to consistently analyse the NBO performance and the long-term effects. Thus, consistent analysing requires resources and more advanced capabilities.

To conclude, the implementation and management of any marketing analytics is relatively comparable. However, a lot is dependent on the starting point of the company, its size and the existing organizational capabilities. As each organization is different, every implementation and management are unique and might have different challenges. However, this research creates a comprehensive illustration and organizations implementing predictive analytics to their marketing can expect similar challenges and can learn from the implications of this research.

6.2 Managerial implications

In this research the managerial focus was on identifying the success factors and challenges in implementation and management of an NBO recommendation model. Based on the research findings and analysis, this research provides relevant insight into managerial decision-making. As the use of predictive analytics including the recommendation models such as NBO are becoming more common in marketing in many organizations world-wide, many organizations that have not already implemented predictive analytics to their marketing, can gain many valuable insights from this research. Particularly the managers responsible for the implementation and management of a corresponding model can gain valuable learnings.

The analysis showed, that the NBO model was developed to clarify the marketing team's responsibilities and foster customer-centric marketing, and to optimize marketing communication. The research showed, that the case company achieved these goals and thus, companies facing the same challenges could benefit from implementing an NBO model. Further, organizations willing to optimize ROMI and target marketing communications based on customer interest to foster customer relationships could benefit from implementing an NBO model. However, it can be deduced from the analysis, that if a company wants to move from product-centric strategy to customer-centric strategy, NBO model is not a straight-forward solution. The whole organization needs to be involved and committed to the transition already in the adoption and implementation phase. It was seen particularly important, that all employees from top management to CSR's are involved in the implementation, and that the change is communicated clearly and repeatedly to all stakeholders throughout organization. Communication and repeating the message were seen highly important throughout the implementation and also during continuous use of the model. Additionally, organizations implementing customer-centric strategies should pay attention to aligning the business goals to the customer-centric strategy and implement aligned performance metrics.

If an organization wants to implement a predictive analytics model such as NBO, it should have a clear business need and create a business case. The model should be developed together with data science with required analytics knowledge, and marketing or sales with required business knowledge. This way, the organization ensures the model is useful for business. In addition, particular attention should be paid to testing the model and showing the model's results and value for higher management to get their support. Showing the good results was seen as a successful way to engage the whole organization in the implementation.

An organization implementing predictive analytics should also reserve enough time for building the needed technical capabilities. The research showed, that the implementation and learning a new way of working took all in all more time than the case company expected. In addition, it is more reasonable to implement the model in smaller pieces, step by step, and not try to implement it to all customer touchpoints at the same. This way, the organization can manage the implementation better and retain the transparency and control. In addition, the organization should document the implementation and all decisions clearly. Lack of documentation can slow down the process and create knowledge-gaps, especially if a key employee leaves the company.

It can be deduced from the analysis, that the model should be managed by a cross-functional team including marketing and analytics professionals. The team members should be closely working with the practical use of the model to ensure agile and fast testing, optimization and development. Further, a compact team enables more agile decision-making, thus, the team should be relatively small.

The NBO model performance should be analyzed by comparing the NBO model performance to other targeting methods by targeting the same marketing action to different target groups and comparing the results. Conversions and in digital channels click-through rates were seen as good metrics to measure NBO performance. Additionally, different business-specific quality metrics should be used to evaluate the NBO recommendations' quality. However, measuring the results comprise also challenges, as the overlapping effect of different channels and ROMI are difficult to measure. In addition, analyzing long-term effects of the NBO recommendations and measuring CLV were found difficult and would need lots of resources. Thus, it would be important for an organization to have enough resources and skilled analysts to analyze the results and to develop the model.

6.3 Limitations of the research

The purpose of this chapter is to evaluate the reliability of this research and trustworthiness of the results. Yin (2003, p. 37) states, that the reliability of a study means how reliably the research can be repeated. Thus, if another researcher would reiterate the same research using the same methodology, the researcher would arrive at the same the same results. As the methodologies and data collection procedure in this research were firmly presented, another researcher could follow the same procedure and thus, replicate this research. However, as qualitative research involves several human factors such as communication differences between different researchers and interviewees, those could have an influence in the interviews.

As this was a case study research which studied the implementation and management experiences in one organization, the research results are not generalizable. The case organization is unique, has its own structure, organizational culture and capabilities. However, to enhance the reliability of this research, the interviewees were selected carefully and included the employees from the case organization who were most knowledgeable of the research topic. Further, the resemblance of the interviewees' responses improved the reliability of the findings. In addition, in this research the data collection method was semi-structured interviews and the interviewer asked additional questions during the interviews.

Thus, the interviews could be different in another organization and context. As each organization is unique, the implementation and management are different in every organization. Thus, also the interview questions and findings might be different when researching another organization.

This case study research was done in a case organization that operates in the financial industry, which signifies that the implementation process might be different in companies operating in another industry. Also, the size of the organization and the organizational structure create their own limitations for this research. A smaller organization can have different resources and budgets, which can create additional challenges, whereas in bigger organizations the change can be more challenging and take more time due to more complex processes. Further, this research was conducted in a Finnish retail bank that operates solely in Finland. The regulations for how the NBO model and customer data can be used might vary between countries and in international organizations.

Another limitation of this research is, that the sample size of the interviewees was relatively small, as the case company was a middle-sized organization. However, the sample of this research included every relevant manager and specialist in the case organization and thus, the sample for this research could not have been larger. If the research would be replicated in a larger organization, the sample size could be larger, which could enable a wider perspective to the topic and gain deeper understanding of the implementation and management of an NBO model.

The validity of research denotes how well the researcher has succeeded in researching what was intended to (Tuomi & Sarajärvi, 2009). Further, the internal validity of the research signifies that the conclusions are consistent (Grönfors, 1982). To achieve the research objectives, a qualitative research method was chosen, and every step of the research process was justified and documented. As the conclusions were derived from the data from the interviews and presentations provided by the case company, the findings are reasoned. Furthermore, the theoretical, methodological and empirical parts are in line with each other. To conclude, the validity of this research can be justified.

Schramm (1971) states, that if a researcher enters the situation of the case study too late, some of the early failures and issues might be forgotten and events are restored only through the memories. Further, when the case is researched afterwards, the knowledge relies too much on project administrators' memories and might neglect the official events of what has really happened. As this case study was commenced in the later phase than the planning and implementation started, the data is likely to neglect some problems and failures that took place in the earlier stages of the planning and implementation. Further, many of the interviewees' answers are based on memory, and some important factors might have been forgotten. Thus, the research findings ought to be interpreted with this factor in mind.

Even though adoption and implementation are tightly tied together as partly overriding steps in academic literature, the scope in this study is in the implementation and management with touching on the adoption. The choice was made, as the research was conducted after the adoption, thus, it was not seen reliable to research something that happened relatively long time ago and what can be relied only on memory. However, also the adoption drivers and hindrances are discussed together with implementation. Further, the scope was seen as value-adding to current literature, as implementation and management of data-driven decision-making is not yet studied.

The researcher had worked in the case company during the implementation and management and also had a role in the implementation. Thus, the researcher could not be fully objective. The researcher's attitudes and prior knowledge of the topic could have affected the results. However, the researcher tried to stay as objective as possible when interviewing and when analyzing the results.

6.4 Further research suggestions

As in this research the focus was solely on the management level experiences, understanding and implications for implementing and managing a predictive analytics recommendation model, a further research area could be studying how the end users of the model experience the implementation and management. As this research lacked insight on how the end users experienced the implementation, and what they think are good practices and which kind of challenges they had faced, it would be valuable insight to research whether the same challenges and best practices are aligned with the ones the end users experienced.

Another further research opportunity would be to replicate this research for a major bank or in another larger organization. As major banks and large organizations are likely to have a larger implementation and management team and more advanced resources, it would be interesting to find out if the same challenges and practices apply to larger organizations as well. Further, it would be valuable to understand how organization-wide involvement, cultural change and managerial support are realized in major organizations.

Additionally, a further research area could be to study how thorough understanding and how deep knowledge the end users including for example CSRs and marketing practitioners should have about the model, its functionalities and backgrounds. As it became clear in the findings, some managers thought the end users do not need almost any insight about the model and they should just use the recommendations if they are told to, when other managers thought the opposite, that the end users should have a thorough understanding of the model in order to use it and be motivated to recommend the services to customers. As this research did not study what level of knowledge and understanding is either adequate or beneficial for the end users to have, gaining knowledge about this topic could be a valuable further research area.

Another major topic for further research would be how to measure the return on marketing investment when the NBO model is used simultaneously with other targeting methods. As it became clear in the interviews, the case company's managers were finding it very troublesome to measure the marketing activities where the NBO model was used compared to marketing activities where other targeting methods were used. As the interviewees noted, this is a real challenge in the marketing field. Studying how much each targeting method, each ad and each channel generate ROMI and also how should the channels be valued in different phases of the customer journey would be a significantly valuable area for further research, as marketing managers and analysts are currently struggling with the topic in their daily work.

Another issue that arose in this study was how to link CLV to the NBO model. Hence, it would be an interesting further research topic to study how to measure CLV and utilize that information in planning and developing the NBO model and especially in optimizing the NBO recommendations.

Lastly, it would be very valuable for both the businesses that currently have a next best offer model, or are considering implementing the model, to understand the testing and development process more thoroughly than what is presented in this research. Even though the details might vary between business fields and companies, it would be helpful for many managers to understand the best practices in the development process and how to create a long-term testing plan for the NBO model to continuously improve it and get better results.

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APPENDIXES

Appendix 1 Interview questions in English

Background questions

1. Position
2. What are your major responsibilities in the organization?
3. How long have you worked in the case organization and current position?
4. What are the KPI’s and most important priorities for you and your team?

NBO model and its usage

5. Please briefly explain what the NBO model is and how it is utilized in practice in your team.
6. In your opinion, how is the usage of the NBO model managed and supervised in the case organization and in your team?
7. Do you think the NBO model is used as it is intended, and do you think the usage is coherent?
8. How have you experienced the quality and benefit of the NBO model in your work?

Implementation of the NBO model

9. Please describe your role regarding the implementation of the NBO model.
10. What challenges have you experienced in the implementation of the NBO model?
    a. adoption as part of the operating model
    b. implementation around the organization
    c. have you noticed any changes in the project management processes since the introduction of the NBO?
    d. what lessons have YOU learned from the NBO development process?
11. What has been successful in the implementation of the NBO model in your opinion?
12. Do you think you have achieved your goals regarding the implementation of the NBO model?

Management of the NBO model

13. Who has the main responsibility of the strategic management of the NBO model in the organization?

14. What is your role regarding the management and development of the NBO model?
15. What challenges have you experienced in the management and development of the NBO model?
16. What examples of success can you offer regarding the management of the NBO model?
17. What plans and goals do you have as a team regarding the development and management of the NBO model in the future?
18. In your opinion, what do you think should be done next?
19. In your opinion, are the current resources adequate or do you need more resources to manage and develop the NBO model and its utilization? If yes, what kind of resources?

Evaluating the NBO model performance

20. How do you measure the NBO model performance?
21. What metrics do you use?
22. What results have you gotten so far? Have the results fulfilled your expectations?
23. Have you faced challenges in measuring the results, what kind of challenges?
24. How do you utilize the results from measuring the NBO model performance?

Cooperation and relationship between the teams

25. How do you experience the relationship between the teams and managers that use NBO model?
26. Have you experienced any challenges in this inter-team collaboration? What works out well in your opinion?
27. How do you align the NBO marketing activities and development of the NBO model between the teams?

Other lessons

28. What else have you learned from the process?

Thank you for the interview!

☐ I accept the privacy notice

Appendix 2 Interview questions in Finnish

Taustakysymykset

1. Roolisi yrityksessä?
2. Mitkä ovat tärkeimmät vastuualueesi yrityksessä?
3. Kuinka kauan olet työskennellyt yrityksessä ja nykyisessä roolissasi?
4. Mitkä ovat sinun ja tiimisi tärkeimmät prioriteetit ja KPI:t?

NBO-malli ja sen käyttö

5. Kerro lyhyesti mikä NBO-malli on, mihin NBO-mallia käytetään ja miten NBO-mallia käytetään käytännössä tiimissäsi.
6. Miten NBO-mallin käyttöä johdetaan ja valvotaan mielestäsi yrityksessä ja tiimissäsi?
7. Käytetäänkö NBO-mallia mielestäsi kuten pitäisi ja onko mallin käyttö johdonmukaista?
8. Miten olet kokenut NBO-mallin laadun ja hyödyn?

Käyttöönotto

9. Kuvaa rooliasi NBO-mallin käyttöönotossa.
10. Mitä haasteita olet huomannut tai kokenut NBO:n käyttöönotossa?
    a. omaksumisessa osaksi toimintamallia
    b. käyttöönotossa eri puolilla organisaatiota
    c. johtamisessa
    d. ja kehittämisessä?
11. Minkä tekijöiden koet ja olet huomannut onnistuneen NBO:n käyttöönotossa?
12. Koetko, että olette saavuttaneet tavoitteenne NBO-mallin käyttöönotossa?

NBO-mallin johtaminen

13. Kenellä on päävastuu NBO-mallin strategisesta johtamisesta ja kehittämisestä yrityksessä?
14. Mikä on sinun roolisi NBO-mallin johtamisessa ja kehittämisessä?
15. Minkälaisia haasteita olet huomannut ja kokenut NBO-mallin johtamisessa ja kehittämisessä?
16. Mikä on onnistunut NBO-mallin johtamisessa?
17. Millaisia suunnitelmia ja tavoitteita teillä on NBO-mallin johtamisessa ja kehittämisessä lähitulevaisuudessa?
18. Mitä sinun mielestäsi pitäisi tehdä seuraavaksi?

19. Pitäisikö NBO-mallin kehittämiseen ja johtamiseen olla sinun mielestäsi käytössä enemmän resursseja? Jos, niin millaisia?

NBO-mallin mittaaminen

20. Miten mittaatte NBO-mallin toimivuutta?
21. Mitä mittareita käytätte?
22. Millaisia tuloksia olette saaneet tähän mennessä? Ovatko ne täyttäneet odotuksenne?
23. Oletteko kohdanneet haasteita mittaamisessa, mitä haasteita?
24. Miten hyödynnätte NBO-toimenpiteiden mittaamisesta saatuja tuloksia?

Yhteistyö ja suhde tiimien välillä

25. Millaisena koet suhteen ja yhteistyön tiimien välillä, jotka käyttävät NBO-mallia?
26. Oletko kokenut haasteita yhteistyössä? Jos, niin millaisia? Mikä mielestäsi sujuu hyvin?
27. Miten sovitatte NBO-toimenpiteet ja kehittämisen yhteen eri tiimien välillä?

Muita oppeja

28. Mitä muuta olet oppinut prosessista tähän mennessä?

Kiitos haastattelusta!

☐ Hyväksyn tietosuojalomakkeen