Aalto University
School of Business

AI IN CRM SYSTEMS: EVALUATING THE PREREQUISITES FOR SUCCESSFUL ADOPTION

Multi-case study testing the use of fit-viability model to evaluate companies' prerequisites for their AI-CRM initiatives

Master's Thesis
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Abstract of master's thesis

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Abstract

Artificial intelligence (AI) technologies have advanced greatly during the recent years. Previously the use of these technologies has demanded difficult to get internal capabilities for developing machine learning algorithms and implementing them in applications such as social media platforms and virtual assistants. Today the idea of implementing these novel technologies also in enterprise systems (ES) has aroused the interest of many companies.

One of the most important enterprise system categories is the CRM (customer relationship management) system, which is constantly growing its significance as the companies in different industries aim to become more customer centric. Different CRM system providers, such as Salesforce, Oracle and companies operating in their ecosystems have begun to offer various AI-CRM applications for their customer companies to utilize in enhancing their own business operations. Even though the topic is growing interest, companies' experience of these applications is limited and there are few available roadmaps to follow.

This thesis aims to offer organizations planning on implementing AI-CRM applications a tool to analyze the potential prerequisites to be fulfilled to maximize the chances of successful adoption. The fit-viability model (FVM) has been previously used to analyze different IT initiatives. This study aims to develop it further and tests it in the context of AI-CRM applications. The study consists of two parts, first of which is a background research focusing on collecting insights about implementation of AI-CRM applications from expert sources and recognizing different applications on market through an Internet research. The second part is a multi-case study testing the FVM to analyze the selected AI-CRM applications in the context of various companies.

The results of this thesis indicate that using the FVM to analyze AI-CRM applications provides meaningful insights and can help in recognizing and fulfilling the potential prerequisites for successful implementation. The model provides the insights in clearly understandable and visually presentable form that can be used to help decision-making processes. As the CRM system market is growing and the biggest providers on the market have a strong focus on providing AI-CRM applications, the significance of these solutions is not expected to decrease. Nevertheless, the topic is still in its early maturity and cases of successful adoption are limited. The research conducted in this thesis provides viewpoints for future research, and organizations can utilize the tested FVM in their own decision-making and implementation processes regarding AI-CRM applications.

Keywords Artificial intelligence, CRM systems, FVM

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Tiivistelmä

Tekoälyteknologiat ovat kehittyneet viime vuosien aikana merkittävästi. Aiemmin tekoälyteknologioiden hyödyntäminen on vaatinut yrityksiltä vaikeasti hankittavia kyvykkyyksiä koneoppimista (ML) hyödyntävien algoritmien kehityksestä ja implementoinnista eri järjestelmissä, kuten sosiaalisen median alustoissa tai virtuaaliassistenteissa. Sittemmin ajatus tekoälyteknologioiden hyödyntämisestä myös yritystietojärjestelmissä (ES) on alkanut herättää kiinnostusta yrityksissä.

Yksi tärkeimmistä yritystietojärjestelmistätyypeistä on asiakkuushallintajärjestelmä (CRM), joka kasvattaa merkitystään jatkuvasti eri aloilla toimivien yritysten pyrkiessä asiakaskeskeisemmiksi. Eri CRM-järjestelmien tarjoajat, kuten Salesforce ja Oracle, sekä näiden ekosysteemeissä toimivat yritykset, tarjoavat nyt yritysasiakkailleen erilaisia AI-CRM-applikaatioita, joita nämä voivat käyttää oman liiketoimintansa kehittämiseen. Vaikka kiinnostus aiheen ympärillä kasvaa, yritysten kokemus näistä uusista sovelluksista on rajallinen eikä tarjolla ole montaa mallia, jota käyttöönotossa voitaisiin hyödyntää.

Tämä tutkimus pyrkii tarjoamaan AI-CRM-applikaatioiden käyttöönottoa suunnitteleville yrityksille työkalun, jolla nämä voivat tunnistaa ja täyttää mahdollisia onnistuneen käyttöönoton onnistumistodennäköisyyttä parantavia ennakkovaatimuksia. Fit-viability -malli (FVM) -nimistä teoriaa on aiemmin hyödynnetty erilaisten IT-hankkeiden analysoinnissa. Tutkimuksen tavoite on kehittää mallia pidemmälle ja testata sitä AI-CRM-applikaatioiden kontekstissa. Tutkimus koostuu kahdesta osasta, joista ensimmäinen on taustatutkimus, joka keskittyy kokoamaan tietoa AI-CRM applikaatioiden implementoinnista asiantuntijaläheistä sekä tunnistamaan tarjolla olevia AI-CRM applikaatioita Internet-tutkimuksella. Toinen osa on monitapaustutkimus, jossa testataan FVM:ää valittujen AI-CRM-applikaatioiden analysointiin usean eri yrityksen kontekstissa.

Tutkimustulokset osoittavat, että käyttämällä FVM:ää AI-CRM-applikaatioiden analysointiin voidaan löytää merkityksellistä tietoa sekä tunnistaa ja käsitellä mahdollisia onnistuneen implementoinnin ennakkovaatimuksia. FVM tarjoaa selkeää ja visuaalisesti esitettyä tietoa päätöksenteon tueksi. Koska CRM-järjestelmien markkina kasvaa ja suurimmat palvelujen tarjoajat ovat ottaneet AI-CRM applikaatioiden tarjoamisen yhdeksi painopisteekseen, ratkaisujen merkityksen ei oleteta heikkenevän. Aiheen maturiteettiaste on kuitenkin vielä matala ja onnistuneiden käyttötapauksien määrä on rajallinen. Tämä tutkielma tarjoaa näkökulmia, joiden päälle uutta tutkimusta voi tulevaisuudessa tehdä ja organisaatiot voivat hyödyntää testattua FVM:ää oman päätöksentekonsa sekä AI-CRM applikaatioiden implementoinnin tukena.

Avainsanat Tekoäly, CRM-järjestelmät, FVM

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1 Introduction

Artificial intelligence (AI) has been described as a General Purpose Technology (GPT) like electricity and steam engines previously in history (Brynjolfsson et al. 2017). As the people, companies and most importantly data move to digital platforms, developing advanced digital solutions becomes more and more attractive. Already companies like Amazon, Facebook and Google utilize various kinds of AI technologies in their services, but the topic is still novel for the majority of businesses. As the amount of digitally structured data, AI algorithms and computing capabilities of hardware develop, so does the number of potential applications and the interest in AI (Quarteroni 2018).

On the other hand, even as AI has an increasingly disruptive potential on businesses, there is no consensus on the definition of AI and the viewpoint on it has changed over the course of time (Simon, 2019). One proposed definition is that "Artificial Intelligence is that domain of computer science that focuses on development of systems that think like humans, act like humans, think rationally and act rationally." (Kanetkar & Chanchlani, 2014). As computers have developed greatly during the previous decades, they can today complete tasks that were previously only possible to handle by humans, like recognizing errors in text, which is not today seen as an AI application. The same may happen over time to some tasks that are currently seen to belong in the field of AI; e.g. natural language processing, as the novel solutions become more technologically advanced.

Due to this vague definition and the broad nature of potential use cases and different types of applications the AI can be utilized in, it may be difficult for an individual company to understand the concrete business potential in AI. Additionally, building novel AI applications often requires machine learning algorithms, and designing new automated algorithms requires evolved analytical capabilities (Davenport 2018). As the potential use cases of AI are interesting for a wide majority of businesses, but not all of the companies have capabilities to develop these applications on their own, there is value in looking into applications that build upon the companies' current IT infrastructure.

From the beginning of the 21st century, CRM systems have attracted the focus of companies from more traditional ERP systems (Pliskin & Ronnie 2005). In 2018 the CRM software market grew 15,6% and reached the value of 48,2 billion dollars (Gartner, 2019). Today the CRM system is a critical tool for many companies and Luftman et al. (2015) even argue that CRM has become an integral part of any business. CRM systems are used for a wide range of tasks, like following up on the results of the sales and service employees and the level of customer satisfaction (Bull, 2010). In addition, CRM systems are used by multiple functions of a company, e.g. sales, marketing and customer service (Pliskin & Ronnie, 2005).

As CRM systems have a significant meaning for many businesses, they also provide an interesting environment for AI applications. Research on business executives (Deloitte, 2018) has shown that utilizing AI in enterprise software is currently the most popular way companies are introducing AI to their operations. CRM system providers like Salesforce, Zoho and SugarCRM are already offering AI applications in their services portfolios (Chatterjee et al., 2019). On the other hand, academic research studying what kinds of AI-CRM solutions exist and how these initiatives are being managed, is scarce.

Many business organizations see the implementation of AI-CRM applications out of their reach or the concept as an irrelevant buzzword rather than as a relevant and modern business concept (Chatterjee et al., 2019). To make the concept of AI useful in general and in the context of CRM applications, businesses would benefit from seeing the potential use cases in their operations. In addition, they could gain value from evaluating together their current state and the AI-CRM initiative at hand. By recognizing the possible prerequisites, organizations can act upon them before implementing the solutions to enhance the possibilities of success.

Due to these reasons, evaluating prerequisites for utilizing AI in the context of CRM systems is an interesting topic for a study. On the long run, AI technologies could affect the majority of the companies utilizing CRM systems and other enterprise systems and they could benefit from tools and methods they can use to plan, prepare and implement the applications. Researching prerequisites there are to fulfil to enable successful implementation of AI-CRM applications will provide valuable insights for business practitioners.

On the other hand, the research of AI is currently an active topic in academia, but the studies focusing on applications from the perspective of CRM systems are few. This thesis aims to contribute to this novel topic by connecting insights from previous research on both AI applications and CRM systems with evidence about real AI-CRM implementation projects collected through expert interviews and Internet research. Additionally, this thesis aims to adapt and test theory-based fit-viability model (FVM) in an empirical multi-case study to enable organizations and academia to use it to evaluate prerequisites of AI-CRM initiatives of different types of companies.

1.1 Research objectives and research question

In this thesis I will be researching how companies can evaluate the prerequisites of different AI applications in CRM system context. As the previous research conducted on AI-CRM initiatives is limited, I will additionally be looking into the previous research on AI and CRM systems and connect them to provide novel insights. First, to base the rest of the thesis, aim is to explain the role of CRM systems, how they are used in companies and how they are constructed as information systems. In addition, I will present different types of technologies that fall under the concept of AI; like machine vision, natural language processing and machine learning. Finally, these topics will be combined to discuss how the AI technologies can be utilized in the context of CRM systems and what kinds of factors have been recognized to affect the organizational readiness to implementing them.

There are two main objectives for the research. Firstly, the study aims to successfully test the FVM in the context of AI-CRM initiatives and improve the model's generalizability. Secondly, the aim is to provide a usable method to help companies that are looking into implementing AI in CRM system context to evaluate potential prerequisites to increase the chances for successful implementation.

A qualitative multi-case study is included into the research. The aim of this study is to find out how different companies could enhance the chances of success of their AI-CRM initiatives by analyzing their current operations. The study will use FVM as a theoretical framework. In the research, evidence from the case companies is collected with semi-structured interviews and other sources of information, e.g. company websites. The aim of the study is to focus on selected AI-CRM initiatives and evaluate how well they would suit different companies based on the criteria of the FVM.

Additionally, as the research topic is very novel but in real business context companies are already introducing AI in their CRM systems, there can be seen value in studying the topic further by conducting a background research. This research consists of two parts; interviews on experts with practical understanding and experience of implementing AI in CRM systems and an Internet research studying different AI-CRM initiatives companies have conducted and shared in open data. The results of this background research are utilized to develop FVM to better fit the topic of this thesis and to find the ideas for the initiatives that the model can be used to analyze. In addition, as the expert interviews were conducted in the early part of the study and their scope was quite open, the evidence collected from them was used to scope the research question and empirical study.

This thesis is conducted in co-operation with Fluido Group, which is the leading Salesforce consulting partner in Europe. Fluido provided the access to business decision-makers from established companies in different industries, their own CRM consulting professionals and AI experts. This co-operation greatly enhanced the quality of evidence that could be collected for study, and therefore it can be expected to significantly enhance the quality of the research results.

In this thesis the following research question will be addressed:

How can companies evaluate the prerequisites for implementing AI applications in the context of CRM systems?

1.2 Scope of research

As the research topic of this thesis is novel, a descriptive approach has been selected in conducting the study. Due to this, the scope of the thesis is limited to selected number of case companies and all results may not be generalizable. Additionally, as AI is a vague and exceptionally broad topic, some scoping needs to be made, e.g. when discussing the individual technologies in the field of AI. Similarly, as the CRM system market is very fractured, there can be expected to be many differences in how the various systems operate. Due to this the scope of discussion on CRM systems is also sometimes limited, e.g. as the background interviews only focus on Salesforce, which is the leading CRM provider on the market (Gartner, 2019). In addition, the implementation of AI-CRM applications could be looked at from multiple viewpoints and to increase the quality of this study the viewpoint of prerequisites was selected as a scope.

Finally, the scope is limited by focusing the empirical research on selected AI-CRM initiatives. It can be expected that there are various ways to implement AI technologies in CRM systems and that this number is above the reach of individual research. Nevertheless, as the thesis includes a background research aiming to enhance the quality of the empirical study, the selection of initiatives will be based on the ones that are expected to provide currently the most value and attract the widest interest among companies.

1.3 Thesis structure

The rest of the thesis is structured as presented in Figure 1. First, previous literature on CRM systems, AI and AI-CRM implementation and prerequisites for it is discussed. After that, the research methods consisting of the background research and multi-case study are presented. Next, the evidence collected in background research is presented and discussed. Then the data collection and analysis processes of the multi-case study utilizing the fit-viability model as the theoretical framework are discussed. Finally, the study will be concluded and limitations, implications and recommendations for future research are presented.

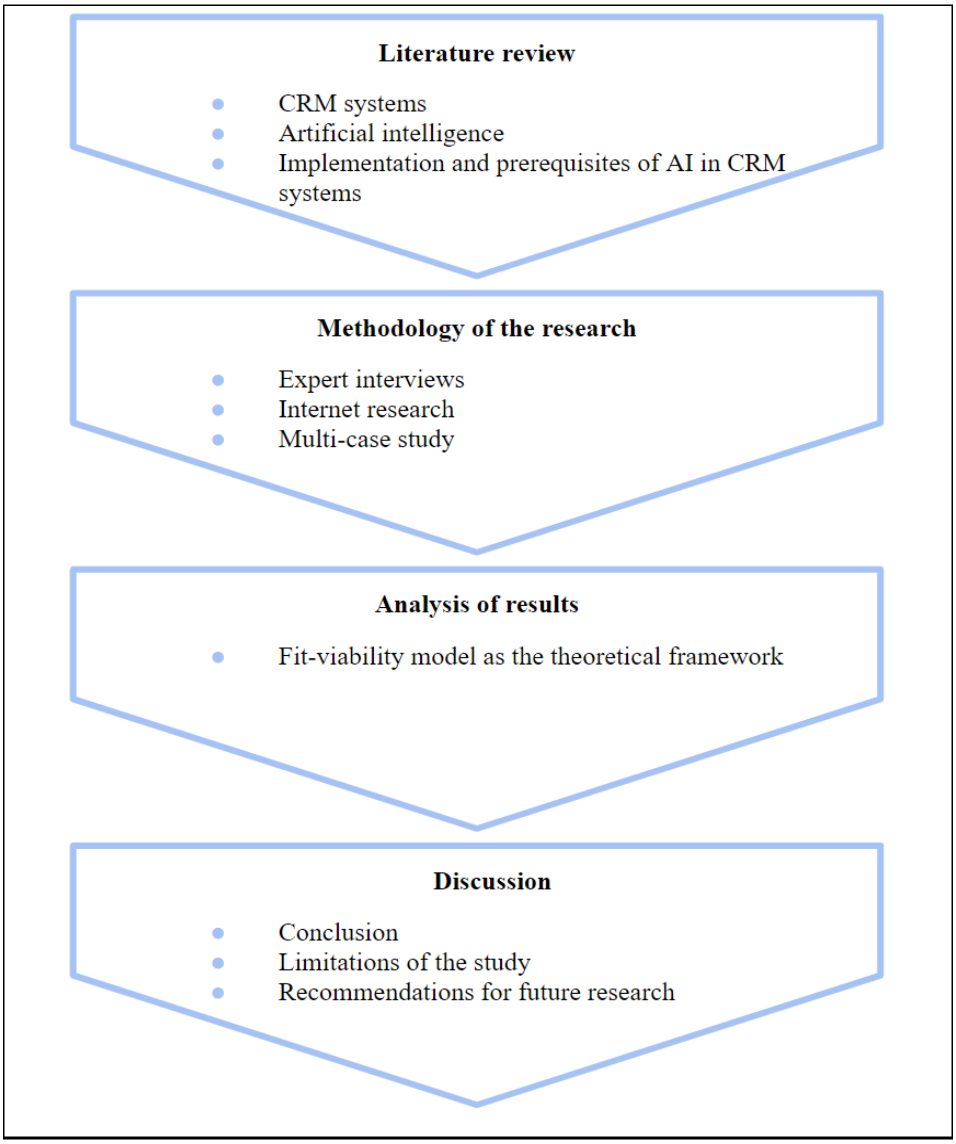

Figure 1. Thesis outline

2 Literature review

This chapter focuses on the previous discussion about the research topic. Due to the novelty of the research topic of AI and its implementation in CRM systems, there is limited amount of previous academic literature conducted on it. This is even more the case for the specific research topic of this thesis, the prerequisites for successful AI-CRM implementation. The aim of this chapter is to present the previous discussion on different sub-topics of the research topic to form a thorough basis for discussion. CRM systems and AI will be first presented individually and after that the focus moves to the topic of implementation of AI in the context of CRM systems and the possible prerequisites the organizations planning to take on these initiatives should assess to enhance the possibilities for successful implementation.

2.1 CRM systems

In this first section, the previous discussion on CRM systems will be presented to form the understanding for discussing artificial intelligence in this environment. Previous research on the organizational readiness for AI-CRM implementation has recognized that challenges around data, infrastructure, expertise and context should be assessed (Chatterjee et al., 2019) for successful implementation. These are related greatly to both the role and functions of the specific AI application, but also to CRM system acting as the operative environment. Due to this, to evaluate potential prerequisites for AI-CRM initiatives, it is important to understand what the CRM systems are.

Firstly, the CRM systems are defined, and their background and current role in business are discussed. Secondly, the different functions of the CRM systems are addressed from the viewpoint of different business units. In the final part the architecture of CRM systems will be discussed.

2.1.1 CRM systems and their role in business

Customer relationship management (CRM) has been a popular research topic for a long time. Payne and Frow (2005) define CRM as a cross-functional approach that focuses on creating profitable and long-term relationships to cocreate value with customers and other key stakeholders. Daif et al. (2015) define CRM as a business strategy integrating human resources, processes, technology and organizational culture to acquire and retain valuable customers.

These cross-functional views emphasize the strategic role of CRM in business and its significance for companies. It has been argued that CRM has not always been seen as that meaningful, but that in the recent years companies have shifted their focus from product-orientation to customers and CRM (Mohammadhossein et al., 2014; Daif et al., 2015). This change can be seen quite clearly in many industries as companies are focusing their communications and operations around the customers. Luftman et al. (2015) even claim that CRM has become an integral part of any business.

The CRM viewed from the strategic perspective affects companies on multiple levels. Previously researchers have recognized CRM technology, organizational alignment, customer management and CRM strategy implementation as the four dimensions of CRM (Dalla et al., 2018). Even though these dimensions are overlapping and most likely cannot be discussed completely separately, this study focuses especially on the dimension of CRM technology and CRM systems. Researchers have argued that leveraging IT to improve customer experience will be a key initiative of businesses for the foreseeable future (Luftman et al. 2015). Due to this, researching and developing this technology dimension of CRM further can be expected to provide insights for businesses.

In fact, the change of orientation from products to customers can also be seen in the context of information systems. For example, Pliskin and Ronnie (2005) argue that after the year 2000 CRM systems have attracted the companies' attention from the traditional enterprise resource planning (ERP) systems. This increased interest can be seen for example in the growing of the CRM software market, which in 2018 grew 15,6% to reach the value of 48,2 billion dollars (Gartner, 2019). In addition, an extensive study on senior IS executives has shown results that CRM system is the sixth largest IS investment in corporations and in addition rated sixth most important information technology that should be invested more in (Kappelman et al., 2019). Due to both its significant cross-functional role and the increased business interest, the topics related to CRM systems are highly relevant for variety of companies.

2.1.1.1 Defining CRM systems

Both CRM and ERP systems can be categorized as enterprise systems (ES) that are defined to be software applications supporting the core business processes across departments and different organizations (Schneider et al., 2018). ES first emerged already in the 1990s and have since then supported business growth and improved businesses' competitiveness by enabling process integration and cost reductions (Li et al., 2016). As stated in the previous section, CRM is often viewed from this cross-functional perspective and due to that it has many different roles inside an organization and its different units.

First perspective presented is the viewpoint of the IT function of the company. Previous research has recognized CRM applications as one of the most important developments of IT management viewed by the IT managers globally (Luftman et al., 2015). Previous research suggests that companies which exceed in adopting the best IT resources are associated with increased frequency of managerial actions like market expansions and product introductions (Luo et al., 2016). It can be argued that this also gives significance on the enterprise-level CRM system investment and adoption. Due to this managing the adoption process and risks related to it should be a high priority for IT management of the business. On the other hand, researchers have also argued that if an organization sees CRM only from the technological perspective, then the scope is too narrow and the system has a higher chance of failure in comparison to a strategic approach involving several departments, processes and people (Pedron et al., 2016).

Second important perspective is one of the end users in different business functions. CRM can be utilized by people working in various roles; managers, analysts, customer service agents and others (Hsieh et al., 2012). Some researchers have claimed that the frontline employees are the primary users of CRM system (Chen et al., 2020). Even though the use frequency of different user groups most likely varies, as an enterprise application CRM system is not just a tool for individual business functions like customer service or sales. It has been suggested that CRM system creates the connection with the customer within the service, sales and marketing functions of the companies (Selk et al., 2005). The more detailed use cases for CRM systems in different business functions and industries will be discussed in later sections.

2.1.1.2 Implementing CRM systems

The increase in companies' CRM system adoption can be seen from aforementioned growth of the CRM software market. Nevertheless, the reasons for implementing CRM are naturally business-related and vary between organizations. Research has been conducted on both these reasons and the actual implementation process of the CRM systems. Empirical research by Steel et al. (2013) shows that for many companies the drivers to implement a CRM system arose from external changes, e.g. in their competitive environment and expectations, customer profiles or knowledge of their customers.

The significance of external factors forcing the company to adapt and utilize technology in its customer relationship management is logical, but also raises the question if it is a better source of motivation than internal changes in the organization. For example, Pedron et al. (2016) emphasize that in the context of implementation of CRM systems it is exceptionally important for companies to be aware of their organizational culture and take it into notion. Researchers have recognized that many companies have been struggling with adopting CRM systems and there is a need to strengthen companies' CRM capabilities (Wang & Feng, 2012). To see the role of CRM systems, it is important to understand why and how the companies are implementing the software. This is also an important baseline when thinking about utilizing novel AI applications on top of CRM system.

In previous research companies have been recognized to adopt CRM systems to reach different objectives, e.g. enhancing customer relationships, developing the flow of business processes and gaining better understanding of customers (Pedron et al. 2016). In addition, Li and Mao (2012) suggest that CRM can enable a better visibility to business processes for management through monitoring and increasing knowledge sharing between different users. It has also been claimed that even though CRM system primarily provides value on this process level, it can evolve into a system affecting the company on an enterprise-level by e.g. increasing revenue, market share and profitability (Tallon et al., 2016). Due to the significance of these pursued business benefits, it is easy to see why companies are taking on CRM system initiatives.

Even though companies are investing more and more in CRM systems, they are continuing to face problems in for example getting the users to adopt the use of the software (Chen et al. 2020). Research conducted by Hendricks et al. (2007) on almost 80 companies shows that for many companies the impact of the CRM system on the company profitability can be insignificant. So merely adopting a CRM system does not guarantee increased revenue or profit. The CRM system market and solutions have developed greatly in the last 20 years along with other enterprise software, but implementation still has its risks of failure. Research suggests that reported reasons of failures in CRM adoption initiatives include misalignment between corporate and CRM strategy and the absence of a clarified CRM strategy (Steel et al. 2013).

As CRM should be viewed as an enterprise software, also the implementation should be designed from the perspective of enterprise level. The extensive research conducted by Pedron et al. (2016) consisting of 62 in-depth interviews recognized that companies are managing risks related to CRM projects e.g. by measuring tangible benefits of the CRM software and by implementing the system gradually and responsively to employees. Wang and Feng (2012) on the other hand claim that for companies to strengthen their CRM capabilities, they need to organize continuous CRM monitoring processes, become more customer oriented, develop their customer-centric organizational system and implement CRM technology.

All in all, the CRM systems have a highly significant role on the enterprise level and companies aim to reach significant objectives when adopting them. On the other hand, due to the broad scope of the systems, there are multiple risks related to CRM systems that need to be managed. In addition to this role as an enterprise system, CRM also plays a part in specific business functions of companies and the use of the system varies between different businesses. To understand the potential value for artificial intelligence in the context of CRM systems, these different functions and features will be explored in the next section.

2.1.2 Functions of CRM systems

The CRM system market is somewhat fractured as in 2018 the five biggest vendors (Salesforce, SAP, Oracle, Adobe and Microsoft) held 41,1% of the whole market and other smaller providers made up the majority (Gartner, 2019). Due to this, there can be expected a lot of variety between various software categorized as CRM systems. Making an exhaustive list of all functions of CRM systems is difficult, and in this chapter mainly the ones most discussed in previous literature or ones viewed interesting from the perspective of AI applications are discussed.

Fardoie and Monfared (2008) studied some of the architectures of different CRM systems on the market, summarized different features they offered and presented the idea that they can be categorized as collaborative, operational and analytical technologies. Some examples of these recognized features are shown on Table 1. Fardoie and Monfared (2008) argue that collaborative technologies focus on customer touchpoints of the different communication channels, operational technologies include customer-facing applications e.g. for sales and analytical technologies integrate and process the collected data to convert it into actionable information. This section will discuss the functions of CRM systems from these three perspectives.

Table 1: Examples of functions modified from table Comparison of technology architectures by Fardoie & Monfared (2008)

Collaborative technologies	**Operational technologies**	**Analytical technologies**
Web, email, call centers	Resale, account management, customer database	Customer intelligence
Self-service website	Marketing automation, contact management	Data warehouse
Voice response systems	Email server, channel management	Data analysis
Queue management systems	Commercial database, ordering management	Data mining

2.1.2.1 Collaborative technologies

Companies are utilizing CRM approach to manage their customer relationships in various channels. There are many ways the companies can collaborate with their customers, but in the context of CRM systems the focus is on the online channels. Feinberg and Kadam (2002) have studied what collaborative online CRM-features companies are offering for their customers and state that they include e.g. complaining ability, email, online purchasing, and memberships. Some CRM software providers like Salesforce are offering for example e-commerce site management as a part of their CRM platform and users use these in-built channels or integrate other separate channels to their CRM systems (Favier 29.5.2020, interview). Previous studies have shown that companies utilizing these kinds of collaborative online CRM features have achieved lower levels of dissonance experienced by customers which increases customer satisfaction and repeat purchasing (Clark & Das, 2009).

Many of the collaborative CRM technologies have been around for a relatively long time, e.g. websites, call centers and email (Fardoie & Monfared, 2008), but there are also some more novel ones. These include for example social media sites and chatbots. Of these especially chatbots are interesting from the perspective of this study, as CRM providers like Salesforce are offering chatbots utilizing AI for their customers to implement in their CRM system (Salesforce, 2017a). Researchers have recognized that by implementing chatbots, companies can remove workload from CRM system users (Sydorchuk et al., 2019). The potential of reducing manual tasks and potentially labor costs is highly interesting, but there are also other potential benefits from utilizing chatbots. For example, Blaj et al. (2019) argue that by utilizing a chatbot application the company can provide automated service for their customers 24/7. This can be expected to provide value for customers who value the possibility to contact an organization at the most convenient time for them.

2.1.2.2 Operational technologies

Second category for CRM system technologies is probably the most intuitive one focusing on operational technologies. Front-end employees have been recognized as the primary users of CRM systems (Chen et al. 2020) and the functions these operational technologies enable are mostly utilized by these front-end personnel. CRM system has grown to be a system connecting multiple front-end processes from sales to marketing and customer support (Pliskin & Ronnie, 2005). As CRM systems are used to keep and nurture existing customers and acquire new ones (Mohammadhossein et al. 2014), these three business functions are in especially critical roles.

First the focus is on the sales function. It has been argued that IT innovations have brought considerable benefits to sales function especially in B2B sectors (Rogers & Clark, 2016). The increasing focus on CRM systems is one reason behind the emergence of these innovations. The CRM system e.g. enables users to document relevant information and manage customer contacts (Chen et al. 2020). Additionally, sales opportunities can be managed in a CRM system (Cruz & Vasconcelos, 2015). Through these features, the sales function manages all their sales processes holistically on the same platform. Using one enterprise system to manage different sales tasks can be expected to make the system portfolio simpler for the users when compared to utilizing several individual tools. On the other hand, it has been argued that CRM systems have become increasingly complex and infused with interconnected business logic that makes their operation too difficult to understand for managers (Lyytinen & Grover, 2017). This complexity can be expected to increase if new applications utilizing AI are built on top of a system that's operation is already difficult to understand.

In addition to features related to sales task performance, also other CRM system functions for sales have been recognized. For example, Agnihotri et al. (2017) states that one key function of the CRM technology is collecting information about important decision makers and customers to build detailed profiles of them. Daif et al. (2015) on the other hand suggest that CRM technologies can enable mobile office access to sales and field service functions of the company. Bull (2010) argues that CRM can be used to evaluate employees' performance and customer satisfaction. Li and Mao (2012) emphasize the importance of internal control further, as during their research CRM system strengthened clan control between sales employees and increased performance quality.

Secondly, there are also operational technologies in CRM systems that are utilized in marketing. CRM systems have a role in supporting marketing operations from upkeeping the record of previous contact efforts to delivering marketing messages to customers (Even et al., 2010). As a CRM system is an enterprise system, marketing function can utilize the same customer database as for example sales function. In addition to helping perform marketing tasks, CRM systems have been recognized to enhance customer experience of the company. For example, Mohammadhossein et al. (2014) argue that CRM enables marketing to personalize their service, respond better to customer needs, segment customers and integrate multiple channels.

Thirdly, the operational technologies of CRM systems can also be utilized by the customer service function. For example, CRM can be integrated to company's customer service channels like call centers and it can be used to track customer records and provide relevant information about the specific customer to service agent (Gans et al. 2003). Benefits of utilizing CRM approach to offer service for customers include shorter response times and the ability to serve customers from any location (Sivaraks et al., 2011).

All in all, there are many ways that different business functions are utilizing the operational functions of CRM systems. Even though the focus in previous research has often been on sales, marketing and customer service, as an enterprise-level system there are probably many other business functions that can utilize the CRM system in their operations. Nevertheless, these are not discussed further due to the scope of this thesis and as the already presented functions are viewed to depict the most important CRM system use environments.

2.1.2.3 Analytical technologies

Fardoie & Monfared (2008) state that this category includes integration and processing of accumulated CRM data in an aim to convert it into actionable information. The CRM system functions discussed previously make it possible to collect great amounts of data about customers and the relationships the company has with them. It has even been suggested that previous operational framework of customer information has reached its maximum potential, and an analytical approach is needed to reap new benefits (Ranjan & Bhatnagar, 2011).

The increasing amount of data in general has raised the interest of many industries and for some companies, data has become their most important asset (Daif et al., 2015). The CRM data is most likely not the most valuable form of data for every organization, but it can be expected to provide value for every type of company that makes decisions related to their customers.

In fact, the development of CRM systems has been recognized as one key reason why especially the volume, variety and velocity of customer data has increased during the past decade (Kitchens et al., 2018). This increasing amount of data offers the companies new opportunities to find insights about their customers. Nevertheless, it has also been argued that not all of data is equally important (Even et al. 2010). The increased amount of data has most likely increased the amount of irrelevant data and made it more difficult to find the important insights for specific use cases.

One of the main reasons why analytical functions in CRM systems should be invested in is that they make it possible to find unseen information from the customer data (Ranjan & Bhatnagar, 2011). For example, the company can see which kinds of companies usually buy from them and what types of customer relationship activities are most effective. When analyzing CRM data, its characteristics should be understood. For example, one recurring aspect of CRM data is the unbalanced distribution between customers and non-customers, meaning that usually there is e.g. 5 % of actual buyers to 95 % of nonbuyers in the customer database of a CRM system (Lehrer et al., 2018).

Especially in the context of analytical technologies, there seems to be endless ways that CRM systems can be utilized by different types of companies and business functions, especially if the CRM data can be enriched with data from other sources. Kitchens et al. (2018) argue that the companies that integrate comprehensively different types of relationship data reap the biggest benefits from the increase of customer data. The previous research has shown that for example in the financial industry enriching CRM data with data from other sources has enabled to automate service and enhance and individualize the customer service of some companies (Lehrer et al., 2018). The analytical perspective to CRM systems is interesting also from the context of AI applications as for example machine learning models could use this data to make predictions for the future.

2.1.3 Architecture of CRM systems

Before looking more closely at artificial intelligence and how it could be utilized in CRM systems, it is good to get a good understanding of how CRM systems are constructed. Software architecture, which describes the set of software components and their relations, has been argued to be an essential component of enterprise software (Niu et al., 2013). As the CRM system market is fractured to multiple providers, there is no singular architecture that is used by all systems, but some general design choices can be recognized.

Cruz and Vasconcelos (2015) studied comprehensively five popular CRM systems and recognized six recurring CRM system modules; Account, Sales, Marketing, Service, Scheduler and Administration modules and five modules which interact with the CRM system; Portal, Contact Center, Document & Knowledge Base Management system, Workflow system and Reporting & Analytics system. The CRM system functions discussed in the previous section are encased in these different modules.

Modularity has been described as the practice of dividing an IT product into multiple subsystems (Baldwin & Clark, 1997). In the context of enterprise software like CRM systems, the modular design seems to be useful for the companies utilizing the software, as they can select which modules and functions provide value for them and can implement only those. The modules and their relationships recognized by Cruz and Vasconcelos (2015) are visualized in the reference application architecture in Figure 2. The presented model helps in seeing how the CRM data flows between different modules targeted for different business functions and administration.

Badea (2009) suggests that the customer database is the foundation of CRM platforms and most important information is enclosed there. Cruz and Vasconcelos (2015) recognized that the data structure of CRM systems they studied can be a complex network of entities classed like Cases, Customers and Campaigns and relationships between them. The different business functions can manage the same data and it can be utilized in different modules. On top of this are the analytical functions discussed in previous section. Analytics built on business rules and processes have extensively been infused into CRM systems (Lyytinen & Grover, 2017). To find potential use cases for AI technologies, it is important to understand these modules forming a CRM system and the ones interacting with it.

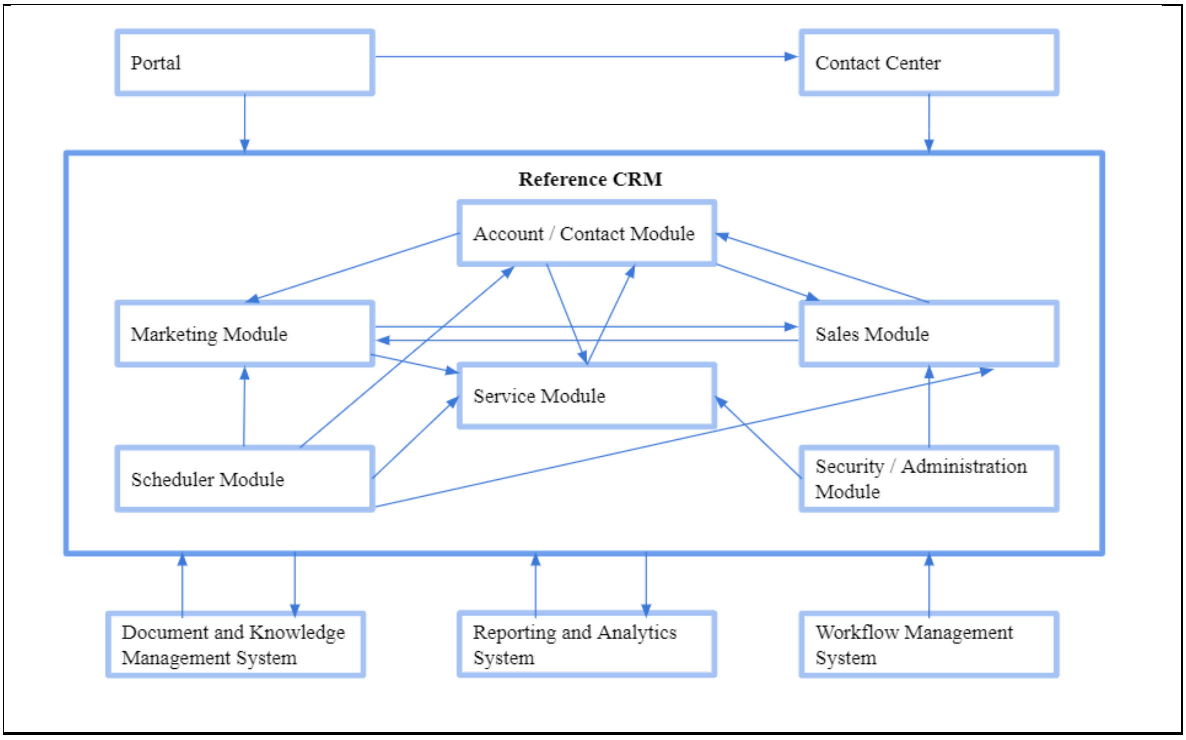

Figure 2. Reference application architecture proposed by Cruz & Vasconcelos (2015)

In the end, a CRM system has a significant role on both enterprise level and the various business functions of the company. The presented functions of CRM systems viewed through the categorization of Fardoie & Monfared (2008) are not exhaustive but they provide an idea of the core use cases of CRM systems. In addition, the discussed reference architecture of Cruz and Vasconcelos (2015) cannot be used to analyze individual CRM systems in detail, but it helps to understand the modular structure of CRM systems and how the data moves between modules and how this data can be utilized in analytics.

As companies are investing increasingly in CRM software, it can be expected to be highly interesting system category from the context of novel innovations, e.g. ones utilizing AI technologies. There can most likely be potential AI applications for all core user groups and modules of CRM systems. The next part focuses on artificial intelligence in general and in the final section of the research, discussion on AI applications specifically in the CRM context will be discussed.

2.2 Artificial intelligence

In this second section the focus is on artificial intelligence (AI). The aim of this part is to understand what AI as a concept is and how it can be utilized in business in general, so that it may be applied to CRM systems. The specific prerequisites for AI-CRM initiatives can be expected to vary depending on the specific application and before discussing them, the concept of AI must be addressed. First, the general academic discussion on AI will be presented. In the second part, some of the different technologies currently recognized to belong to the field of AI will be presented and finally the discussion is on implementation of AI in business.

2.2.1 Growing interest in artificial intelligence

Artificial intelligence (AI) has developed rapidly in recent years due to advancement of the cognitive mechanisms and learning capabilities of machines (Jarek & Mazurek, 2019). In addition, AI has become a popular research topic in the context of business and information systems sciences. Companies too are becoming more interested in building their capabilities for AI (Davenport, 2018). Some researchers have even called AI a general purpose technology (GPT) like electricity and steam engines have been during the history (Brynjolfsson et al, 2017). PwC (2017) has presented a prediction that in 2030 AI could contribute up to 15,7 trillion dollars in the global economy; 6,6 trillion coming from increase in productivity and 9.1 trillion from consumption -side effects.

Based on these points, AI is expected to significantly transform the operations of companies. In addition, AI has potential to change the lives of people. For example, personalization is already one way that AI is shaping lifestyles of humans in almost every aspect of their daily lives (Kumar et al., 2019). Even though the significance of AI grows, it is clear that there are many expectations that the AI needs to fulfil before it can be said to have transformed the world like previous GPTs. Additionally, even though AI has an increasingly disruptive potential, there is no actual consensus on the definition of AI and the viewpoint on it has changed over the course of time (Simon, 2019).

One suggested definition is that AI is a domain of computer science focusing on developing systems that think and act in a human-like and rational way (Kanetkar & Chanchlani, 2014). Simon (2019) argues that AI is an umbrella term encompassing multiple technologies like machine learning (ML), deep learning, computer vision, natural language processing (NLP) and machine reasoning. Many of these technologies like NLP and ML have been around for decades (Quarteroni, 2018; Günther et al., 2017). Due to this, also artificial intelligence can be argued to have existed for a long time. Some see it as a working title and after the technology is mastered, it will not belong to the field of AI anymore (Van Leuken, 5.6.2020, interview). Sometimes in academic discussion AI is also referred to as algorithmic intelligence (Markus, 2017).

One popular terminology used to discuss AI is the separation of narrow or weak AI and Artificial General Intelligence (AGI) or strong AI (Wirth, 2018). The AGI is expected to be able to adapt to different use cases similarly to the human brain, but there is no consensus of when this kind of AI can be developed (Simon, 2019). As we are currently in the phase where the AI solutions on the market belong to the category of narrow AI; applications utilizing the different discussed technologies to solve problems in specific context (Jarek & Mazurek, 2019), also the focus of this study is on the narrow AI without taking a stance on if and when the AGI could become reality.

To understand the potential value of AI in business, it is interesting to investigate how it could compensate or substitute humans. PwC (2017) predicts that 55% of economic gains of AI will be coming from labor productivity improvements from 2017 to 2030. The academic debate around human intelligence and AI has been argued to have gone on for decades (Günther et al., 2017). In the 1980s this debate focused on if then trending expert systems should replace or support humans (Markus, 2017). From today’s perspective, it is easy to see that they have not been capable of replacing humans and tomorrow it will be interesting to look back to the realization of the expectations put up for current AI.

Aleksander (2017) argues that there is a difference in the algorithmic intelligence of robots and the intelligence of human beings. When looking at the currently existing AI solutions, this difference seems very evident as they are far from artificial humans. Ross (2018) claims that the biggest flaw companies have in their view of AI is that they think it as a substitute for human intelligence, when actually the implementation demands new kinds of human intelligence and skills from the organization.

Due to the novelty and broadness of the topic, there can be expected to be even more areas of AI that are insufficiently understood in companies. For example, McKinsey & Company (2017) has claimed that one reason why companies are not utilizing AI solutions currently applicable is that the potential value provided by these investments is not clear and in especially more complex cases, like utilizing AI in medical diagnosing, neither are the costs. To understand the potential use cases and their effects on individual companies, it is important to look more deeply at the technologies that are seen to be encompassed in AI and the different kinds of ways they can be implemented in business.

2.2.2 Different AI technologies

Next, some of the most important AI technologies are presented. This does not aim to be an exhaustive list of all different technologies, but the goal is to provide an idea of what kinds of technologies are seen to belong into the field of AI. These technologies are selected by their popularity in academic discussion and their relevance to the research topic.

2.2.2.1 Machine learning

Machine learning (ML) is an AI method for supervised and unsupervised classification and profiling and it can be used for example to make different types of predictions (Zawacki-Richter et al., 2019). In practice, ML can be seen as programming computers to optimize the chosen performance criterion using example data (Alpaydin, 2011). Different machine learning algorithms are divided mainly into two categories: supervised learning running on labeled data and unsupervised learning algorithms operating on unlabeled data (Kanetkar & Chanchlani).

Supervised learning uses testing data of the set input and output variables and can be used to answer classification or regression problems, when unsupervised learning can be used for example in clustering applications (Alpaydin, 2011). Example of an application of supervised learning is a system that uses the records of stock prices and company data inputted in it to predict the potentially undervalued ones. On the other hand, an application that can be taught to recognize different types of trees, buildings or cars in pictures inputted into it is an example of unsupervised learning.

The higher level of ML that utilizes these algorithms that do not need to be manually managed is also called deep learning (DL) (Jarek & Mazurek, 2019). Deep learning requires labelled data for training, algorithms for neural nets and special purpose hardware to run them (Simon, 2019).

These different ML algorithms make it possible to provide quick answers to complex problems but could also lack e.g. the strategic context of those decisions (Crews, 2019). As discussed in the later parts, even though machine learning can provide valuable use cases in itself, ML also enables many of the other AI technologies. Machine learning has even been referred to as the brain behind AI enabling the applications (Chatterjee et al., 2019).

2.2.2.2 Natural language processing

Natural language processing (NLP) is an artificial intelligence technology utilizing machine learning to analyze text linguistically (Quarteroni, 2018). NLP research is currently focusing on developing systems that can interact with people through dialogue rather than merely reacting to stylized requests (Simon, 2019).

One way to categorize NLP is the division to statistical NLP focusing on extracting meaning and classifying sets of text and to semantic NLP used to analyze decomposition and relationships among words and phrases in text (Davenport, 2018). An example of a use case for statistical NLP would be a customer service system that automatically categorizes the incoming requests based on their meaning. One application utilizing semantic NLP could be a chatbot that changes its communication style based on the style its conversational partner uses.

The development of NLP has also enabled the recognition and use of speech data in addition to text (Hoy, 2018). Speech recognition can for example be utilized in an application of a digital assistant, like Siri and Alexa (Brill et al., 2019). These assistants could be interesting also in business context, but to become adaptable for various use contexts, they may have the same challenges as the AGI in front of them.

All in all, NLP has many use cases especially in the context of collaborative CRM technologies discussed in the previous section. Nevertheless, there are also things to overcome before the technology can reach its full potential. For example, the inaccuracy of the ML models empowering NLP applications has been claimed to be the biggest limitation for their use, but they are expected to develop further in the future (Quarteroni, 2018).

2.2.2.3 Machine vision

Machine vision is a branch of AI that's development has been boosted by deep learning and it enables for example automatic image or video captioning (Simon, 2019). Machine vision can enable for example image detection which is a method to identify images that have defined object in them and image recognition to provide names for an object in the picture (Yossy et al., 2017). Detecting objects from an image could be used for example to recognize if there is a component missing of a photographed manufacturing equipment. Image recognition on the other hand could be used for example to automatically classify pictures customers send of their rented vehicles.

Machine vision is a very versatile technology and it could be utilized in various contexts as picture and video data can also be of almost any kind. Even when scoping to CRM systems, due to their enterprise level role there can be expected to be various use cases for machine vision. This applies to all presented AI technologies and to get a better understanding of how individual companies can get value from them, next section will focus on academic discussion on AI implementation.

2.2.3 Implementing AI

First and foremost, it is important to emphasize that AI is not a singular product like a specific software, but instead it combines software and hardware to enable various AI solutions (Simon, 2019). Implementing AI means implementing these kinds of applications. It has been claimed that AI could be used to improve almost any kind of product and service (Davenport, 2018). Bringing the discussion on AI to the level of applications can help to understand the potential and limitations of the technology, but AI should probably not be viewed only as enabler of singular tools. McKinsey & Company (2017) has claimed that before launching pilots and testing solutions, companies would gain value from creating a prioritized portfolio of AI initiatives in scope of the whole enterprise. Stanek (2017) claims that integrating AI into a specific business model is a strategic and complicated process.

Davenport and Ronanki (2018) argue that when viewing AI through the lens of business capabilities, there can be recognized three types of use cases: automating business processes, gaining insight through data analysis and engaging with customers and employees. On a more detailed level, they argue that based on their study, process automation is the most common type of AI solutions used to automate e.g. back-office administrative tasks. Secondly, Davenport and Ronanki (2018) argue that cognitive insights is the second most common type and is used to detect patterns in data using ML algorithms. Finally, they say that the least common type of AI solutions is the cognitive engagement that focuses e.g. on utilizing NLP chatbots to engage with customers.

As it can be seen, these three solution types are very different from each other and it is important for businesses to understand these differences to recognize the potential use cases. By successfully implementing AI solutions, companies can be expected to get significant financial results. For example, Bain & Company (2019) states that by introducing AI to its order management systems, a global packaged food company was able to reduce waste by 40-50 percent and 50 percent reduction in dedicated working hours.

Ross (2018) suggests that rather to base their expectations of AI implementation on the biggest triumphs of AI applications like computer beating humans at playing Go, companies should instead look into their own experiences e.g. on implementing enterprise software. Companies sometimes mistakenly see AI as a magic bullet that can solve all their problems (Van Leuken, 5.6.2020, interview). In addition, even if companies understand the limitations of AI, the implementation can be expected to be difficult. Kumar et al. (2019) propose that companies need to complete three preparatory steps before introducing AI in their operations: developing functional data ecosystem for achieving data maturity, aligning AI with company goals and establishing clear control parameters and instructions.

As said, taking on AI solutions can be a complex process, and there are multiple ways the companies can approach it. First, it is naturally possible for companies to build these applications themselves. The process of building novel AI applications often requires ML algorithms, and designing new automated algorithms requires evolved analytical capabilities (Davenport 2018). Many companies may not have these competences in-house.

In fact, many smaller companies have decided to seek technology partners to harness the AI (Stanek, 2017). An example of a technology partner is IBM that has developed an AI computing system Watson that makes it possible for their customers to use different AI technologies like ML and NLP (Kanetkar & Chanchlani, 2014). These kinds of AI resources can be utilized in many ways by the companies to support their existing applications. In addition, companies can buy individual applications that utilize AI for individual use cases, like an app called Legal Robot for assisting in handling legal documents (Kumar et al., 2019). Finally, there are also AI solutions integrated to already utilized information systems assets. The interest of this thesis is in utilizing AI in the context of CRM systems. A survey conducted by Deloitte (2018) showed that utilizing AI inside an enterprise software is the easiest and most popular way for companies to utilize AI, which makes this an interesting research topic. How AI can be used in an AI-CRM context and what its potential prerequisites are will be discussed in the next section.

2.3 Utilizing AI in CRM systems

In this last section of the literature review, the focus is on the academic discussion on utilizing AI especially in CRM systems and business functions utilizing CRM systems. All in all, the research topic is very novel and there is a limited amount of studies conducted on the topic of AI in the context of CRM systems. This is also true when referring to the academic literature about potential prerequisites for AI-CRM implementation. Due to this, this chapter will also discuss previously addressed separate research on AI and CRM systems together to find novel connections.

As described before, CRM systems are enterprise systems affecting companies on both strategic level and that of the business operations. There have been multiple use cases recognized for utilizing AI in CRM systems, like automation of customer support (Chen, 2012). CRM providers like Zoho, SugarCRM and Salesforce have recognized the business potential and integrated different AI-solutions to their provided CRM systems (Chatterjee et al., 2019). In addition to offering their own solutions, for example Salesforce has provided integrations to other AI platforms, like IBM's Watson (Salesforce, 2017b). This means that companies have possibilities to buy AI solutions from their CRM software providers but also integrate some other supported AI solutions into their CRM system.

As AI can be implemented to CRM systems in various ways, firstly the categorization of CRM features by Fardoie & Monfared (2008) presented in the first section will be used as the framework for structuring this part. Lastly the previous discussion on the organizational readiness from the viewpoint of AI-CRM implementation is discussed and a framework for evaluating this readiness and recognizing prerequisites suggested by Chatterjee et al. (2019) is presented.

2.3.1 Collaborative use cases for AI

Previous studies have discussed AI-CRM applications used by companies to enhance their collaboration with customers. These include automated online assistants and automated customer support (Chen, 2012). Through these kinds of applications CRM systems can collect and utilize data about customer behavior and add value to personal interactions with customers (Galitsky & Galitsky, 2011). Researchers suggest that for AI-contributed technologies to work effectively in CRM context, organizations must be able to capture actionable and effective customer data from the CRM activities (Chatterjee et al., 2019). This also applies to collaborative AI use cases, as companies need to have an understanding of their current customer interactions to build tools for automating these processes.

Many large companies for example in the financial sector are already using automated online assistants instead of call centers to provide the first point of contact to their customers (Chen, 2012). Additionally, according to a study by Deloitte (2017), 56% of companies in industries of multimedia and technology are planning investing in contact centers. The interest in these technologies seems to be spreading, as more and more companies are adopting AI applications like chatbots to collaborate with their customers. In addition to these popular solutions, also some more novel AI use cases for CRM systems have been presented, for example an application to automatically recognize the age of a customer through machine vision (Fu et al., 2010).

2.3.2 Operational use cases for AI

Many different types of operational use cases for AI from the perspective of CRM system users like sales and marketing functions of companies have also been discussed. On the other hand, even though some functions most likely utilize CRM more than some others, as an enterprise system there can be expected to be potential AI applications in the context of CRM systems for all fields of business that utilize customer data. Nevertheless, as the research topic is novel, the academic discussion is still focusing strongly on the core functions.

It has been proposed that if CRM systems become more intelligent by utilizing AI, the time of the system users is released to other tasks like personal customer contacts (Galitsky & Galitsky, 2011). By helping users to focus on value-creation that cannot yet be automated, AI in CRM systems can be expected to provide value for the organization. McKinsey & Company (2017) has forecasted that AI technologies may globally unlock value for marketing and sales functions of companies by 1,4-2,6 trillion US dollars.

From the perspective of sales, there are already AI solutions offered by CRM providers for example to recognize new future customer leads (Crews, 2019). In addition, Bain & Company (2019) has recognized that one use case for AI in sales is the optimization of accounts so that the company can align its investments and individuals effectively on most likely profitable customers. Previously the development of information technology has raised predictions that the sales profession could be replaced, but they have not realized (Rogers & Clark, 2016). In the case of AI applications for sales these innovations also seem to focus on helping users to focus their work rather than replacing the human employees.

It has been suggested that utilizing predictive AI solutions in CRM systems will help companies to maximize their marketing profits (Chen, 2012). Kumar et al. (2019) suggested that through AI, marketers can tap into enormous potential for customer value creation by e.g. enabling stronger personalization. The ever-increasing available customer data has been a driver for increasing the role of AI for marketing (Jarek & Mazurek, 2019). All in all, utilizing customer data in operational marketing offers possibilities for a wide variety of AI applications.

2.3.3 Analytical use cases for AI

One reason behind the need for AI applications in the context of CRM systems has been suggested to be that the amount of customer data collected from various sources is growing and analyzing it has become too difficult for previously used tools (Chatterjee et al., 2019). Previous research suggests that traditional CRM systems have for example successfully produced profiles for at-risk accounts but failed in providing reasons behind their likelihood of churn or suggestions on how they could be retained (Chen, 2012). In this sense, AI can be seen to take the analytical technologies of CRM systems, discussed previously, further. As CRM systems can be used to collect vast amounts of data from customers and operations the different business functions conduct, there can be expected to be widely different use cases for advanced analytical capabilities of ML solutions in different organizations.

Collected data is not very useful unless it is accompanied by mechanisms and methods that enable understanding the information hidden in it (Cioca et al., 2013). Due to this, companies need to find ways on how the collected customer data can be utilized. Amnur (2017) suggests that within CRM system context machine learning can be utilized for building predictions on this data. The ML algorithms currently favored in analyzing customers are e.g. collaborative filtering, clustering and k-nearest neighbors (Kumar et al., 2019). The ML enables many of the AI-CRM applications presented previously.

On the other hand, also the potential challenges and problems in data that these AI models use may affect the quality of those predictions. For example, poor data quality caused by missing value forces to make subjective choices that may affect the created model (Danesi

& Rea, 2016). In addition, it has been proposed that it is critical that the company owns internally created data from customer interactions, as it is almost impossible to buy it outside (Grover et al., 2018). In the context of AI-CRM applications, the historical data is needed for training the ML algorithm to provide predictions. This thesis is based on the expectation that there may also exist other prerequisites for implementing AI in CRM systems and previous discussion related to this specific topic is presented next.

2.3.4 Prerequisites for utilizing AI in CRM systems

As can be seen, the variety of use cases for AI in CRM systems is broad and there are many challenges for implementing different solutions. This study aims to help companies to plan their AI-CRM projects and prepare for these initiatives by recognizing and addressing potential prerequisites. Due to the novelty of the research topic, not much previous academic discussion on the topic exists. Nevertheless, Chatterjee et al. (2019) have discussed the topic in their previous research and have suggested a framework to evaluate organizational readiness for effective AI-CRM integration (Table 2).

Table 2: A conceptual framework for organizational readiness for effective AI–CRM integration by Chatterjee et al. (2019)

Develop effective data and AI algorithms and related strategy	Approaches for actionable customer data for AI-CRM integration	Indicator	Different challenges (need to overcome)	Indicator	Next steps for AI integration (After updating of data)	Indicator	Adoption of AI-CRM System
	Social Approach		Data Challenges		Close all possible gaps		
	Integration Approach		Expertise Challenges		Push information to organization		
	Auditing Approach		Infrastructure Challenges		Effective training and readiness strategy		
	Regularization Approach		Context Challenges		Effective change management strategy		
	Analytical Approach		Any additional Challenges		Close alignment between business & IT		

● → Indicator showing the organization is not ready
● → Indicator showing the organization is somehow ready (In progress)
● → Indicator showing the organization is fully ready

Chatterjee et al. (2019) propose the framework for organizations' that are looking into utilizing AI in CRM systems and claim that it could help the authorities responsible for these initiatives to evaluate the status of the different operational procedures needed for successful adoption. The different procedures are divided into three categories: approaches, challenges and next steps. The approaches relate to the structuration, collection and preparation of customer data to be used by AI and the CRM system architecture discussed before. Chatterjee et al. (2019) argue that companies should adopt these different approaches and with their framework organizations are able to evaluate how well they are adopted in the context of the AI-CRM initiative.

Challenges on the other hand are potential obstacles the organization must assess to be ready for successful AI-CRM implementation. Chatterjee et al. (2019) argue that these challenges are related especially to data, expertise, infrastructure and context. These challenges relate to the previously discussed AI use cases and technologies, role of CRM systems for businesses and their architecture and functions.

Next steps are procedures proposed by Chatterjee et al. (2019) for companies to take on and evaluate after preparation of data but before adopting AI applications to improve and strengthen their potential features. These next steps can also be viewed as prerequisites for AI-CRM adoption. The different approaches, challenges and next steps categorized in the framework affect the different prerequisites for AI-CRM implementation and the framework can be expected to provide value for the empirical research of this thesis.

The model provides interesting ideas which resonate well with other discussion presented and it also could have potentially provided the theoretical framework for the empirical study of this thesis. Nevertheless, to the researcher's knowledge the model has not been tested in context of actual companies previously and a detailed research instrument explaining how this model could be tested in an empirical study is not provided. Due to this, more developed model was chosen as the theoretical framework for this thesis and it is discussed more thoroughly in the next chapter.

3 Methodology

The aim of this thesis is to develop an academically designed managerial method to help companies recognize and evaluate potential prerequisites of AI-CRM initiatives. A theory known as fit-viability model was selected as the theoretical framework for the study. This thesis develops the model further and tests it with multiple case companies to prove its usability for organizations and researchers in the context of AI-CRM applications. In addition, due to the novelty of the research topic a background research was conducted before the multi-case study to collect additional evidence of the research topic and to scope the thesis. In this chapter, the methodology and structure of the research is presented. First, the fit-viability model is discussed and after that the research process is explained.

3.1 Theoretical framework

This thesis includes an empirical multi-case study. The plan of the study is to collect evidence from interviews with company decision-makers and open data to evaluate different AI-CRM initiatives and their prerequisites for these companies. This study will utilize the fit-viability -model (FVM) by Liang and Wei (2004) and this framework will be introduced in this section.

The original idea of companies being able to evaluate different Internet initiatives by utilizing a matrix with fit and viability as axes was first presented by Tjan (2001). This idea was later developed further, proposed as a scientific framework for technology adoption and tested in the context of mobile applications (Liang & Wei, 2004; Liang et al., 2007).

Tjan (2001) argues that the traditional portfolio theory can be developed to become a tool to allocate organizations' limited resources in the context of at the time increasing Internet investment opportunities. The simplified idea of the model is that it helps companies to evaluate the fit of a specified technology investment with the company's current state and the viability of the solution; how much is its potential payoff in the company's context. The fit and viability are used as axes to form a matrix with four quadrants. To evaluate the projects on these axes, there are sets of criteria; for fit e.g. alignment with core capabilities and for viability the personnel requirement of the project, which are used to derive singular values for both constructs. This matrix is argued to provide companies rough guidance on the best strategic course for each project; invest more, redesign it, sell or spin it out or kill it. (Tjan, 2001.)

From the perspective of the research question of this thesis, the initiatives falling into the bottom-right corner of the matrix are especially interesting, as Liang et al. (2007) argue: “For those in the restructuring category, actions to strengthen organizational support are essential for their success.” Due to their essentiality, manageable constructs affecting the viability can be viewed as prerequisites for successful implementation. This thesis aims to guide companies to use FVM to evaluate these prerequisites for AI-CRM applications.

Liang and Wei (2004) named their modified framework FVM and enforced its academic credibility by basing it on previous research on task-technology fit (Goodhue & Thompson, 1995) and general notion of organizational viability of IT. When developing this model further they created a research instrument and a set of questions that can be used to evaluate the task-technology fit and the company’s viability for specific applications. They divided the fit to subconstructs of task and technology and viability to those of economic viability, IT infrastructure and organizational support for the project; these are visualized in Figure 3. In addition, Liang & Wei (2004) altered the matrix and this newer framework was utilized in the empirical research by Liang et al. (2007) and is visualized in Figure 4.

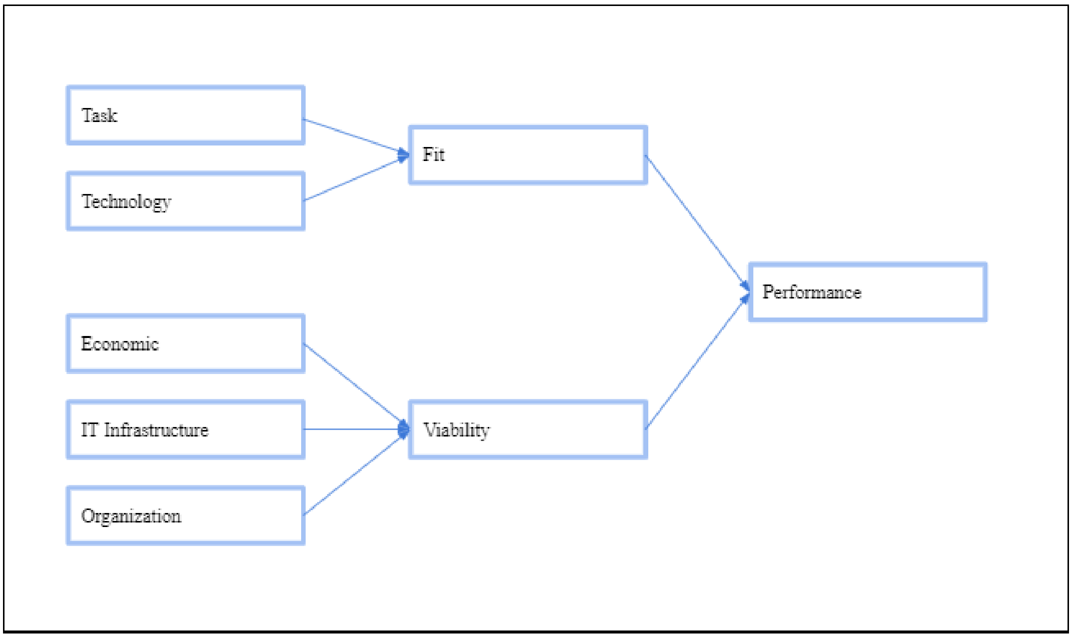

Figure 3. Research framework of Liang et al. (2007)

Liang et al. (2007) state that testing the model’s generalizability is a required topic for future research. Due to this, testing FVM in the context of AI in CRM systems can be expected to provide theoretical value for generalizing this model further. FVM has been already tested in multiple contexts, like for electronic government (Larosiliere & Carter,

2016) and cloud computing (Tripathi & Nasina, 2017). Studies on utilizing this model in the contexts of AI-CRM applications or topics close to it could not been found by the researcher, and this thesis is aiming to fill this interesting research gap.

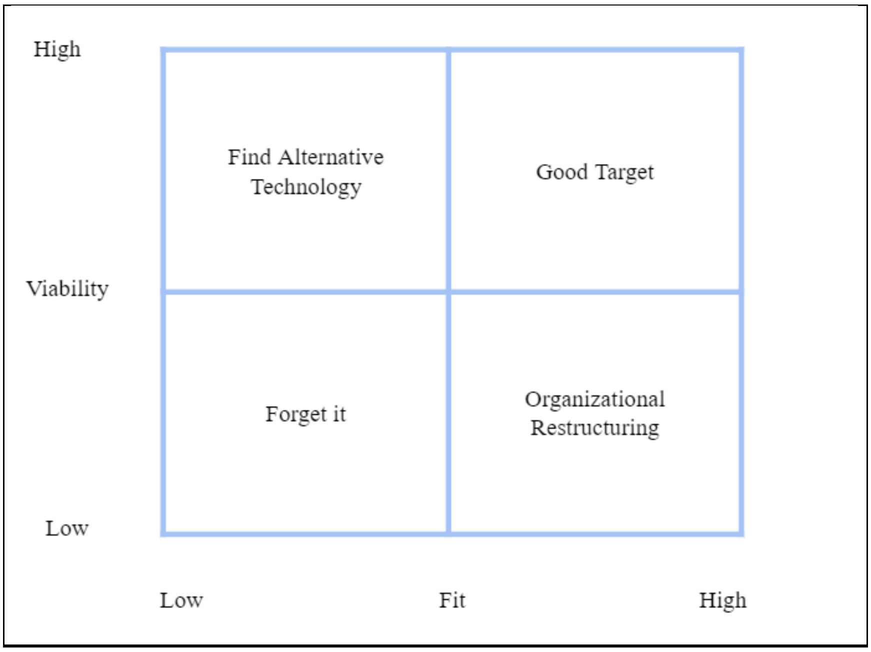

Figure 4. Fit-Viability Framework of Liang & Wei (2004)

In addition to potential academic insights, the results of evaluating different AI applications in the CRM context for various case companies is expected to provide valuable managerial insights for many companies. Liang et al. (2007) claim that the results of their empirical research shows that FVM can help companies to evaluate the potential advantages of the technologies they studied. Based on the previous discussion on utilizing AI in the context of CRM systems, the model is expected to work well also in the context of this thesis. For example, the different tasks for AI, its technical capabilities and limitations have been discussed in chapters of both literature review and background research and there is a limited number of frameworks that combine them, but they could help organizations making decisions related to investing in and preparing for implementing AI-CRM applications.

Nevertheless, some alterations to the framework must be made so that the model can be utilized in this novel research context. This applies especially to the research instrument that is used to collect evidence from companies for evaluating different AI-CRM investments and the prerequisites to implementing them. These alterations will be based on the previous academic discussion and empirical evidence collected in background research.

3.2 Research structure

The empirical research is divided into two parts: background research and a multi-case study. Both parts have distinct purposes to support the research objective of this thesis. Background research is conducted to complement information acquired from previous academic literature, as the number of relevant studies is quite limited due to the novelty of AI-CRM implementation as a research topic. The background research consists also of two parts: interviews with AI-CRM experts to collect evidence about the applications and their implementation and an Internet research to recognize currently available AI-CRM applications. Additionally, the decision to focus on prerequisites of AI-CRM applications was made based on the analysis of emerging themes in background interviews. Some researchers who have previously combined methods of expert interviews and case study have found the approach to support conceptual evaluation and creation of both theoretically and practically based models (Walterbusch et al., 2013) and these are the objectives of the this thesis also.

The multi-case study on the other hand is conducted to test the fit-viability model in the context of AI-CRM applications and propose it as a tool for organizations to evaluate the prerequisites of their planned initiatives. Case study as a method provides a way to collect, organize and analyze data to gather comprehensive and in-depth information about each case of interest (Kuo et al., 1999). In this multi-case study, the studied phenomenon is the current operating environment of CRM software and the system usage in selected companies. The case context is evaluated from the perspective of implementation of AI-CRM applications.

In the next chapter, first the process and results of the background research are presented. In the chapter that follows the process of organizing the multi-case study is discussed.

4 Background research

This chapter explains the background research process and its results. The specific research topic of this thesis is novel and there is not a great number of case studies on the topic of AI-CRM implementation. Some IS researchers, have in fact, argued that often IS studies play catch-up with applications of novel technologies of actual businesses (Seymour et al., 2018). It can be expected that there are some AI applications in CRM systems already used by companies, but no previous research has been conducted on them. Due to this, also other information sources to form the background for this thesis are analyzed.

Firstly, 6 semi-structured interviews with experts from a CRM provider and a CRM consulting company will be conducted. The aim of this part is to understand what kinds of AI initiatives companies have already implemented in the context of CRM systems. As the expert interviews were organized in the early part of the research, their scope was quite open and the specific research question related to prerequisites for AI-CRM initiatives was selected after the topic of organizational readiness emerged in multiple interviews. The empirical research conducted as a part of this thesis requires to understand how the current states of the case companies affect the value they can gain from AI-CRM investments. The interviews with consulting experts with experience of implementing AI-CRM applications for actual businesses are expected to provide these insights.

Secondly, an Internet research is conducted to find information about both current and potential AI-CRM applications from secondary data sources. The aim in the empirical research is to evaluate different AI-CRM initiatives so understanding solutions on the market is evaluated be essential. Even though the background interviews are expected to provide insights to these solutions, their number is limited. There can be expected to be evidence about the potential initiatives that does not emerge in interviews or has not been studied by academia yet. To gain a better understanding of what initiatives are currently possible, open data published online has been recognized as the most likely place to locate cases of these initiatives.

In the end, data collected from interviews and Internet research will be utilized together with the presented academic literature to provide a comprehensive background for the empirical research discussed in the later chapters. Next, the process of organizing the background interviews and the collected evidence are presented.

4.1 Background interviews

Elliott & Jankel-Elliott (2003) suggest that one way to conduct interviews is to focus on samples that seem likely to provide rich data or who may have specialist knowledge. As this study has been conducted in co-operation with Fluido, there was an access to interview some established experts in the field of AI-CRM solutions. The number of background interviews was six consisting of two interviews with experts from Salesforce and four with experts from Fluido, who have taken part in consulting projects utilizing AI in CRM systems. All of the interviews were semi-structured and based on the interview framework (Appendix A) developed to collect evidence on the research topic. Additionally, all the interviews except one were organized in English.

As the access to this evidence was enabled by collaborating with a consulting company focusing on solutions of only one CRM system provider, there can be argued to be limitations to generalizability of this part of the research. The reasons behind why Salesforce was seen to be the best source of rich evidence with an access to only to one system provider are presented later. In addition, the focus on other AI-CRM software providers is broadened in the Internet research.

Grinsted (2005) argues that by aiming for strict neutrality by minimizing interaction with the interviewee may threaten the validity of the research. Due to this, the interviews were somewhat conversational, as the interviewer e.g. asked follow-up questions to gain better insight. On the other hand, limiting the interactions was emphasized in that the interviewer did not take strong stances to points of topic.

Because the COVID-19 pandemic was ongoing at the time of the interviews, all interviewees were working from home. Therefore, a remote video conference tool Google Meet was used to conduct them. All but one of the interviews utilized video in addition to voice and due to the situation, everyone had become familiar with organizing meetings and interviews remotely. For this reason there is expected to be no major losses of evidence due to not being able to organize interviews physically. Every interview lasted for one hour and they were recorded, transcribed and analyzed. As the interviewees are not anonymized, they were also given a chance to make alterations for mentions of their interviews before publishing this research.

In this section, first the companies represented by interviewees are presented and reasons to focus on these two companies are explained. Secondly, the insights of each individual interview are presented. Individual representation is included, because the different people had experience from very different types of projects related to AI-CRM implementation. Finally, the summary of the interviews is presented to provide a managerial view on utilizing AI in CRM systems.

4.1.1 Introduction of the represented companies

4.1.1.1 Salesforce

Salesforce is the world's biggest CRM provider, with 19,5% share of the whole market in 2018 (Gartner, 2019). Because of the status of Salesforce as the world's biggest CRM software company, the researcher views them as the best candidate to collect evidence from when focusing only on one provider. In recent years Salesforce, like its competitors Oracle and SAP, has begun to have a growing interest in AI and for example the company has acquired several AI startups like PredictionIO and MetaMind (Emerj, 2019). Salesforce has its own research unit Salesforce Research and some of their AI applications are based on the team's efforts (Salesforce, 2017c). They also publish academic research on AI (Salesforce, 2016) and it can be expected that due to this emphasis, Salesforce has vast knowledge about the research topic of this thesis. In addition, the biggest CRM companies are investing heavily in analytical capabilities that support AI, of which the Salesforce's acquisition of Tableau for 15,7 billion dollars stands as an example (Forbes, 2020).

Today, Salesforce offers a wide variety of AI services under its product category named Einstein (Chatterjee et al., 2019). These services can be divided roughly to two categories; ones infused into different CRM modules or "Clouds" like automated lead scoring into the marketing module or predictions on the success rate of offers into the sales module and individual AI applications like Einstein Discovery utilizing ML or Einstein Vision providing machine vision capabilities (Teljo, 2.6.2020, interview).

Additionally to being a software company, Salesforce has been recognized as a software ecosystem, which has been defined to mean a system consisting of interaction of various actors on top of a shared technology platform, in this context a CRM system (Manikas & Hansen, 2013). The company offers a marketplace Salesforce AppExchange where their partners can sell their own applications (Salesforce, 2017d). This kind of ecosystem built around an ES could offer companies interesting additional ways of utilizing AI in their CRM systems.

It can be clearly seen that Salesforce and other CRM software companies have already moved to offering AI solutions for their customers around the world. Due to this, it is highly interesting from the perspective of this study to find out how companies are already utilizing these opportunities. Salesforce's size and emphasis on AI makes it the most likely singular source of evidence on how the CRM systems are offering use cases for AI.

4.1.1.2 Fluido

Fluido is an international consulting company based in Finland and a partner of Salesforce ecosystem. They are the leading Salesforce consulting partner in Europe with over 350 employees serving over 300 clients in various industries. Fluido is part of Infosys, which is one of the top IT consulting companies in the world. (Fluido, n.d.). Fluido helps its customers with various projects related to the Salesforce platform, e.g. system and new module implementation, integrating Salesforce to other systems and developing novel applications on the platform. In addition, they have expertise from various projects of implementing artificial intelligence in CRM systems. (Favier, Janhuba, Nyjil & Soni; 2020, interviews.)

Due to the status of Fluido as the biggest Salesforce consultancy operating in Nordics and Salesforce as the world's biggest CRM system provider, they are the most likely companies to provide rich evidence. Additionally, Fluido has the connections that made both the Salesforce experts and case companies of the empirical research accessible to study in this thesis.

4.1.2 Insights from interviews

4.1.2.1 Raphael Favier

Favier has worked at Fluido in multiple roles and is now in the position of Service Engagement Management. He has over 20 years of professional expertise especially from B2B and B2C commerce, digital asset management and marketing. In his current role he is the point of contact for some of Fluido's customers and additionally he plans the roadmap for projects made for them and supervises these projects. He has worked with many types of companies, especially with some of the biggest B2C commerce companies in Finland.

Recently Favier led a project where Fluido infused AI tools to e-commerce websites of some of its clients.

In this project, the customers were using other services to manage their e-commerce website than Salesforce. If the company wants, there are AI tools infused directly to different CRM modules of Salesforce, like “Commerce Cloud” which can be used for managing the company’s commercial channels. As the customers were using other service providers to manage their e-commerce sites, the idea of the project was to integrate these websites to the Salesforce CRM so that its AI solutions could be utilized to enhance the experience of the companies’ customers using the site.

The goal of the project was to enable the companies to offer both personalized email and website product recommendations for customers predicted by the AI applications of Salesforce CRM to e.g. increase conversion and average purchase amount. Fluido used the marketing module called “Marketing Cloud” and its AI features called Einstein Web and Email Recommendations to create affinity profiles for identified customers, that predicted what kinds of products the customer was interested in based on the customer data it was provided with. Then these recommended products were visualized in different pages of the e-commerce site and through email promotions. One interesting feature of this project was that the historical data used to teach the application was collected in only 4-6 weeks before the solution went live.

> *“As you see, it’s not just that you switch on Einstein and it will start working. You need to all the time improve it, look how it works and how you should be configuring it.”*

Favier says that the potential of AI recommendations is not limited just to ads, but they can also improve search and product sorting. The use of these solutions demands some decision-making from the customer so that the system can be configured to support the selected goals. He expects that as the tools are constantly developed further, implementing them will get easier for companies in the future. Favier sees much potential for AI also in many other cases in CRM system context, e.g. helping customer service agents by understanding the contexts of customer requests and automatically suggesting a right knowledge base article for the task or suggesting the service agent to recommend products that the system believes the customer would be likely to buy to increase upselling.

4.1.2.2 Radek Janhuba

Janhuba has a PhD in economics and econometrics and a professional background in economics and mathematics. Due to this he understands analytics, like regression methods, behind some ML applications. Currently he is working as a Data Scientist at Fluido doing different tasks related to projects around e.g. marketing analytics, data visualization and implementation of AI solutions of Salesforce.

Janhuba has worked with almost 30 companies at Fluido, but often only on individual tasks where his specialist expertise is demanded to conduct the project. He has taken part also in some of the discussed AI projects managed by his colleagues. Usually the main stakeholders from the customer's side are from different business functions, but sometimes Janhuba works with e.g. technical staff of customers.

The AI project business is still quite new at Fluido and there are not that many public reference cases on AI-CRM system projects yet. Janhuba sees that the interest is growing, and he expects that some of the next new projects could be about automated actions to e.g. prevent customers churning or automatically segmenting customers.

In addition, Janhuba has tested machine vision and NLP solutions offered by Salesforce: Einstein Vision and Einstein Language, respectively. Even though there have not been customer projects on those yet, Janhuba sees there could be potential in them. These products offer an AI API which companies can use e.g. to teach their systems to classify images based on objects in them or text samples based on the predicted sentiment of customers. Janhuba says that these solutions return both the value of the prediction, e.g. "Negative" but also the likelihood for that value to be correct, e.g. "85% likely to be negative". The NLP solution is currently working only in standard English, which in Janhuba's eyes currently limits the number of potential customer companies. He sees that the open source and crowdsourcing movements could be valuable for teaching the ML models behind these applications.

Finally, Janhuba emphasizes that there are also risks if AI solution is implemented incorrectly. For example, if the company utilizes AI chatbot as their first point of contact, but it is not able to answer customer's inquiries, then it may actually just make a hindrance for customers having to spend more time to get in contact with a human representative. He sees that companies often may have unrealistic expectations for at least the current capabilities of AI e.g. in replacing human workers.

> *"Usually when you talk to them, they will say "Yeah, we would like some AI and machine learning to help us work" but they don't really have a clear picture of what it should do and how it could do and how it could help them. They would like to use it but it's somewhere on top of the mountain, and we are still under the mountain."*

4.1.2.3 Nyjil Joshi

Nyjil works at Fluido as a Solution Architect working with different types of projects with companies from various industries, like finance and automotive. He has been working in the field of IT for 19 years and used technologies of Salesforce for almost 10 years. In his current role, Nyjil guides companies through major CRM projects, e.g. ones related to business intelligence and analytics. In addition, recently Nyjil has been working as the architect of implementing the ML capabilities of the Salesforce platform.

In this project, Nyjil utilized a solution called Einstein Discovery to analyze the data of one of his customers to determine what are the factors affecting customer churn. Einstein Discovery studies the data it is provided with and selects the best ML algorithms to use to find the wanted insights. It is not integrated to any individual CRM module but is rather a highly customizable tool. Nyjil on the other hand customized the solution so it best fits the business problem of the client, e.g. by opting out some variables and manipulating the thresholds of the model. In the end, the created ML solution now utilizes the customer's data to find out what variables affect the customer churn. This model also makes it possible to make predictions for individual customers based on their values of these variables the company has collected.

Nyjil sees that this type of project of utilizing ML in the context of a customized project in a CRM system is still novel but may provide significant value. He sees the analysis of customer churn only as the baseline and believes that by introducing more and more of these models the companies can gain the capability to use AI to holistically analyze customer lifetime value (CLV), attribution and customer satisfaction data. Nyjil states that to get actual value from these insights, they must be acted on and used in decision-making e.g. to affect the variables that minimize the churn. These insights are presented to the analyst in the form of stories that shows you what happened, why it happened (correlation between influencing factors) and predictions on outcomes based on changes to these factors or variables, like will it increase or reduce customer churn.

> *"Data history is very important and a well-defined structure. Then business models where its most applicable is where customer data is in form of subscriptions, like in this case. These are some things I can think of. Then again, the outcome to expect should be some business insights or recommendations the Einstein can give. So they have to be particular on what they are looking for. Then based on that outcome we define the model."*

In addition to showcasing this use case, Nyjil's project also provided interesting insight on the fact that customer companies are proactively interested in AI. In this project, the customer had not used Salesforce products before, but moved to the platform due to the AI capabilities of Einstein products. The customer data was originally collected on a legacy system, and the data was moved to Salesforce so that it could be utilized by Einstein AI applications.

Nyjil sees many benefits in using AI solutions provided by an ES company like Salesforce. For example, the customer is not required to have the same analytical capabilities as the provider company, and when designing solutions by themselves, they would need to develop the model constantly further, when as of now it is taken care of by the provider.

4.1.2.4 Khushboo Soni

Soni has been working with CRM systems for over six years and is currently in the position of a Solution Consultant at Fluido. In her role, Soni designs new solutions for Fluido's customers and she has expertise in projects especially around the fields of sales, customer service and field service. She has worked with customers from e.g. the fields of manufacturing, healthcare and energy. Currently she has begun to focus on the analytics and AI solutions and has taken part in projects of implementing them.

Recently, Soni took part in a project utilizing two AI applications offered by Salesforce: Einstein Prediction Builder and Einstein Next Best Action. The first one is an automated machine learning tool used to create custom predictions for different data points in the CRM. The second one is a tool integrated to some modules of Salesforce CRM and it offers advice for the users on what kind of action could be valuable to commit in a certain situation based on the set goals and the historical data in the system.

These predictions and suggestions can be related to core CRM activities, like predicting if the customer will buy or suggesting a customer service agent to offer a promotion. On the other hand, they can be contextual, as the system allows to predict things built only for the customer's specific business. Soni emphasizes that it is important to approach any AI initiative systematically, even when using already built AI applications. She sees that a pilot project is a great tool to test the solution before advancing with the initiative to see what is for example its financial potential.

> *"I would say that with every AI project, the pilot project is necessary to analyze the real potential outcome of using AI".*

In this project, Soni implemented the Prediction Builder for their customer's service team. As filling different fields in the system usually takes a lot of time from the service team, by automatically predicting some of the fields, manual inputting can be reduced. In addition, this tool can be used to classify service cases, which means that the CRM analyzes the different data points in the service request and can e.g. give it a class of "repair request". Both the NLP and AI chatbot tools offered by Salesforce work together with prediction tools and they utilize the same data.

Einstein Next Best Action, on the other hand, was used to provide suggestions for customer service agents for upselling and ensuring more sales opportunities. In action, as the tool is infused into the service module of the CRM, when the agent opens a customer record, there could be a pop-up window suggesting a product to recommend for the customer. These suggestions can take into note the customer data like the previous purchases and interactions the company has had with the customer. In addition, Soni sees that by utilizing different automation tools of the CRM system together with AI solutions, the companies could utilize these suggestions automatically, like through a chatbot or other digital channels.

4.1.2.5 Juha Teljo

Teljo has worked in the field of business intelligence for 30 years and currently works as a Senior Director, managing the Solution Engineering team in EMEA, APAC and Japan at Salesforce. The team manages implementation projects of several technologies of Salesforce in these markets, including the Einstein AI portfolio. He has a good understanding on how analytics has changed CRM systems over time and how the AI will transform them further. This interview was the only one conducted in Finnish and translated.

Teljo sees that both currently and in the foreseeable future, narrow AI is the scope that should be used when discussing AI in CRM system context, as artificial general intelligence is very far away. He says that the approach should be pragmatic; instead of aiming for revolution, the companies should advance rationally and evolutionally in taking on AI initiatives. The value that AI provides is in that the different technologies it encases can improve the efficiency and operations of different business processes. Teljo sees that people, when acting as individual consumers, utilize AI products daily, but somehow that is not transitioned to business when these people are in the roles of executives.

When thinking about CRM system context, Teljo sees that there are some use cases for AI that are common for the majority of the software users, and therefore can be automated. For this Salesforce has developed different products integrated easily to different CRM system modules it offers. On the other hand, there are also many non-standard cases that need customization and potentially utilize multiple data sources, and for that Salesforce has developed also more robust AI solutions, like the Einstein Discovery.

> *"Of course, it is clear that as more and more of these (AI projects) are delivered and when we can tell more about them and companies learn from each other, it fuels the growth of it (AI adoption)."*

Teljo sees that often stakeholders interested in utilizing AI are halted by their own insecurity about the data quality. He thinks that the data must first be utilized and tested in the context of AI to see its limitations and to know how it can be enriched. In fact, he emphasizes that for many use cases the core CRM data should be enriched with data from other sources too. This is also why Salesforce is focusing on enabling the integration between the CRM and external data sources. As today data can be generated rapidly, a company can collect a lot of data for training the model even in just one month, depending on the context.

Even though Teljo says that companies are increasingly utilizing AI in their CRM systems in different ways, there are also challenges to overcome before AI reaches its full potential. First thing is that it is often difficult to attribute gained profits or even cost savings to individual AI initiatives as there are usually multiple simultaneous development projects aiming for the same goals. Secondly, he sees that the companies should have a defined data culture, as adopting AI can demand broad engagement.

4.1.2.6 Reinier van Leuken

Van Leuken has a PhD in artificial intelligence and a professional background in optimization. Currently he is working as a Senior Manager in the Solution Engineering team of Salesforce in markets of EMEA North, France and Japan. He manages different customer projects utilizing the more customizable AI products of Salesforce. In these projects, the Solution Engineering team advices customers on AI solutions and builds prototypes or proofs of concepts.

One example of a project could be a case where they utilize the structured data in the CRM system and other data sources to determine the best discount level for a salesperson to offer to a customer in a specific industry or location. The projects are often about capacity management and aim to help companies to focus their employees' efforts to most profitable tasks. Salesforce aims to be a partner in the whole digital transformation of its clients and van Leuken says they often try to get the top management engaged with the initiatives.

Even though Salesforce has made some solutions integrated to different CRM system modules to be very easily adoptable to customers without the need for significant customization, van Leuken does not believe that utilizing all the AI-CRM solutions will get that easy. For example, many companies could have an interest in understanding variables affecting customer churn, but even the concept of churn varies greatly depending on the specific business model. Due to this, some customization is always needed to get good results.

Currently, Salesforce is working hard to make the technology even more suited to work with smaller data sets. As van Leuken sees that AI could provide value for many types of businesses, he believes that the AI solutions should not be applicable only for customers with extremely large amounts of data. This idea affects the decisions of Salesforce of what kinds of algorithms it wants to use in its AI products. As the accuracy of how well the data depicts reality may drift over time, van Leuken sees that the novelty of data may also provide value.

> *"There is no point in trying something on the side. What does that proof? There is only point in trying something with a group of users; if it drives business value and the people like it, go for it. If not, scrap it."*

Finally, van Leuken emphasizes that companies should stop doing AI in laboratory experiments and begin doing actual pilots. This requires focus and a dedicated team. He sees that the barrier for adoption is rarely the financial investment, but more often the organization' limited capability to absorb new initiatives. Usually the drive for change comes from business units and there can be other development ideas the AI competes with.

4.1.3 Summary of interviews

The interviews provided rich and valuable information about how AI is actually utilized by businesses in the context of CRM systems. Even though the focus was only on the Salesforce CRM platform, as some of the interviewees had practical experience in managing AI projects, others had insights about how the CRM providers operate and some had academic background in AI, the interviews provided multiple points of view.

There were multiple similar ideas that emerged both in the interview evidence and the academic research presented previously. For example, Chatterjee et al. (2019) state that challenges for AI-CRM integration include context and data challenges, which also emerged in multiple interviews. Additionally, Chen (2012) suggests that AI can enhance many customer service operations by providing e.g. automated monitoring and correction, automated assisted support and automated self-support. Similar tools that are already in use were presented in the interviews.

The collected data is valuable evidence and it will be utilized in the next chapter focusing on the empirical research. The main discussion points from the interviews are summarized in Table 3. To limit the scope of the thesis, after analyzing the background interviews the prerequisites for AI-CRM adoption was chosen as the scope of the empirical research. The prerequisites were discussed with all interviewees and as the AI is a novel concept from both the perspective of academia and actual businesses, finding a method that companies can use to evaluate and access their readiness for concrete AI-CRM initiatives is expected to provide both managerial and academic value.

Even though the interviews provided good understanding of implementing AI in CRM systems, the evidence found on the different use cases for AI is limited. The selected theoretical framework and method for the empirical research require to determine concrete AI investments. Due to this, different AI-CRM applications offered on the market will be discussed further in the next section of the background study focusing on the Internet research.

Table 3: Summary of the background interviews

Interviewee	Favier	Janhuba	Nyjil	Soni	Teljo	van Leuken
AI-CRM initiatives discussed	Recommender system to promote products predicted to be most interesting for customers	Machine vision and NLP solutions used to classify pictures and text	Machine-learning solution for finding insights from customer data not previously accessible	AI applications making predictions for different CRM objects and recommending actions for service	AI applications integrated to CRM systems and customized solutions	Different customized AI solutions to solve business-specific problems
Potential use cases for AI in CRM systems	Tailoring customer experience, suggesting right articles and products for customer success agents	AI chatbots, automated case classification, optimizing customer interaction channels and times	Predicting risks of loan-giving of banks and improving patient management in healthcare	AI making customer interactions automatically, using AI applications in field service	Analyzing brand visibility with machine vision application and automating pricing of complex services and products	Using AI to prioritize work, segment customers and utilizing machine vision to e.g. evaluate vehicle's condition
Views on the potential of AI	Perspective of customer experience should be considered in addition to the company's internal viewpoint	Generally, people seem to put too many expectations on AI and its capabilities to do tasks requiring human intelligence	AI has three roles: AI enhancing processes, AI offering novel insights and AI gaining a personality	When looking only at outcomes, it is not easy to see the difference between rule-based automation and AI, even though they differ greatly	Everyone has an opinion on AI and often it comes from science fiction or dystopias, when in reality, AI is quite pragmatic concept	AI offers decision support; it is good at quickly exploring large data sets, but some expectations are unrealistic
Prerequisites for using AI applications in CRM systems	Not too many prerequisites, as when the company is using solutions of major software provider, the adoption is not that complicated	Clearly defined business question and basic understanding of analytics	Historical data in structured form, applicable business model and clear goal for the initiative	The concept of AI must be understood, and the capability gap should be filled e.g. by recruiting new personnel	Data culture supporting adoption of AI initiatives and forerunners driving the projects onward	Will to go quick and start testing and the capabilities to drive change and become data-driven
Challenges to implement AI in CRM systems	It can be difficult to engage top management in AI initiatives and the deployed solution demands to be regularly adjusted	There needs to be resources to allocate into enhancing the quality of the training data if needed	Stakeholders must be educated to understand the solutions' workings and limitations	Companies should be able to evaluate and prioritize AI initiatives based on their concrete value	Depends greatly on how the company embraces the digital transformation in general	There is often a want to have a perfect model, but it is never possible

4.2 Internet research

In this section the process and results of conducting an Internet research as a part of this thesis are presented. The reason to study the Internet in addition to expert interviews and literature review is that this thesis aims to evaluate prerequisites of concrete AI-CRM initiatives. Previously in this thesis some examples of these applications have already been discussed, but due to the novelty of the research topic and limited number of interviews, this evidence may not be comprehensive enough. As this thesis includes an empirical multi-case study focusing on various types of companies, it can be expected that not all AI applications provide the same value for all businesses, so selecting the most potential ones is important. In addition, by looking at actual initiatives provides insights on what kinds of applications are currently available and seen worth investing in.

With this Internet research the objective is to find a variety of examples of AI-CRM use cases by using the open data on the web as the source for evidence. The aim is to use this more comprehensive list together with evidence on initiatives presented in previous chapters to select a limited number of AI-CRM applications to focus on in the empirical research. The results of the Internet research are visualized in table format. The initiatives are categorized in the same categories of AI technologies presented in the literature review. Some of them utilize multiple of these technologies, so some subjectivity is used.

As the different AI technologies in the scope of this thesis have been discussed earlier and the context is limited to CRM systems, research topic is clearly defined. Due to this, the researcher uses a search engine to look for evidence on the different AI-CRM applications from the Internet. On the other hand, Fornaciari and Roca (1999) argue that even with a well-defined topic, conducting Internet research can be difficult due to differences in use of terminology of the research topic in different web pages. This can also be expected to be the case as AI consists of multiple technologies and there is no strict definition for the term "artificial intelligence". Due to this, the research method is not limited to certain keywords or a set of sites but will adapt based on the results. The reliability of all sources is evaluated before being included and references to the evidence is provided.

The results of the Internet research are presented in Table 4. Based on the research, many CRM providers seem to be offering novel AI applications for their customers. In addition, there seems to be a relatively great variety of different types of applications. These results will be used to select the AI initiatives in the focus of the multi-case study. This part of the research is discussed in the following chapter.

Table 4: Results of the Internet research

Enabling AI technology	**AI-CRM initiatives**
Machine learning	• Trasmediterránea uses machine learning tools of Salesforce to predict loyal customers (Salesforce, n.d.-a). • AI assistant Zia of Zoho CRM analyzes audit logs and makes automated suggestions for workflow automations based on the data (Zoho, n.d.). • CaixaBank has improved its risk analysis of loan customers by utilizing ML products of Oracle (Oracle, 2020). • KONE aims to streamline workflow of equipment service technicians by combining IBM Watson IoT and AI tools of Salesforce (Salesforce, n.d.-b). • UNICEF Netherlands uses AI tool on Microsoft Dynamics 365 to recognize the most likely donors to target more personalized communication to them (Microsoft, 2019) • Black Diamond has achieved increased conversion rates and revenue per visitor rates by using the AI product recommendation features of Salesforce (Salesforce, n.d.-c).
Natural language processing and voice recognition	• One Call uses an AI voice assistant of Salesforce to track customer status and notes (Salesforce, n.d.-a). • Grant Thornton uses AI tools in their Microsoft Dynamics 365 CRM to analyze the contents and sentiment of communications they have with their clients (Microsoft, 2020) • Groupe Mutuel uses a chatbot built with SAP Conversational AI to automate its customer service (SAP, 2019). • S-Bank has adopted the Salesforce-integrable AI tool of Ultimate.ai to recommend answers for customer service agents (Ultimate.ai, n.d.).
Machine vision	• Auction Nation uses machine vision solution of Salesforce to assess status of damaged vehicles and evaluate their current price (Salesforce, n.d.-a). • Coca-Cola is implementing a machine vision -based object detection application in their Salesforce CRM to manage their soft drink cooler inventories (Salesforce, 2017e). • Macty AI provides a machine vision tool integrable to Oracle's CRM that makes it possible for customers to search similar products to ones they provide a picture of (Oracle, 2019).

5 Multi-case study

In this chapter, the multi-case study is presented. Firstly, the selected method is discussed and rationalized. Secondly, the sample selection of the study is discussed. Thirdly, the selection of the focused AI-CRM applications is argued and after this all applications are presented individually. Finally, the research instrument of Liang et al. (2007) is presented and the alterations done to it for the needs of this research are discussed.

5.1 Structure of the study

As said previously, the fit-viability model uses the collected evidence to evaluate constructs that can be used to analyze and compare the different initiatives in the context of a specific organization. As with the research of Liang et al. (2007), the technologies in the scope of this study are novel for businesses at the time of research. In addition, FVM has not been tested in the context of AI-CRM applications yet, so the selected approach is both explanatory and descriptive. This research will aim to be as similar as possible with the original research conducted by Liang et al. (2007) to enhance the generalizability of the fit-viability model.

The multi-case study was selected as a research method similarly as in the study of Liang et al. (2007) to include multiple different types of companies. Benbasat et al. (1987) argue that multi-case method allows cross-case analysis, extension of research and more general research results. As Yin (2013) argues that the conditions of a case study research are especially relevant for evaluating broad initiatives like system reforms, the method seems viable to this case, especially as the context of AI-CRM applications is novel. Additionally, similarly to the study of Liang et al. (2007), data is collected from interviews, websites and other openly available sources.

FVM does not strictly dictate the sources of evidence to be used and depending on the specific research topic they could vary from employee surveys to ethnographic observation of technology users. Implementing these in a multi-case study would have demanded much more effort and resources in taking the notion of the thesis format. Due to the novelty of the research topic the goal of having multiple case companies was emphasized in selecting the approach. In this study the interviewing was used as the main source of evidence. Elliott & Jankel-Elliott (2003) state that one way to conduct interviews is to focus on samples with potential to provide rich data and interviewees who may have specialist knowledge. The informants from the companies were selected by their status and are presumed to provide rich evidence about the organization's they work in. Naturally, study focusing on a limited number of informants from sizeable companies has its limitations in providing evidence to evaluate the current state of the case, but with successful selection and scoping they are expected to be managed as well as possible.

The research is structured as follows. First the potential AI applications and case companies are identified. In the original research of Liang et al. (2007) all selected companies had already identified the applications that were analyzed with FVM. As AI-CRM applications are still novel, it is most likely that not all case companies are planning to already implement them in their operations yet. Nevertheless, as evaluating the prerequisites, fit and viability of these initiatives is valuable for the companies in the beginning of their AI-CRM implementation processes, the FVM is expected to offer valuable insights for all selected companies.

On the other hand, this means that some of the studied AI-CRM initiatives must be identified before the research. The applications should be interesting for a wide variety of companies and business functions to increase the practical usefulness of this study. The selection will be done based on the previous theoretical discussion and evidence collected in the background research. The process of selecting both the sample companies and the AI-CRM applications are explained in the next section.

Simultaneously to selecting the case companies and studied initiatives, the research instrument used for the interview data collection will be developed and the research process planned. The changes to the instrument are discussed in more detail later in this chapter. After preparation, the interviews will be conducted and simultaneously relevant information about the case companies was collected from open sources. Finally, the collected data will be interpreted and analyzed with the FVM framework. This process and the results are presented later in the next chapter.

5.1.1 Identifying sample companies

Before the research was conducted, the profile of the wanted case companies was defined. The main criteria were accessibility, size of the operations and use of CRM systems. Accessibility was enhanced as this thesis was written in co-operation with a company partner, as it enabled the researcher an access to interview decision-makers from established companies. This was especially valuable as during the research process the COVID-19 pandemic put companies widely in distress and limited their resources to put in secondary activities. Secondly, based on the background research understanding AI-CRM applications seems to demand or at least benefit from some familiarity with customer data analytics, and financial and organizational resources. Due to this, the scope was on more established companies that were seen to be more likely to have this previous experience and resources in comparison to smaller companies. Final criterium was that the companies use a CRM platform that offers, includes or can be integrated with AI applications.

Based on these criteria, 4 companies were selected for the study. All of them filled the requirements and represented different types of industries. Some of them had already begun planning to implement or had implemented AI-CRM initiatives in their operations. To gain access to established companies, anonymity needed to be offered to them. The companies were anonymized also in the research of Liang et al. (2007). Since all the case companies operate in Finland where the markets are relatively small, to maintain confidentiality the profiles of the companies and informants needed to be disclosed more effectively than Liang et al. (2007) have. Due to this, the industries the companies operate in, their precise annual revenue or any other information that could be used individually or together to identify the company and the informants is not provided. The profiles of the companies are presented in Table 5.

Table 5: Case company profiles

Company	**A**	**B**	**C**	**D**
Core output	B2C & B2B services	B2C services	B2C products	Retail services
Annual revenue 2019	250-500 million €	1000-5000 million €	1000-5000 million €	250-500 million €
Business functions focused on	Sales & Marketing	Customer service	Customer service	B2B partner acquisition & e-commerce
Profiles of informants	Sales development and marketing directors	Customer service systems managers	Customer service manager and IT director	CRM specialist and manager
AI-CRM applications studied	Lead prioritization & Suggestions for action in customer interactions	AI-chatbot & Suggestions for action in customer interactions	AI-chatbot & Suggestions for action in customer interactions	Product recommendation system & Suggestions for action in customer interactions

Two informants were interviewed from each company. All interviews were conducted in Finnish and the interview framework (Appendix C) was utilized in structuring them. The profiles of the interviewees are visualized in Table 5. As CRM system is an enterprise-level system, to get a holistic image for all user groups and business functions would have required resources not available for the researcher. Due to this, the decision to focus on 1-2 business functions per company was made. This also helps to limit the AI-CRM applications studied and discussed in the interviews. Focusing only on applications operable for multiple business functions would have been too limiting even though this was achieved with some companies.

With a lesser amount of case organizations, more data could potentially be collected from the companies. Nevertheless, due to the purpose of this study to test the FVM in similar structure to the original research and the COVID-19 pandemic, focusing on four different companies was selected as the approach. Yin (2013) argues that the only way to increase a sample size of a case study is to sacrifice the depth and contextuality of insights which is inherent to the case study method. The sample sizes of companies and informants were selected by the researcher to optimize the quality of the results achievable with the resources at hand, but naturally there are also tradeoffs with the selected approach. Next, the process of selecting the AI-CRM applications that are in the focus of this study is presented.

5.1.2 Selecting AI-CRM applications

As this study aims to help companies evaluate prerequisites of different AI-CRM initiatives to help them focus their resources and choose from a variety of applications, the approach of focusing on several AI-CRM applications was taken. In the original research of Liang et al. (2007), all the case companies had already begun implementing the solutions studied. In this case, as AI-CRM solutions are a more limited category of technology than mobile solutions of Liang et al. (2007), the approach of finding and focusing only on companies already implementing them was not deemed possible. In addition, this thesis suggests that FVM has potential value for companies even when companies are only looking into potential solutions. As the general operability of the framework has already been tested, using FVM in this context seems viable.

The Internet research was conducted to find potential AI-CRM initiatives for analysis. Based on background interviews and literature review focused AI-CRM applications were selected. Chatterjee et al. (2019) have identified 5 ways for AI to complement CRM systems; Automate routine tasks, Lead customization, appropriate segmentation and prioritization, Customer service and retention, Guide the team and Virtual Assistance. Of these types of use cases the four first ones emerged multiple times in expert interviews.

Four different applications were selected from the applications that already exist on the market. Analyzing even more applications could have improved the desired generalizability of FVM in the context of AI-CRM systems, but on the other hand it would have reduced the depth of evidence collected in the interviews about the discussed solutions. Additionally, discussing partly same solutions with different companies made the implementation of FVM in cross-case context easier. The selected solutions include applications utilizing mostly machine learning and natural language processing technologies. Applications based on machine vision were ruled out due to their specificity to a specific business problem. Nevertheless, when utilizing the FVM from the perspective of only one organization, these initiatives can be expected to be applicable as well. Next, the selected AI-CRM solutions are introduced.

5.1.2.1 Application for prioritizing leads

The applications using machine learning for analyzing the company's customer base and prioritizing leads have emerged in multiple parts of this thesis. The idea of this type of application is to use the customer data inputted to the CRM system to help e.g. the sales and marketing functions of the company to focus their resources on most potential customers. In the Internet research we identified that Trasmediterránea uses AI-CRM solution to determine loyal customers and apply different actions for differing customer segments (Salesforce, n.d.-a). With the categorization of Fardoie & Monfared (2008) presented earlier, this application focuses on the analytical and operational features of the CRM system.

In action, this type of application can e.g. give leads a score or a category automatically based on the different properties of the sales leads in the system and the using organization can prioritize their resources to companies with highest potential. The reason why this solution is interesting for this study, is that it is quite easy to understand for companies with different maturity on AI. Additionally, as customer data is the core aspect of any CRM system, this solution has use cases for a variety of CRM using companies that do not have unlimited resources and need to prioritize. The business functions expected to get value from this solution are the sales and marketing functions that proactively contact customers and sales leads. The solution most likely is not as potential from the perspective of customer service function or CRM module of customer service that focus mostly on handling customer inquiries and service requests in a more reactive manner.

5.1.2.2 Suggestions for action in customer interactions

Application for providing recommendations for the CRM users in customer interactions has also been presented earlier in parts discussing expert interviews and Internet research. The idea of this application type is that it also uses the data inputted into the CRM system and provides suggestions for the system user. The suggestions can be based on data about the customer's profile or their previous interactions with the company. For example, it can be integrated to e.g. sales or service modules of the CRM system and it makes this solution especially adaptive. In the viewpoint of CRM functions of Fardoie & Monfared (2008) this application can be seen to affect especially the collaborative features of the CRM system.

For sales personnel, the system can e.g. suggest what type of service or approach should be taken with the customer. For customer service users the system can offer suggestions for products to offer to increase upselling or offer the representative a knowledge base article that could be of help in addressing the customer's specific problem. Examples of this kind of solutions emerged also in the Internet research (Ultimate.ai, n.d.) and interviews (Soni, 3.6.2020, interview). As the training data the solution could use e.g. all the previous customer interactions with all the interaction history with the specific customer.

5.1.2.3 Product recommendation system

Making product recommendations in marketing and personizing the e-commerce site interface by utilizing machine learning algorithms emerged in the background research ((Favier 29.5.2020, interview; Salesforce, n.d.-c). In this scenario, an AI application is used to evaluate the information CRM system collects from the customer and either customizes the products and offers shown to the customer on the e-commerce site or makes these suggestions e.g. through email and web ads. In the categorization of Fardoie & Monfared (2008) product recommendation system can be seen to enhance the collaborative and operational functions of the CRM system.

The value the application offers can be seen to derive from the increased personalization. Without the solution in place the suggestions must be made manually, e.g. by defining rules on which the propositions are made. AI on the other hand can recognize the patterns affecting the behavior of the customer and make the alterations without humane decision-making, at least to certain extent. Nevertheless, as was noted in the discussion on interviews, the strategies for applying these recommendations does demands some decisions from human operators.

5.1.2.4 Customer service bot

Implementing AI in a customer-interfacing chatbot is an interesting application for multiple AI technologies. It can be categorized as a technology affecting especially the collaborative functions (Fardoie & Monfared, 2008) of the CRM system. For example, the bot can utilize natural language processing to understand the customer's openly inputted responses in comparison e.g. to selection of options to choose from. Additionally, the application can use machine learning to evaluate data collected from previous interactions and stored to the CRM system to provide suggestions. This kind of application emerged in the Internet research (SAP, 2019).

The clearest use cases with AI-chatbot are in the customer service function of a company. Especially if the service cases are repetitive and do not require human intelligence and interaction, implementing AI chatbot could significantly improve the efficiency of customer service and release human resources to tasks requiring it. Chatbot technology can be implemented even without AI technologies, by making rule-based automated conversations. Managing a complex set of rules in an evolving environment can be difficult for humans and especially if the rules are to be based on data, AI could be expected to be more efficient in personalizing the customer interactions. Nevertheless, the chatbots like any other interactive AI solutions are still far from being able to adapt to different interactions as well as humans, so the technology has its limitations.

5.1.3 Designing the research instrument

To collect interview data that is structured and can be analyzed with FVM, the research instrument needs to be developed to guide the interviews and interpretation. Liang et al.

(2007) provide the research instrument they used in their research and it will be used as the base of the research instrument of this study. Nevertheless, as this thesis focuses on AI-CRM applications, which have not been tested in the context of FVM, the instrument requires some adjustments. In addition, as we are expecting that not all of the companies have yet planned different AI-CRM initiatives, this will be taken into account when designing the instrument.

The instrument of Liang et al. (2007) is built on a research framework presented in Figure 3. They have prepared the framework based on their literature review and research and justification of those aspects are not repeated in this thesis. On the other hand, the potential weaknesses of the FVM are discussed in the final chapter. In this section, the alterations made to the model are discussed and argued. Some of the alterations are based on previous literature, but the researcher also used the insights acquired during the research process to make some decisions regarding the instrument. Nevertheless, the aim is to keep the instrument as similar as possible to the original instrument of Liang et al. (2007) to enhance the viability of the research results to support the generalizability of FVM.

In the framework, constructs of fit and viability are assembled from 5 subconstruct; fit of task and technology and viability of economic viability, IT infrastructure and organizational support. These subconstructs are modified from items evaluated with a seven-point Likert-scale. The items are questions that are answered by the researcher to evaluate the scores for the framework based on the collected evidence. Then the averages of the different given values for items under each subconstruct are counted and they become the scores of those subconstructs. The averages of these 2 and 3 values are once again counted respectively, and these become the scores of the constructs of fit and viability. With these, the performance of initiatives can be analyzed and potential prerequisites for implementation of specific AI-CRM applications can be evaluated.

Even though FVM uses a numerical scale, due to the small sample size of a multi-case study, this thesis does not aim for generalization of the insights the model provides. Rather, the idea of using the seven-point scale is to help organizations evaluate different initiatives with concordant scaling. Yin (2013) argues that using analytical techniques based on many data points but a small number of variables, are likely irrelevant for case study. This thesis on the other hand uses a numerical framework with many variables but limited data points. The objective of this study is not to say which prerequisites are recurring in various companies, but to develop and test FVM in the context of AI-CRM applications so that different companies can utilize it to analyze themselves contextually. The research is evaluated successfully by the researcher if the model can be successfully used to analyze AI-CRM applications and the results provide meaningful insight for the model's users.

The research instrument modified from the instrument of Liang et al. (2017) and used to guide collection and interpretation of the data is presented as the Appendix B. Next, the alterations made to the instrument are discussed one by one focusing on different sub-constructs of FVM research framework. Naturally, as the FVM is used to evaluate AI-CRM applications and the original research of Liang et al. (2007) studied mobile technology solutions, all mentions of the applications are altered to match this study and are not mentioned separately. In addition, some grammatical errors have been corrected.

5.1.3.1 Task requirements

In their research Liang et al. (2007) defined the task characteristics of mobile applications to be timeliness and mobility. To analyze the task requirements of AI-CRM applications we need to define these characteristics for these solutions. Davenport and Ronanki (2018) identified three types of business use cases for AI: automating business processes, gaining insight through data analysis and engaging with customers and employees. Based on the previous discussion and the background research, almost all of the emerged AI-CRM applications fall into these categories of AI use cases.

This categorization of use cases is used in formulating the task requirements into items of the research instrument. With these items we can identify what types of tasks could benefit from automation of processes, gaining insights and AI engaging with human stakeholders. In this research especially tasks related to finding insights from large masses of CRM data, automation of CRM processes and some simpler customer and employee engagements have emerged. The research instrument is altered to recognize and focus on applications benefiting from AI through the mentioned use cases.

5.1.3.2 Technology characteristics

As CRM system is only the environment scoped for this study, in which the technologies are implemented and AI is the actual technology category to be analyzed, we need to look at previous AI research discussed in the literature review. Some researchers have determined AI to mean developing systems that think and act in a human-like and rational way (Kanetkar

& Chanchlani, 2014). In the 1980s, the debate about the roles of human and machine intelligence focused on if expert systems are to support or replace human employees (Markus, 2017). Ross (2018) sees that this way of looking at AI as a replacement for humans is the biggest flaw in how some companies view AI as it in reality demands new type of human intelligence from the organization. Based on this, it can be argued that the idea of complete replacement of human workers should not be the goal of implementing AI.

Aleksander (2017) argues there to be a difference between intelligence of robots and human beings. Even though at least currently AI cannot exceed human intelligence in many areas, there are tasks that it can execute better or more efficiently than humans. For example, humans can analyze CRM data and recognize the best potential leads by hand, but as how data depicts reality shifts over time, altering the analysis in real time can be expected to be more efficient when executed by an application utilizing machine learning. Additionally, customer service representatives can be equally good in learning and solving easy and manual service requests but using AI applications can save time that can be invested in more difficult tasks requiring specifically human intelligence. Based on this discussion, technology characteristics for AI-CRM applications are defined to be better decision-making and saving of resources. The items under this subconstruct are aligned with task requirements so that the data collected with them can be used to analyze the task-technology fit of individual AI-CRM applications.

5.1.3.3 Economic viability

In the study of Liang et al. (2007) the first subconstruct of viability, economic viability, consists of the cost-benefit of the system and transaction costs. The cost-benefit is used to measure the project budget; financial investment of developing and maintaining the application studied. This subconstruct is mostly valid for AI-CRM applications as it stands, but the wording of the items needs to be altered. Most of the AI-CRM applications are developed by either the CRM system provider or third parties, so companies can also get initial costs of acquiring the system rather than developing that is the wording in the instrument of Liang et al. (2007). In addition, there may be some costs from maintaining bought or subscribed AI-CRM solutions, e.g. by having to invest in human resources to manage the application, but most of the costs can be expected to be related to subscription and use of the service rather than technical maintenance. The wording of items under the project budget are altered to match this scenario.

Liang et al. (2007) see that the factors affecting transaction costs consist of asset specificity, uncertainty and frequency. They see that transaction costs are important for assessing viability as decreasing transaction costs can increase the users' willingness to use the application. First, we investigate asset specificity, which in the research instrument is divided to physical, human and brand specificity.

The physical assets consist of specific hardware or software the company needs to acquire to use the analyzed applications, even though the naming would easily guide to only consider hardware. This part is valid for AI-CRM applications as it stands. For example, if the company buys the application from the CRM provider and it is integrated directly to the system or one of its modules (e.g. sales, marketing, sales), the need for novel physical assets is low. If on the other hand the company buys the service from a third party or it is not integrated directly to the CRM platform, the transaction costs can rise as the user is needed to utilize different user interfaces to access the platform.

The human asset specificity refers to evaluating human asset capabilities the company needs to use the system. It can be affected e.g. with training and recruiting of new human resources. This is also applicable directly to AI-CRM applications. For example, if the solution needs to be configured to a specific use case or data sample, some understanding of analytics and AI is expected to be needed even when the solution is bought from a provider.

The brand asset specificity is used to analyze the effects of the application on the value of brand and partnerships. This can be affected e.g. if the technology is provided by a company with a negative brand. In addition, if the use of the solution affects the quality of the organization's customer interactions, there can be expected to be some indirect effects. In the AI-CRM context also unethical aspects of the system, e.g. a biased machine learning algorithm that discriminates customers based on their data, could affect the brand negatively. This part of the instrument does not need to be modified for this study.

Alongside the asset specificity, Liang et al. (2007) state that uncertainty affects the transaction costs of the application due to the increased risks. This item is used to evaluate if the environment in which the application is used changes frequently. In the context of AI-CRM applications, the effect of frequency of change depends on the application. For example, lead prioritization applications that learn from data can adapt to changes in the data more easily, in comparison e.g. to how product recommendation systems can adapt to a change in product catalogue. This part does not need modifications to serve the purpose of this study.

Final affecting factor for transaction costs is frequency. As a more frequent task enhanced with an AI-CRM application reduces the transaction costs more than enhancing a task with low-transaction frequency. This part does not need to be modified. Now with these different items the effects on transaction costs can be evaluated and together with the cost-benefit the economic viability of a specific AI-CRM application can be analyzed.

5.1.3.4 IT infrastructure

Liang et al. (2007) identify IT infrastructure as the second subconstruct of viability, as it provides a foundation to support development of technological operation enhances and business. They divide the sub-construct to include three parts; Software and hardware, Data management and The competence of IS staff in the company. As we are scoping in on AI-CRM systems, many things measured in this part, e.g. evaluating the database structure, are not meaningful for this study. Due to this, the scope of this part of the instrument is moved from general IT infrastructure to the CRM platform.

Software and hardware include IT resources needed to support the application. Some of the points, e.g. the capability of organization's hardware to operate the AI-CRM application may be relevant and so is the network management if the application is a cloud application accessed through the Internet. Some of the points are slightly outdated over time and for example a mention of a qualified network management system is removed.

As implementing AI in a CRM system context naturally requires the company to have a CRM system in place, some points are not relevant and need to be altered. On the other hand, as we discussed earlier the modularity of the CRM system, for example evaluating if the company has the specific modules in place to integrate the application to is relevant for this study. The item addressing maturity on the Internet is changed to assess maturity with AI and data analytics, as that is more relevant for this topic.

Even though the data structure is guided by the CRM system architecture, as learned from the previous discussion, the platforms can be customized and configured. Data management and security practices related to CRM data can be expected to differ between companies and so it should be evaluated. An item to evaluate if the CRM system has access to other relevant data sources that could be used to enrich the training data for AI-CRM applications was added.

The competence of IT staff is used to evaluate the skills and capabilities of internal employees taking part in the implementation of the application and the quality of possible outsourcing partners. This part is relevant almost completely as it stands, but once again the original research of Liang et al. (2007) focused on developing and maintaining new systems, when we are also looking at AI-CRM applications mostly provisioned from an external provider. The wordings are altered similarly as was done with the cost-benefit factor. These three factors are now ready to be collected and interpreted with the instrument and together form the IT infrastructure subconstruct.

5.1.3.5 Organizational support

The final subconstruct of FVM is organizational support. Liang et al. (2007) identify it to consist of Process reengineering, User competence and Top management support. This subconstruct is viable as it stands for this study and there is no need for alterations. The need to alter the business process upon adopting the AI-CRM solution, the capabilities of users to use the solution and top management support can all be expected to be valid items to assess for the context of AI-CRM applications.

The researcher evaluates that the made alterations are necessary but implementing them is evaluated successful in preserving the original structure and perspectives FVM provides for analysis. With all the sub-constructs considered, the needed alterations are applied to the research instrument. In addition to these, there are three items for Performance in the original instrument of Liang et al. (2007). As the idea of FVM is to evaluate performance of the selected applications by concluding all subconstructs to constructs for fit and viability and conclude those into performance, this study expects that these are to be used in interpreting and verifying collected data rather than to collect it. As this study aims to help companies evaluate prerequisites of AI-CRM initiatives, the viability construct and its affecting factors are the most important, as they are mostly manageable by the company in comparison to task-technology fit. In the next chapter the findings of multi-case study are presented and values for each company and applications are derived and analyzed with FVM.

6 Analysis and results

In this chapter the results of the study are presented and analyzed. Firstly, the upcoming results and method of analysis are introduced on a general level. After this, all results are discussed in the context of each case company. Finally, the results are visualized in table format and summarized on the fit-viability framework similarly to the original study of Liang et al. (2007). Finally, the results and the analysis are summarized.

6.1 Research findings

As explained earlier, semi-structured interviews were conducted to collect information from two informants from each company. As the research instrument is used mainly for analyzing the data collected, even though it strongly guides the data collection, it was evaluated not to work as an interview framework as it stands. Most of the data is to be collected from interviewing total of eight informants so these interviews must also be planned. For this purpose, an interview framework was developed to guide the collection of evidence, and it is presented as the Appendix C. The questions about the task-technology fit of different solutions were naturally altered based on the ones discussed, so they are not explicitly stated like the questions used to collect evidence for evaluating other subconstructs. As the interviews were semi-structured in format, much of the data was collected from open discussion and follow-up questions in addition to the ones presented.

The companies are referred to as A, B, C and D and the solutions are aliased in the format of e.g. A1 and B2. Collected data is analyzed by using the research instrument and the results of that analysis are discussed next in the same manner as in the original study of Liang et al. (2007). First, the findings will be discussed in detail focusing on one case company at a time. After that, all the values (varying from 1 to 7) determined by the researcher for each subconstruct and the values of constructs formed from them are visualized in Table 6. The values are determined by the researcher based on the items under each sub-construct in the research instrument (Appendix B). Due to both the limited number of informants from each company and subjectivity of the analysis, there are potential limitations to results which are discussed in more detail in the final chapter.

For some subcontracts there is no point to have two separate values for the applications discussed with the same company, but for some it is logical due to the differences in the applications regarding those subconstructs. Finally, the values of fit and viability for each application are visualized in the fit-viability framework and these results are discussed.

6.1.1 Company A

With the informants of Company A, the analysis focuses on B2B sales and marketing operations of the company. The organization has not yet implemented an AI-CRM application, but has been planning to utilize AI-CRM solution to recognize potentially valuable leads and prioritize the resources of sales and marketing. In addition to this application, also a solution that would provide suggestions for sales and marketing personnel of the organization was discussed and analyzed. Currently especially sales personnel spend a lot of time to evaluate what leads to prioritize and marketing function determines the targeted segments mostly based on the requests from sales. The informants saw great potential in an AI-CRM application for recognizing leads to prioritize and as they already have begun planning to implement it, the task-technology fit for this solution (A1) is evaluated to be 6. The informants saw that there would still be limitations to the technology as it could not guide all lead prioritization decisions.

The second application discussed was the AI-CRM tool that would recommend different actions for the CRM user, e.g. proposing to make an offer at a specific price range or send a specific email promotion to the customer based on the data collected of them. Company A had not begun planning to use this solution, but the informants saw that there were some potential use cases for this application. Currently the sales and marketing operations focus on masses of leads and the individual sales representatives have a lot of room to alter their approach with specific leads. Making their work more data-driven could help, but the suggestions would not work for all cases as the services offered by the company vary greatly and are often customized. Due to this, the task-technology fit score for this application (A2) is graded 5.

Both informants saw that the company would have enough financial resources to implement the discussed AI-CRM solutions. Naturally, the investment calculations would need to be made and there are competing initiatives and limits on resources, which is why the company A scores 6 for the project budget. From the terms of asset specificity, the physical assets would not be affected as the solutions would be integrated to the CRM system already in use. Both informants saw that if the solutions make their sales and marketing interactions more targeted and better in quality, it will also increase their brand image. They had already decided to train one employee on how to configure the lead prioritization application. Both applications would operate in a quite stable environment, as the CRM users, customer base and the company's operations are not expected to change frequently. Due to these reasons the solutions score 7 (A1) and 6 (A2) for transaction cost.

From the perspective of software and hardware all users would have access to the needed CRM modules when required. In addition, the company has some maturity in using AI technologies which on the other hand are not located in the business functions of sales and marketing but may be allocated also to projects of implementing AI-CRM solutions in these functions. In addition, the sales team has data analytics capabilities of its own. Sales function is using the CRM system as its core solution, but the marketing team additionally has many other solutions in use. This could make presenting the suggestions for actions by the solution A2 more difficult if it cannot operate on these marketing systems as well as directly on the CRM system. For this subconstruct, A1 scores 6 and A2 scores 5.

Currently the company has some problems with management of customer data. One reason for this is that they have not yet aligned a clear roadmap for the co-operation of sales and marketing functions which is necessary for planning a common strategy to collect and manage customer data. Previously, also the difficulties with integrating the data flows from one system to another have been limiting the data collection. For example, when enriching a lead in the CRM system with information about a website visit from the marketing system, the CRM was not able to recognize the company record automatically due to data formation. In addition, the sales function has recognized some limitations to how it can in a scalable way generate and enrich the customer data based on the operations and interactions that the company has with them. All in all, the management of customer data is planned, but due to these difficulties, Company A scores 5 for both applications for data management.

The company has good implementation partners and inside capabilities to manage implementation of IT solutions. Because they do not have previous experience from AI-CRM implementation, they are open to using external partners to manage the process. The company has established good partner relationships with companies who could help with implementing these solutions and informants see value in external ideas too. Nevertheless, they also value having an internal capability for AI implementation and for marketing function it could require new resources. The company has divided IT capabilities closer to business functions rather than having them fully siloed in a separate function, so there is a good visibility between business processes and IT. The project managers have experience from alleviating user resistance and favor communication, training and user engagement already in the early steps of implementation. The company also has some experiences from failed system implementations. For these reasons, the company scores 6 for the competence of IS staff.

From the perspective of process reengineering, both informants saw that the solutions would not require especially large alterations to current processes, but if the implementation succeeds, the solutions can help much of the decision-making to become more data-driven instead of being based on intuition. The actual scope is dependent on how well the users adopt the solution. In addition, to collect data for the AI application, data generation processes would need to be enhanced. For these reasons, business process reengineering scores 6 for A1 and 5 for A2.

Company A has trained its employees on the principles of AI, but both informants think that the users' understanding of how the suggestions and predictions are conducted is limited. The sales and marketing functions have previously executed a small number of projects around implementation of new systems and they see that the motivation of employees varies, and some resistance can always be expected. The informants value the timing of implementing new tools highly and they see that as there are other ongoing changes in the organization, implementing new tools may be difficult and it may affect user efficacy in adopting the solutions. The company is graded 5 for user competence.

Currently, the top management support for developing sales and marketing varies. Some executives have a more positive stance for developing these functions, but there have also been challenges in achieving commitment to some business functions. Data-driven approach is supported by the management. For top management support, Company A scores 4.

6.1.2 Company B

With Company B the analysis focuses on solutions for their customer service functions. The organization has adopted AI-CRM solutions to manage their customer chat. They use both an NLP-based customer-facing bot that understands the customers messages and automatically can execute some service requests and an internal ML-based system that provides suggestions for the service representatives based on the historical data and the customer's inquiry. These applications are also chosen as the focus of this analysis with the AI-chatbot given the alias B1 and a solution providing automated suggestions for service representatives is named B2. The current systems are limited to their chat channel, and AI-

CRM solution is not used e.g. in customer interactions over the phone. Additionally, the chatbot does not conduct sentiment analysis which is also a potential feature of AI-chatbots. When engaging with the customer, the representative can see the previous interactions with the customer from the CRM and there also exists some rule-based automation that can suggest a relevant knowledge base article based on the words in the title of the customer inquiry.

As the company has adopted these solutions to a limited extent and has found them useful, the task-technology fit is high. In addition, the informants saw that utilizing AI to support other service channels could provide them and their customers value. Even though AI-chatbot is more efficient than automated suggestions for the CRM user as it is more scalable, the informants see that there will always be complex support cases that require human intelligence. On the other hand, the quality of complex cases could also be enhanced with AI-based suggestions for e.g. recommending the knowledge base articles that could help the representative with the current case. One haltering aspect for the operativity of these applications is that the Company B serves customers also in less spoken languages, and the informants have recognized that currently offered AI-CRM solutions that would work also for other channels than chat have limitations to understand these specific languages. For these reasons, the task-technology fit of both solutions is graded 6.

Company B has a clear understanding of the costs of each customer interaction, which is why counting cost savings of each automated customer interaction is relatively easy. This knowledge supports making investment calculations and finding financial resources for the AI-CRM applications. On the other hand, this applies better to the AI-chatbot but evaluation of profits and savings is more difficult with systems supporting the users. For these reasons, the project budget for B1 is given the score 7 and B2 is given the score 5.

As the solutions are integrable to the CRM system Company B uses, there is no need for special software or hardware but neither do the applications reduce the need for the current ones. Users need to be trained to use the system and upkeeping the application demands some effort from system admin, e.g. when different changes in operating environment affect the recommended answers and knowledge base must be edited. Even more dramatic changes in operations and operating environment of the company may happen quite frequently. The amount of customer contacts is quite significant, which increases the potential of automation. No new personnel with special expertise was hired to implement the AI-CRM solutions. The effect on company brand was seen minor for B2 as it is an internal tool, but they have faced resistance for B1 from some customers due to general dissent to the idea of chatbots replacing human service. For these reasons, B1 scores 5 and B2 scores 6 for transaction cost.

Company B has had previous experience from testing an AI solution for automating customer interactions on social media channels, but the implementation failed due to technical restrictions. This helped them to recognize technical features mandatory for the current AI-CRM solutions and the implementation of B1 and B2 has been successful. They have used a CRM system in customer support for a fairly short time, but they have adopted it widely by taking marketing, sales and service modules of the platform into use. They have expertise in analyzing customer data that can be implemented in AI-CRM projects. For these reasons, the software and hardware are evaluated high and scores 6.

The organization has clear guidelines and plans on collecting and securing customer data which is in line with regulations like GDPR. Due to technical limitations, the CRM system is not integrated to some highly important information systems of Company B that could offer relevant customer data for the AI-CRM applications to take into analysis and e.g. increase upselling of customer service. For these reasons, the data management is given the score 5.

Company B has established a good structure for the co-operation and enhanced visibility of IT and business departments. They also have strong practices for change management and aim to communicate with and engage the end users to the projects from the early stages. The company has good implementation partners for outsourcing and they usually share project management responsibilities between internal and external professionals. On the other hand, when implementing B1 and B2 the project managers did not have previous knowledge about AI-CRM implementation projects which may increase their dependency of the system provider. Based on these points, the competence of IS staff is rated 5.

The solutions were relatively easy to introduce to operations and they provided added value and improved current processes. Nevertheless, the technology due to being restricted only to some service channels did not alter all current processes. On the other hand, some AI-CRM applications emerged in earlier parts of this thesis have the potential to be implemented in other channels under the CRM even though the current specific solutions of Company B are used only for chat. Due to this the scope of the process re-engineering is evaluated 6 for both B1 and B2.

When the company implemented the AI-CRM solutions they faced some user resistance which affected the efficacy of adoption. Nevertheless, as the users are generally interested in novel technologies, the motivation to use new applications is usually high. The employees have a very positive attitude for the CRM system. With B2 the challenge was that the service representatives wanted to show their own personality in communications rather than accepting the suggestions of the application and with B1 as the AI-chatbot automates repetitive tasks it also aroused fear in the representatives for the essentiality of their jobs. On the other hand, AI-chatbot is easier to use as it can completely automate simpler customer interactions. The general understanding of AI technologies the organization and the users have is limited. For these reasons, the user competence is given the grade 6 for B1 and 5 for B2.

Previously the top management has provided support for CRM initiatives and the attitude towards developing operations with technology is positive. The top management supports a strong culture of using the novel innovations in operations and they provide financial and human resources to implement them. For this reason, the top management support is given the grade 7.

6.1.3 Company C

Company C had not yet implemented AI-CRM solutions, so discussion with informants focused on analyzing potential fit and viability of two applications for the company's customer service operations. First one is an AI-chatbot for customer service referred to as C1 and the second one is the application providing suggestions for action based on analyzing the historical data with machine learning algorithms referred to as C2. Company C is soon going to implement a service chat channel and later a rule-based chatbot integrated to their CRM system, but the aim is to enhance the filtering and steering of customer interactions rather than completely automate customer interactions. Nevertheless, AI-CRM applications are offered by the chatbot provider so evaluating the value and prerequisites for introducing them is interesting for the company.

The organization could profit from having a natural language understanding AI-chatbot, as they would like to offer personalized and high-quality service and the frequency of customer support contact requests in relation to the size of the current service team is significant. Informants of Company C have also identified that finding NLP solutions for multiple languages they offer service in is either difficult or very expensive. Due to the novelty of these applications, the biggest AI-CRM solution providers are still focusing on the globally most spoken languages. The informants see that these solutions could help their employee resources to focus on engaging with customers rather than on manual tasks. They see personal customer service important for their brand and this limits the use cases for C1.

Marketing and communication activities of Company C arouse emotions in their customer base, and they get also many inappropriate messages. Sentiment analysis offered by an AI-CRM application could help the company in filtering and steering the discussions to human service representatives. Currently the service representatives read all customer contact requests and they have been trained on how to address them and some specific cases are already automated. Automated recommendations for action based on ML could increase the efficiency even further. These recommendations can e.g. suggest a model for a response message or a process for completing a service request. Nevertheless, the cases are not too complicated to upkeep a service relying on the personal capabilities of service representatives. The task-technology fit of C1 is given grade 5 and C2 is given grade 4.

The company offers fair resources for implementing supportive IT applications if they are well rationalized. As with completely automated customer engagements it is easy but evaluating the value of more supportive effects the C1 and C2 could have on the customer service operations is more difficult. Informants have previously identified that there are not too many ready models for doing this evaluation. For this reason, for the project budget subconstruct C1 is given a score of 7 and C2 is given a score of 5.

As the already decided implementation of a chat and chatbot is done directly in the CRM system, also AI-CRM solutions would be integrated to the solution with no changes to the need of special software or hardware. The company's employees would be interested to take on the solutions and they would be trained, but the need for training is not expected to be broad with automated solutions and due to the service team's criticality, removing them for training is difficult. Company C would have fair employee resources to organize the upkeep of the solutions with no need for new recruitments.

The company has surveyed their customer base about their service channels and have identified that some customers have a resent for communicating with automated chatbots. This could signal a risk of negative brand effect of implementing a solution, but on the other hand the informants see that if the AI-CRM applications can make the user experience better and more seamless, positive brand effect may be possible. The operating environment of these applications would be quite stable and changes to e.g. customer base or themes of inquiries do not happen often. The number of customer contact requests is not exceptionally great, but the requests are frequent. Based on these reasons, transaction cost is scored 5 for C1 and 6 for C2.

Company C has some experience from testing other AI-CRM solutions in their operations. The organization has good capabilities of analytics and statistics that could be applied to AI-CRM solution implementation. The informants see value in understanding how the algorithm making the predictions works. The different business units have adopted the different CRM platform widely, e.g. with marketing, sales, customer service and customer community modules. For software and hardware, the company is given the score 7.

The company has created clear plans and guidelines for data security and alignment with regulations like GDPR. They see that a strict stance to protect privacy of customers supports their organization's brand, but it also demands increased effort for customer data management. The collection of customer data is structured clearly and by using the CRM platform for operations widely, much of the customer data is already in standardized format. They are currently developing their customer data models and designing how they can utilize the data in an optimal way. For data management Company C scores 6.

The company has a good implementation partner network and they have a habit of using partners when executing projects around novel IT applications. Their IT function is aligned well with the business functions by utilizing business partners and both parties participate in the implementation projects. Depending on the initiative, the project manager can be either from business units, internal IT or partners, so the manager can have previous experience from AI-CRM implementation if that is valued. The company has acquired experience from change management in IT implementation projects and that perspective is always implemented, but they do not have an established framework for the change management process for these projects. Informants have found that aligning the operations is essential for successful adoption of e.g. AI-CRM applications. For the competence of IS staff the company is given the score 6.

C1 and C2 would have potential to affect the majority of customer service interactions, so the change to the processes would be significant. Nevertheless, the current emphasis of Company C to offer human contact in customer interactions limits the business process re-engineering potential. For this reason, the scope of business process re-engineering is evaluated with score 4 for C1 and score 5 for C2.

The current employees have a limited understanding of AI technologies and possible knowledge is acquired through personal interest. The informants see that these capabilities should be developed further if AI-CRM applications are applied. The motivation to adopt new solutions is expected to be generally high and many employees get enthusiastic about using novel innovations. The company has a culture of people taking part in system projects to ensure that they are designed for them. For these reasons, the user competence is given the score of 6.

Top management of the company has a strong vision of modernization of the company and support for new novel innovations is expected. Resources allocated for the current chat implementation can be taken as a proof that this support reaches customer service function. There have been some changes to important top executives and transition may cause uncertainty for the short term but should not weaken the support on a longer term. For these reasons top management support is evaluated quite high and given the score of 6.

6.1.4 Company D

Company D has implemented an AI-CRM solution that makes personalized product recommendations for the users of their e-commerce site and personalize their marketing activities (D1). In addition, an AI-CRM solution providing suggestions for actions for the CRM users working with B2B partner acquisition operations (D2) was discussed with informants and is analyzed.

The company uses the sales module of their CRM system to manage their B2B retail partner relationships. The users of this solution use it similarly to how a B2B sales function would, by following the relationships and co-operation agreements with these partners. Even though the process and platform are similar to sales function, due to focusing on partnerships there are limitations to how well the AI-CRM solutions could support them. For example, Company D has recognized that it is very difficult to find data to verify wanted partner profiles and due to that automating or guiding the prioritization of the employees is difficult. Also, the process is very clear and similar between different customer cases, which decreases the value gained from insights of AI-based suggestions. On the other hand, automated suggestions combined with automating some internal processes is recognized to hold potential value in making the operations of the users more efficient. For this reason, D2 scores only 2 for task-technology fit.

On the other hand, the recommendation system has been in use for the company and they have achieved varying results with it. The company has previously used other solutions for personalization and currently has an AI-solution integrated to their CRM system. The use potential of this application is great, as their e-commerce sales are increasing and personalization supports the online sales and enhances customer experience. The system enables the use of previous customer data to personalize marketing and e-commerce site experience more efficiently than human could do it. The task-technology fit of D1 is given the score 6.

Financial resources are limited in the company, but if the potential profits or cost savings can be calculated, the funding is expected to be found. In addition, the organization has previously provided resources for indirect projects targeting to enhance the operational capabilities of the CRM system users. Evaluation of the profits of especially D2 may be difficult. As they have a team dedicated for CRM system development and maintenance and have outsourcing partners in use for more technical requirements, resources for maintaining the system are in place. Based on these points, the score given for the project budget for D1 is 6 and for D2 is 4.

The implementation of either solution demands no acquisition of additional special hardware and the AI-CRM application provides all necessary features. Both solutions would be integrated directly to the CRM system with no effects on required assets. Company D always allocates resources to end user training. The responsibilities of administering the recommendation application have been managed internally but are currently managed by an outsourcing partner. The effects of the solution to the brand can be either positive or negative, depending on if the AI-based recommendations for CRM users or directly for customers are more personalized and valid than the ones achieved without using the AI-CRM application. Operating environment of the applications is expected to be stable and the effects of especially D1 are frequent if it can provide recommendations for many e-commerce site users. For these reasons, Company D is given for transaction cost the scores 7 for D1 and 6 for D2.

As the company has implemented a recommendation system, they have some previous experience of AI-CRM applications. In addition, the organization has analytical capabilities but they have not been utilized in the context of the retail partner network as well as with customer data. Company D uses multiple CRM modules that can be integrated with the focused AI-CRM applications and they are currently planning to implement more to enhance the operativity of D1. For these reasons, the company is given scores 6 (D1) and 5 (D2) for software and hardware.

The organization has had some technical issues with e.g. integrating their email system and real-time stock management information to the CRM system. These integrations are important for both applications, as e.g. if the product's stock is sold out, it should not be recommended for the customer. The company has slightly ambiguous guidelines for customer data collection and quality management, and there is a need to enhance the quality of customer data. Especially in the B2B partner unit they collect a lot of unstructured data in open text fields, which is more difficult for an AI application to analyze than data collected e.g. with structured drop-down selection. Due to these reasons, data management is scored 5 for D1 and 3 for D2.

The IT function has a specific team for administering and developing the CRM systems which works in close co-operation with business units. Change management practices, continuous communication and engaging with the end users is emphasized in alleviating user resistance. The company has good outsourcing partners and even though the internal project leaders may not have had experience from implementing AI-CRM solutions, the organization has utilized these partners to complement the missing capabilities. There may be a need to build more in-house resources as they invest in the AI-CRM applications, but the situation is satisfactory. The competence of IS staff is evaluated with the grade 6.

The expected scope of developing processes for D2 is expected to be significant, as the company has modernized its operations greatly over the recent years and the wanted scope of transformation of business processes is often broad. This solution would aim for the same too. This was the same when they implemented D1 as automated recommendations are much more scalable to upkeep when compared to trying to personalize the e-commerce site and marketing campaign recommendations by hand. Naturally, the collection of data is limited and dependent to permissions provided by the customer. For this reason, the scope of business process reengineering is given the score 6 for both applications.

The implementation team faced great problems when implementing the CRM system for the partner function due to the problems with user intent and efficiency. The general understanding of information technology, data and AI of users is not especially high. This naturally varies between teams and individual users and the user competence is expected to be higher for D1 than D2 users. For these reasons, user competence is evaluated and given grade 5 for D1 and 4 for D2.

Top management support for implementing technology in general is evaluated to be quite high, but they do not encourage users to use CRM in the best way, e.g. when it comes to CRM data analytics. Some management reporting activities that could be done on the CRM platform with real-time data are conducted on spreadsheets. Top executives support adoption of new solutions, but they may sometimes view them as individual tools rather than e.g. provide a holistic plan for advancing data-driven operations. For these reasons, the top management support is given the grade 4.

Table 6: Summary of findings

Construct		Item	A1	A2	B1	B2	C1	C2	D1	D2
Viability	Economic	Project budget	6	6	7	5	7	5	6	4
		Transaction cost	7	6	5	6	5	6	7	6
	Scores		**6.5**	**6**	**6**	**5.5**	**6**	**5.5**	**6.5**	**5**
	IT infrastructure	Software and hardware	6	5	6	6	7	7	6	5
		Data management	5	5	5	5	6	6	5	3
		Competence of IS staff	6	6	5	5	6	6	6	6
	Scores		**5.67**	**5.33**	**5.33**	**5.33**	**6.33**	**6.33**	**5.67**	**4.67**
	Organization	Business process reengineering	6	5	6	6	4	5	6	6
		User competence	5	5	6	5	6	6	5	4
		Top management support	4	4	7	7	6	6	4	4
	Scores		**5**	**4.67**	**6.33**	**6**	**5.33**	**5.67**	**5**	**4.67**
Total scores			**5.72**	**5.33**	**5.89**	**5.61**	**5.89**	**5.83**	**5.72**	**4.78**
Fit	Task-technology fit		6	5	6	6	5	4	6	2
Total scores			**6**	**5**	**6**	**6**	**5**	**4**	**6**	**2**

Notes: A1 – Lead prioritization application; B1 & C1 – AI-chatbot, D1 – Product recommendation system A2, B2, C2 & D2 – Application providing suggestions for action for the users

6.2 Analysis of results

As can be seen from the Table 6 and Figure 5, the given values for subconstructs form the constructs of fit and viability which can be visualized in the fit-viability framework. The results can be viewed to assess the success of the analyzed initiatives (Liang et al., 2007) and with some of the applications their potential success. The aim of this thesis is to develop the fit-viability model further to be used in analyzing the prerequisites for implementing the AI-CRM applications and the results should support that for the test to be successful.

As mentioned before, this study does not aim to make generalizations of the different prerequisites so the model should not be used to compare different companies with others, but the different AI-CRM initiatives from the perspective of each company. The construct of task-technology fit is something that is very difficult for the company to alter, if the technology is not developed by themselves. A low score of task-technology fit means that the task does not fit the nature of the technology (Liang et al., 2007). As it can be seen, only D2 has a very low score of fit.

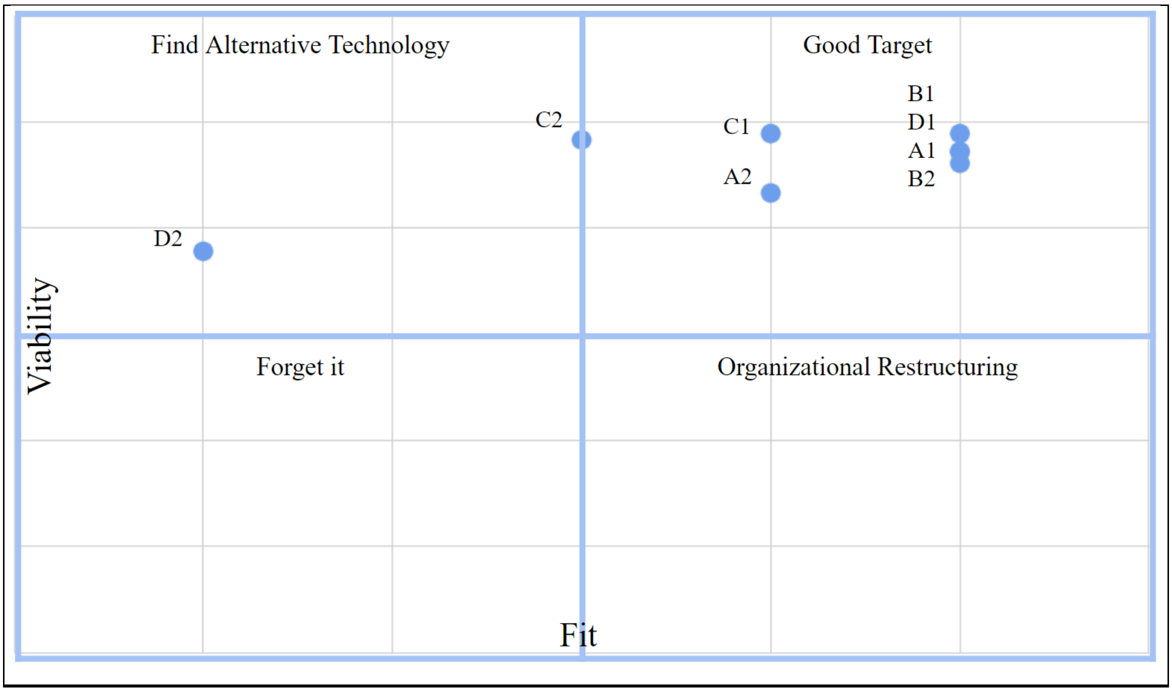

Figure 5. Results mapped on the Fit-Viability Framework of Liang & Wei (2004)

The reason for this was that the tasks done with the CRM system that could be integrated with D2 were not what the solution was designed for. As the framework suggests, the company is viable for an AI-CRM solution, but they should find an alternative technology like automation of manual CRM processes with AI that emerged in the interviews. From the perspective of a company or a researcher utilizing the fit-viability model it is probably wise to leave technologies with low fit outside of the scope of evaluation of viability. Nevertheless, as this study aims to test the model, it is also seen as valuable to have one example of an application with low-scoring fit. As this thesis aims to develop the model so that it can also be used to evaluate not yet implemented AI-CRM solutions, it is expected that companies evaluating different initiatives with the model will also face applications with low task-technology fit.

Subconstructs of viability on the other hand is used to measure organizational readiness for the specific application (Liang et al., 2007) and as these can be managed by the company, they can also be viewed as prerequisites for successful adoption. All the focused companies scored quite high scores for viability, which means that their organizational readiness for AI-CRM applications is also generally on a desired level. The applications that would have belonged to the organizational restructuring would be especially interesting, as for those the viability would be so weak that raising the factors affecting the construct would have been essential prerequisites for successful adoption. Nevertheless, none of the applications scored 7 for viability, which means that they all have factors they can assess for increasing the chance of successful adoption and enhancing performance of the solution. Especially when analyzing solutions not yet adopted, the factors causing low scores can be viewed as prerequisites.

The factors lowering the viability can be recognized by looking at the values of different subconstructs. If the company can recognize and enhance factors affecting the specific subconstructs, also the value of viability will get better and according to the model the performance of applications is enhanced. Since the construct of viability is evaluated of an average of scores given to three categories and economic viability has only two subconstructs, the viability can be increased the most by affecting budget and transaction costs. This is logical, as it can be expected that any solution can be implemented in some inefficient way even with an incapable team and unfitting IT infrastructure, but without especially financial resources to develop or buy the application, implementation is not possible.

When assessing the scores of subconstructs and selecting the ones to be focused, companies with limited resources need to prioritize. As all three main subconstructs of viability are important for implementation, the company should most likely aim to develop the factors affecting the lowest scoring subconstructs. It can be expected that focusing on one subconstruct is easier than trying to improve multiple ones at the same time. For example, the company D can increase its viability evaluated with FVM for the AI-based product recommendation system (D1) the best by enhancing the top management support. On the other hand, it can be expected that altering some factors affecting the subconstructs is easier than others and they may be causally connected to each other.

This understanding of the company’s capabilities to develop different subconstructs should be included in the prioritization process but evaluating the most easily alterable factors is outside the scope of FVM and it is also highly contextual and dependent on the organization. For example, for Company A recruiting AI-capabilities to the marketing unit can be expected to be easier than improving the data structure by aligning sales and marketing data processes, even though user competence and data management subconstructs have identical weights and effect on viability construct.

The subconstructs of viability; economic viability, IT infrastructure and organizational support have based on this study stayed relevant since being recognized in the FVM by Liang & Wei (2004). All of them provide important insights for analyzing AI-CRM applications and as the model has been tested in the context of multiple IT initiatives over time, the generalizability of the model can be viewed as high and this study extends it. Making generalizations about the significance of different subconstructs is difficult due to the limited number of sample companies, but it can be argued that this thesis enforces the validity of the FVM and its selected subconstructs for analyzing both AI-CRM applications and on more general level other IT initiatives.

Other limited research on prerequisites of AI-CRM applications seem to be aligned with the results of this thesis. For example, Chatterjee et al. (2019) argue that challenges related to expertise, data and infrastructure are important from the context of organizational readiness for AI-CRM integration. These challenges are directly connected to the subconstructs of organizational support and IT infrastructure analyzed in this study. The economic viability on the other hand is quite self-evident when discussing IT initiatives as they have been viewed as investments for a long time, e.g. in the original paper of Tjan (2001). Together with other studies related to FVM and AI-CRM implementation, this thesis validates the argument, that economic viability, IT infrastructure and organizational support have significant effect on viability of AI-CRM adoption.

The results offered by the FVM provide interesting insights about the different factors supporting the successful adoption of AI-CRM applications. Not optimally performing factors can be viewed as prerequisites to be fulfilled for maximizing the chances of success. The model offers numerical values that can be used in prioritizing on which prerequisites to focus on and it also presents the results in a visual form. This makes the model more usable in practical context.

7 Discussion

In this final chapter, the research is summarized and its results are discussed. Firstly, a summary of the research and the found results are presented. Secondly, theoretical and practical implications of this thesis are discussed in more detail. Thirdly, the limitations of the study and topics that should be developed further when conducting similar studies are presented. Finally, the suggestions for future research around the research topic of both the prerequisites for AI-CRM applications and the topic on more general level are provided and the thesis is concluded.

7.1 Research summary

All in all, the empirical research of utilizing the FVM in the context of AI-CRM applications can be considered successful. The developed model aims to be a tool researchers and organizations can utilize when analyzing and assessing the prerequisites of AI-CRM initiatives. As the model provided meaningful insights about different types of companies from the context of AI-CRM applications and clear guidance on how the company can evaluate prerequisites to enhance their viability, the model can be argued to fulfil its wanted purpose. Naturally, the model is not by any means perfect in recognizing the factors affecting AI-CRM implementation and it should be developed further in future research. The implications and limitations of the research and ideas for improvement are discussed in more detail later in this chapter.

In addition to the successful multi-case study, this thesis also included a background research. The evidence collected from the expert interviews provides many interesting viewpoints of actual AI-CRM implementation projects. As the topic is still novel and based on the interviews and literature review the of AI-CRM implementation cases are still scarce, the evidence presented in this thesis can be considered as rich. These insights can hopefully be used to design future studies around the topic of AI-CRM applications. Singular organizations can reflect their operations on some other presented insights from the interviews that were not focused on the multi-case study, e.g. challenges and potential new use cases for AI in the context of CRM systems. This can be seen to enhance the usability of this study.

The second part of the background research focused on Internet research. The results provide a good view of the different AI-CRM applications on the market. As the CRM system market is growing and many of the presented AI-CRM applications seem to have emerged in recent years, the market situation of AI-CRM applications can be expected to shift over time. Nevertheless, the insights can be expected to stay current for some time and can hopefully help companies to understand the current AI-CRM application market better. The results of the Internet research can be viewed to reflect the current state of AI-CRM applications based on the currently most prominent AI technologies and may provide insights even retrospectively.

All in all, this thesis fulfills its set objectives and sheds light to the novel research area and successfully delivers a theoretically based framework for practical implementation. How these results can be used is discussed in more detail in the following section.

7.2 Theoretical and practical implications

This thesis contributes to academic research both by developing the FVM further and by enhancing its generalizability. As the technological scope of AI is exceptionally broad and the concept shifts over time, there are limits in creating generalizable rules or arguments that stay relevant for different companies and technologies. More general frameworks like FVM developed to evaluate prerequisites of different types of technological applications may have a better chance in retaining their relevance. This thesis enhances the validity of this framework also in the interesting and currently relevant context of AI-CRM initiatives.

Liang et al. (2007) state that testing the generalizability of FVM is a required research topic. As this thesis successfully uses the model in the context of AI-CRM applications which has not previously been analyzed with it, this thesis can be seen to enhance the generalizability of FVM. Nevertheless, additional studies testing the model in this context are required to enhance the validity of it even further.

On the other hand, theoretical implications of this thesis are not limited to the results of the fit-viability model. This study also discusses previous research on both AI and CRM systems and connects these topics to provide novel insights. For example, the research discusses AI-CRM implementation and individual AI applications from the perspective of CRM system research conducted by Fardoie & Monfared (2008). Multiple other connections are made between the previous research and the empirical evidence throughout the thesis.

From the practical perspective, this research provides a model that individual organizations can use to evaluate AI-CRM applications and their prerequisites. The thesis explains the process of using the model and provides a research instrument that companies can adopt to base their analyses. The framework is easily usable and the results are understandable. The numerical values can be easily presented in a table format and the applications are visualized on the matrix providing guidelines for approach and allows the comparison of different AI-CRM applications. This thesis suggests that companies can recognize the most significant prerequisites for successful adoption by looking at the subconstructs of the model that have been given the lowest scores or the ones that are most easily enhanced.

Additionally, the insights of the expert interviews can help companies understand how AI-CRM application implementations are conducted. These insights can be utilized in almost all phases of AI-CRM implementation. The Internet research on the other hand can be used to see what kind of solutions are currently offered in the market.

7.3 Limitations of the study

This study has limitations to generalization of the results due to the research methods and limitations of the theoretical framework. The multi-case research was selected as the research method due to the novelty of the research topic. As FVM had not previously been tested in the context of AI-CRM applications, there was a need for a more descriptive approach to determine how the framework could be utilized in this context. Yin (2013) argues that there is a tradeoff between the sample size and the in-depth nature of collected insights. For this research the depth and sample size were balanced, but as the functionality of the FVM in this context is now tested, studies aiming for generalizability of the insights can also be conducted.

This study does not claim to provide especially deep visibility to CRM usage in the case companies, but when taking into notion the limitations of thesis as a format, the selected approach is retrospectively seen as the most suitable choice. With focusing on one company or singular AI-CRM application, the study would have been much narrower than the original study of Liang et al. (2007). In addition, the interviews were the main source of evidence in the original study, and similarity was selected as an approach for this study to increase the validity of testing the use of FVM in this novel research context. Nevertheless, collecting evidence from more and different types of sources could provide a better basis to evaluate the prerequisites for different applications.

The FVM itself has several limitations that could be developed further. First, the research instrument includes some items that are irrelevant at the current time. For example, in the category of software and hardware, the evaluation of hardware specificity is not relevant in the context of AI-CRM applications, as Internet connections and hardware to run the CRM systems are a default for modern companies. Some of the items that had lost their relevance were removed or altered in the preparation of the instrument as explained before. Nevertheless, like the aforementioned item, all of them were not removed at the time as their lack of relevance was not recognized before collection of evidence. They, like all other items, should be re-evaluated when designing future studies to develop the model further.

In addition, the research instrument is vulnerable to biased analysis, as the seven-point scale requires subjectivity from the researcher. This limitation may be even more difficult to assess than enhancing the quality and amount of collected evidence as the concepts FVM evaluates are complicated. Collecting quantitative evidence e.g. from CRM users could be an interesting addition to the model, but in such case the level of abstraction of the research instrument might need to be lowered. Some previous research, e.g. Pedron et al., (2016) emphasize that CRM should be viewed as a strategic concept involving several departments and processes and Dalla et al. (2018) have defined CRM technology as one of the four dimensions of CRM. This can be argued to support the relevancy of engaging various business functions to the process of also analyzing the CRM systems use in an organization.

On the other hand, utilizing FVM in a practical context has limitations that should be taken into notice. For example, when companies consider using the model to analyze the prerequisites of different AI-CRM applications themselves, they should consider collecting more in-depth evidence. This can be expected to require less resources than in the case of multi-case study. In addition, organizations could reduce the subjectivity by e.g. introducing multiple business functions using the CRM system when deciding the grading. Additionally, the weights of different sub-constructs the model provides may not be the best option in all situations and customizing them could also be considered.

Finally, singular companies have limited visibility to other companies, which may make it difficult to evaluate the different subconstructs. Nevertheless, as the model is not aimed to be used to compare different companies with each other, but the AI-CRM applications, subjectivity should not pose a too big limitation for using the framework. On the other hand, as can be seen from the results of this study, informants describe their viability to be quite high, so there is a risk of the results being biased. Nevertheless, with a small sample size this cannot be assessed with evidence collected in this thesis and it could be a topic for future studies. More suggestions for them are provided in the next section.

7.4 Suggestions for future research

The research topic of prerequisites of AI-CRM applications can be studied further from multiple viewpoints in the future. Utilization of FVM is not mandatory, but this study has developed it further into a usable tool for analyzing these applications. The research instrument and methods used to collect evidence to FVM can also be developed further.

The first possible way to build on this research is to test the FVM in the same context in a different environment. For example, the individual AI-CRM applications and case companies can be varied. In addition, the research instrument can be developed further e.g. by reviewing all individual items and altering them to better evaluate task-technology fit and viability of AI-CRM applications. Additionally, sample size can be increased and other research methods can be utilized. For example, a mixed method -approach combining semi-constructed interviews and a user survey could provide even more insights for the conductor of analysis.

Future studies could also aim to make the FVM in this context even more useful, by e.g. providing a more detailed framework on how to fulfil the prerequisites for implementing AI-CRM applications that can be evaluated with FVM. Finally, as currently many of the items in the research interview are open for and even require subjectivity from the researcher, developing the model more objective by providing clearer guidelines for analysis is a valid objective for a study.

Additionally, different subconstructs analyzed with the FVM could also be studied further individually. For example, the results suggest that data management has the lowest mean score of viability subconstructs. The small sample size of this thesis prevents from making strong generalizations, but especially as data management emerged also in some expert interviews, it could be interesting to look more deeply into its role in relation to AI-CRM applications.

Secondly, the prerequisites of AI-CRM initiatives can be studied also by using other theoretical frameworks than FVM. For these endeavors this study can provide interesting insights about AI-CRM implementation based on the evidence collected from expert interviews and the multi-case study. For example, the future research can focus on understanding the presented AI-CRM solutions more deeply by focusing on them e.g. one at a time. There is almost unlimited way to choose which aspect of the research topic to focus on.

As can be seen from the evidence of Internet research, in the recent years many different AI-CRM applications have entered the market. The evidence of the background interviews and the multi-case study signal that there is an increasing interest and will in many companies to invest in these solutions. As AI-technologies are expected to only enhance their technical capabilities, also the task-technology fit of the applications utilizing them can be expected to evolve. In these early stages of AI-CRM adoption, helping organizations to understand the solutions and manage the potential prerequisites could increase the success rates of implementation projects. There are no signals of the research topic of the prerequisites of AI-CRM initiatives becoming less relevant for different organizations in the future. Due to this, the topic will hopefully attract interest of more researchers so that new theories and managerial methods developed with scientific methods can be created.

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Appendix A: Background interview framework

1. What is your professional background and what is your current role?

2. What kinds of companies have you worked with?

3. What kinds of customer cases have you worked on?

4. What kinds of stakeholders do you usually have participating in the projects?

5. Have you utilized AI applications in your customer projects and if you have, how?

6. Which types of AI technologies do you see as the most applicable now and in the near future?

7. What kind of understanding of AI do you think your customers have?

8. What kinds of potential use cases do you recognize for AI technologies in the context of CRM systems?

9. What kinds of prerequisites have you recognized for companies for utilizing AI solutions in their CRM?

10. What kinds of challenges do you expect to emerge especially in projects involving AI applications?

Appendix B: Research instrument

This research instrument is modified from the instrument of Liang et al. (2007).

1. Fit

Task requirements:

- Do users often need to make decisions based on collected customer data?
- Do the tasks include repetitive steps that could be automated for better efficiency?
- Will the performance of the task be substantially worse if it is performed by a AI-CRM application?

Technology characteristics:

- Does the technology allow the user to make better decisions?
- Does the technology enable the same work to be done with less resources?

2. Viability

(1) Economic.

Project budget:

- Does the organization provide adequate budget for commissioning the system?
- Does the organization provide adequate budget for maintaining and using the system?

Asset specificity:

(1) Physical asset specificity:

- Does the adoption of AI-CRM application need to obtain special hardware/software?
- Does the use of AI-CRM application reduce the need for physical asset on-hand?

(2) Human asset specificity:

- Can users use AI-CRM applications to better perform with no need of more training?

- Does the adoption of AI-CRM application need to hire employees with special expertise?

(3) Brand specificity:

- Does the adoption of AI-CRM application affect the value of the brand and partnerships?

Uncertainty:

- Whether the environment and business process are subject to frequent changes?

Frequency:

- Is the task supported by the AI-CRM application a frequent activity of the organization?
- Does the executor of the task need to use AI-CRM application for information or decision frequently?

(2) IT infrastructure.

Software and hardware:

- Does the organization have adequate hardware for operating the AI-CRM application?
- Does the organization have maturity in using AI, data analytics or related technologies?
- Does the organization have systems to ensure network connections?
- Does the organization have necessary CRM modules for implementing AI-CRM applications?

Data management:

- Does the organization have established policies on CRM data management and security?
- Can the training data for the AI-CRM application be enriched with data from other sources?

The competence of IS staff:

- Does the project leader have prior experience in AI-CRM applications?
- Are the IS personnel experienced in initiating and maintaining applications?
- Does IS department know the business process well enough to implement the application?
- Are there any programs for alleviating user resistance?
- Does the organization have good outsourcing partners for IS projects?

(3) Organizational support.

Process reengineering:

- Is the scope of process re-engineering due to technology adoption large?

User competence:

- Does the user have adequate knowledge of IT and AI-CRM application?
- Does the user have a high intention of accepting new technology?
- Does the user have high efficacy in using new technology?

Top management support:

- Do key executives in the corporate headquarter participate in the project decision?
- Do key executives in the corporate headquarter assigned members into the project team?
- Do key executives in the corporate headquarter appropriate adequate budget to finance the project?
- Do key executives in the corporate headquarter use the system and/or encourage employees to use the system?

3. Performance

- Is the system usage consistent with the expectation?
- Does the user have a positive attitude toward the system?
- Does the system satisfy the user needs?

Appendix C: Interview framework for informants

1. What is your role and how is it related to the CRM system of your organization?

2. What AI applications is your organization using or planning to implement?

3. Questions related to the task-technology fit of the selected applications

4. Economic viability

- Do you see that your organization provides adequate financial resources for implementing the potential AI-CRM application?
- Do you usually have an implementation partner when taking on new IT solutions?
- How fast would you see the CRM users to get familiar with using the AI-CRM application?
- Do you have resources (e.g. working time) to commit to development and upkeep of the application?
- Do you recognize the implementation of the application to influence your organization’s brand?
- Does the environment in which this application operates change frequently?

5. IT infrastructure

- Does your organization have previous experience from AI implementation? How about in a CRM context?
- Does your organization have existing capabilities to analyze customer data?
- What types of access do the users have to the CRM system and its modules?
- Do you have guidelines for collection and managing the security of CRM system data?
- Who operates as the project manager responsible for implementing the potential AI-CRM application?
- Would the project manager have experience from previous IT implementation projects? How about implementation of AI-CRM applications?
- Have you learnt best practices to alleviate user resistance?

- Do you have good CRM system implementation partners?

6. Organizational support

- How large do you see the scope of process re-engineering due to implementation of AI-CRM application to be?
- Do the users have a good understanding of the AI-CRM application?
- How do you expect the user’s motivation to accept the AI-CRM application to be?
- How do you expect the user’s efficacy to use the AI-CRM application to be?
- Does the implementation of a potential AI-CRM application have the support of the key executives of your organization?