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EXPLORING VALUE IN ECOMMERCE ARTIFICIAL INTELLIGENCE AND RECOMMENDATION SYSTEMS

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ABSTRACT

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Artificial intelligence (AI) aims to develop a system which exhibits natural characteristics we associate to intelligent human behavior. Recommendation systems are a research area and AI applications. A recommendation system offers personalized content, such as products for end users. This Master’s Thesis explores how AI applications create value for eCommerce merchants and what are the value propositions of recommendation systems. This research was conducted as a qualitative case study with ten interviewees from two companies. Interviewees represented merchant and supplier organizations. Research explained what interviewees felt AI to mean. Research identified most important subfields of AI for eCommerce merchants, in addition with features and value propositions. For recommendation systems value propositions identified from literature were strengthened. Empirical part was able to identify new value propositions. A recommendation system can personalize shopping experience of customers, remove barriers from making successful transactions, reduce amount of manual work and improve brand image of the eCommerce store. Regarding recommendation systems, empirical research also indicated how recommendation systems should be utilized and how should value be measured.

Keywords: artificial intelligence, recommendation systems, value co-creation, value propositions of artificial intelligence, value propositions of recommendation systems

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Tekoälyn päämääränä on saavuttaa järjestelmä, joka jäljittelee ihmisen luonnollista älykkyyttä. Suosittelujärjestelmä on tieteenala sekä tekoälyä hyödyntävä järjestelmä. Suosittelujärjestelmä tarjoaa käyttäjilleen personoitua sisältöä, kuten tuotteita. Tässä pro gradu -tutkielmassa tutkitaan kuinka tekoälyn sovellutukset luovat arvoa verkkokauppiaille sekä mitä suosittelujärjestelmien arvolupaukset ovat. Tutkimus toteutettiin laadullisena tapaustutkimuksena, johon osallistui kymmenen haastateltavaa kahdesta eri yrityksestä. Haastateltavat edustivat verkkokauppiasta sekä verkkokauppiaan palveluntarjoajaa. Tutkimuksessa selvitettiin, mitä haastateltavat kokevat tekoälyn olevan. Tutkimuksessa identifioitiin verkkokauppiaille tärkeimmät tekoälyn osa-alueet ominaisuuksineen sekä arvolupauksineen. Suosittelujärjestelmien osalta empiirisessä osiossa kirjallisuudesta löytyneitä arvolupauksia vahvistettiin. Empiirinen osio kykeni tunnistamaan uusia arvolupauksia. Suosittelujärjestelmä muun muassa personoi asiakkaiden ostokokemukset, poistaa muureja ostamisen tieltä, vähentää verkkokauppiaan manuaalista työmäärää sekä parantaa verkkokaupan brändikuvaa. Suosittelujärjestelmien osalta empiirinen osio selvitti myös, kuinka tuotesuosittelujärjestelmät parhaiten luovat arvoa, sekä kuinka niiden luomaa arvoa tulisi mitata.

Asiasanat: tekoäly, suosittelujärjestelmä, verkkokauppa, arvon yhteisluonti, tekoälyn arvolupaukset, suosittelujärjestelmien arvolupaukset

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1 INTRODUCTION

Artificial intelligence (AI) as a field has existed over seven decades, and during this time it has had many achievements. It is considered to be one of the most promising technologies to this day. Amount of potential AI applications is substantial (Bai, 2011). Naturally, one of the areas where AI can be harnessed to create value is eCommerce. Having human-like intelligence accompanied in online business can offer great possibilities for eCommerce merchants.

Recommendation systems are applications of AI that are commonly associated with eCommerce. They are frequently used in eCommerce to help consumers find relevant products from a large catalog (Matt, Hess & Weiß, 2013). They are also applications that have been researched extensively through different perspectives.

Despite recommendation systems being a widely studied topic, there is much less research on the effect on markets (Matt et al., 2013). Research can be lacking, but it’s still well established that recommendation systems impacts consumer behavior, firm level ad market level. (S. S. Li & Karahanna, 2015.)

Rate of new technological innovations have led us to a situation where the amount of potential AI applications is huge, but the organizational effects of are not well-known. According to Peffers, Gengler and Tuunanen (2003) it can be hard for managers to identify the most relevant and valuable potential investments, as selecting the most valuable projects is a difficult task.

Due to introduced reasons, this Thesis aims to explore how AI creates value for eCommerce merchants. Recommendation system is chosen as an application of AI, whose value propositions are inspected. There are two main research questions:

- How artificial intelligence applications create value for eCommerce merchants?
- What are value propositions of recommendation systems for eCommerce merchants?

This Thesis begins with a literature review that serves as a base theory for the empirical research. Literature review discusses three topics – AI, recommendation systems and value creation. Literature review focuses on explaining the phenomena of AI. It identifies most important subfields of AI for eCommerce merchants. For each subfield, features and values are gathered. Recommendation systems are defined and prior literature regarding firm-level impacts of utilizing recommendation systems is introduced.

Thesis continues as follows: second chapter introduces AI, third chapter recommendation systems and fourth chapter value creation. Fourth chapter also concludes literature review. Empirical part begins by introducing research methodology in chapter five, findings in chapter six and discussion in chapter seven. Thesis is concluded in chapter eight. Appendices contain theme interview form in Finnish and in English. Interview citations in this Thesis are translated originally from Finnish. Citations are numbered and original untranslated citations can be found from the end of the Thesis.

2 ARTIFICIAL INTELLIGENCE

As Russell & Norvig (2010) describe in one of the most important works of AI, we as humans have for years tried to understand how we think, understand, perceive and manipulate the world that we are living in. AI does not only try to understand, but to replicate this behavior (Russell & Norvig, 2010). Even though the recent hype surrounding AI may implicate that the subject is a new and emerging field of science, the field traces all the way back to 1950s.

An unthinkable amount of research conducted within seventy years exists, but AI still seems abstract and hard to grasp at least for researchers new to the subject. Thematical or chronological approaches can be used to summarize the field but the lack of recognized achievements and commonly adopted frameworks pose challenges (Brunette, Flemmer and Flemmer, 2009).

In the first years AI was considered as a field of computer engineering but has since evolved into multidisciplinary field that is linked with numerous areas and field of studies (Pfeifer & Iida, 2004). This makes encapsulating AI difficult, as the field is involved with, for example, biology, psychology, linguistics and mathematical logic (Ning & Yan, 2010; Tecuci, 2012). Luckily however, the vast amount of diverse research with no effort on determining any formalism has also positive effects, as it enables the researcher to explore the subject with no rigorous boundaries (Brunette et al., 2009).

This chapter is organized as follows: to understand the phenomena of AI, we briefly go through the history of the field. Then we review definitions and most common characteristics and subfields of AI.

Literature review was conducted as guide to systematic literature review introduced by Okoli and Schabram (2010) proposes. Key step in conducting systematic literature review is drafting a protocol, which states how papers are gathered and accepted for further review (Okoli & Schabram, 2010).

Google Scholar was mainly used in acquiring the papers for review. Keywords searching for material were “artificial intelligence”, “recommendation system”, “ecommerce”. Additionally, papers concerning value were searched with keywords “value”, “value creation”, “value co-creation” and “value proposition”. Searches were also done with combinations of different keywords.

Additional papers were also taken in from the references of other research papers. Papers were screened based on abstract, which indicated whether they were taken for further review or discarded. Emphasis was on papers that were part of journals, but books were also accepted.

2.1 History and Current State of AI

There is little to no controversy regarding the birth of AI. In the 1956 the famous Dartmouth conference was attended by first AI researchers, who later also became the most influential persons in the field. Some went on opening research centers focusing on AI in MIT, Edinburgh and Stanford to mention few. (Brunette et al., 2009; Russell & Norvig, 2010; Tecuci, 2012.)

Recent years of AI development were the golden age, when great amount of research was conducted and governments were interested in investing AI projects (Li & Jiang, 2017). Golden age started to come to an end before the 1970s. Some predicted that AI would rapidly surpass human intelligence, thus creating intelligence which could handle problems far more wider and complicated that humans could. (Russell & Norvig, 2010.) As researchers were not able to produce real world applications, it began to seem like AI couldn't deliver to its expectations (Tecuci, 2012).

After the field suffered from hard times, during 1980s there were signs of positive progress. Much thanks to expert systems, AI became an industry, and this industry was booming again (X. Li & Jiang, 2017). Organizations across U.S. were adopting expert systems to help the them to save money (Russell & Norvig, 2010). Expert systems also proved that intelligent decision making can be achieved with only a small amount of knowledge (Buchanan, 2005).

These positive signs also contributed to new national AI projects. British government resumed the funding cut in 1973, U.S. began to conduct AI research to assure competitiveness and Japan went on with "Fifth Generation" to achieve intelligent computing. (Russell & Norvig, 2010.)

The industry grew from millions to billions in just few years, and this positive growth continued until 1988 (Russell and Norvig, 2010). Companies focusing on building expert systems failed to deliver the promises, and funding was again reduced substantially (X. Li & Jiang, 2017; Russell & Norvig, 2010; Tecuci, 2012). All the national projects in Japan, United States and Britain failed to succeed (Russell & Norvig, 2010).

Despite the setbacks, AI was slowly recovering during 1990s thanks to machine learning. Previously discarded neural network technologies slowly gained attention, leading to something we now call deep learning. (Li & Jiang, 2017.) According to Russell and Norvig (2010) scientific aspect in AI undergone a transition in 1990s. Rather than proposing new theories and technologies, it became more prevalent to draw upon existing methodologies. This meant that AI finally fostered its place as a scientific method. Researchers began to test hypotheses and analyzed the results statistically. (Russell & Norvig, 2010.)

AI has promised great implications, but often it has not been able to deliver up to its expectations. Currently we are experiencing the upstream to which multiple factors have contributed. Greatest impact to the revival and emergence of AI has had the increasing amount of data, availability of computational power and the growth of Web (Cassel, Dicheva, Dichev, Goelman and Posner, 2016; Li & Jiang, 2017; Russell & Norvig, 2010). Earlier on emphasis on AI has been on algorithms, but it's slowly turning towards data (Russell & Norvig, 2010).

If we look back at the history of AI, there have been multiple transformations in the field. Currently we are experiencing another transformation which stems from the increasing amount of data. Data Science (DS) and AI are actually closely linked, as while DS has had a great impact on the recent emergence of AI, the breakthroughs in DS are partly thanks to AI techniques (Cassel et al., 2016). The current advances in speech and image recognition, text processing and machine translation are achieved through processing and analyzing large amounts of data (Cristianini, 2014). In the future the combination of DS and AI will be beneficial for both of the fields, thus leading to impressive results (Cassel et al., 2016).

Pan (2016) states it is hard to argue against the effectiveness of data. Much of this data is produced and stored on the Web. Different sensor networks and humans produce data like never before. The information environment and the emergence of big data has shaped and will continue to shape the landscape of AI. (Pan, 2016.) According to Halevy, Norvig and Pereira (2009), the intelligence everyone is pursuing lies in fact in the data. Developing new algorithms or creating heuristics were once seen as the key to develop an intelligent machine, but no more. This statistical (also referred to as data-driven) approach to pursue intelligence is now considered to be very promising (Cristianini, 2014; Halevy et al., 2009).

Halevy et al. (2009) from Google Research are not afraid to argue that acquiring vast collections of raw data is the key to achieving intelligent behavior. Cristianini (2014) states that he adopts the perspective but takes a more cautious view. Data-driven approaches can be powerful, but they are only few of the possible paradigms. Rooters of data-driven approaches usually emphasize the things it can do, while shadowing the problems it cannot solve. This type of blind view can be dangerous for the whole field. (Cristianini, 2014.)

2.2 Definitions and Subfields of AI

One could say that there are as many definitions to AI as there are authors. As Li and Jiang (2017) mention, even the intelligence itself lacks a commonly accepted definition, and so does AI. Many papers discussing AI in any form neglect to define AI itself. Brunette et al. (2009) describe research on AI peculiar or atypical, as there is no agreed formalism on the field, nor there are commonly recognized achievements. Scarce number of definitions might result from the field being multidisciplinary and consisting of numerous subfields. These qualities have led to a disconnected research and researchers have failed to adopt a mutual view on AI. To gain an overview, a taxonomy of the definitions is illustrated in TABLE 1.

TABLE 1 Definitions of AI

Reference	Definition
Bai (2011)	"AI – – is a field of science and technology based on disciplines such as computer science, biology, psychology, linguistics, mathematics and engineering. The goal of AI is to develop computers that can think, as well as see, hear, walk, talk, and feel."
Cheng and Wang (2012)	"AI makes machines to imitate human thinking and behavior. AI has been developed into a new and comprehensive discipline – –, which involves computer science, cybernetics, information theory, neurophysiology, psychology, linguistics and other many subjects"
Li and Jiang (2017)	"It is generally believed that AI is a discipline that studies the process of computer simulation of certain human intelligent behaviors such as perception, learning, reasoning, communicating, and acting – – "
Min (2010)	"– – AI is referred to as the use of computers for reasoning, recognising patterns, learning or understanding certain behaviors from experience, acquiring and retaining knowledge, and developing various forms of inference to solve problems in decision-making situations where optimal or exact solutions are either too expensive or difficult to produce – –"
Ning and Yan (2010)	"Artificial Intelligence – – is a new technological science, which researches and develops for simulating, extending and expanding human intelligence theory, methods, techniques and applications"
Pan (2016)	"– – ability of machines to understand, think, and learn in a similar way to human beings, indicating the possibility of using computers to simulate human intelligence."
Russell and Norvig (2010)	"We define AI as the study of agents that receive percepts from the environment and perform actions. Each such agent implements a function that maps percept sequences to actions – –"
Tecuci (2012)	"Artificial intelligence (AI) is the Science and Engineering domain concerned with the theory and practice of developing systems that exhibit the characteristics we associate with intelligence in human behavior, such as perception, natural language processing, problem solving and planning, learning and adaptation, and acting on the environment. Its main scientific goal is understanding the principles that enable intelligent behavior in humans, animals, and artificial agents."

AI encapsulates large variety of different subfields, from which some are more mature than others. In the literature subfields are also referred to as fields, research areas, research subjects, research topics, AI techniques and methods (Cheng & Wang, 2012; Flasiński, 2016; X. Li & Jiang, 2017; Oke, 2008). This proves that the AI research is tangled. Subfields are the top-level categories of AI research, and to gain an overview of the subject, subfields found from the literature added to a table. Table is a result of the systematic literature review.

Main principle of TABLE 2 is to provide an overview of the broad areas that the field of AI encompasses, while not organizing the found fields. This illustrates just how large the paradigm of AI is.

TABLE 2 Subfields of AI based on the literature review

Subfield	Reference(s)
Machine learning	(Bruderer, 2016; Brunette et al., 2009; Cassel et al., 2016; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Oke, 2008; Pan, 2016; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Strickland, 2017; Tecuci, 2012)
Neural networks	(Bai, 2011; Brunette et al., 2009; Buchanan, 2005; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Oke, 2008; Pan, 2016; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012)
Reasoning	(Bai, 2011; Buchanan, 2005; Cheng & Wang, 2012; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Oke, 2008; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012)
Robotics	(Bai, 2011; Buchanan, 2005; Cheng & Wang, 2012; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Pan, 2016; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012)
Theorem proving	(Brunette et al., 2009; Buchanan, 2005; Cheng & Wang, 2012; Flasiński, 2016; Oke, 2008; Pan, 2016; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012)
Problem solving	(Bai, 2011; Brunette et al., 2009; Buchanan, 2005; Flasiński, 2016; X. Li & Jiang, 2017; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012; Qi Zhang et al., 2010)
Natural language processing and understanding	(Bruderer, 2016; Buchanan, 2005; Cheng & Wang, 2012; Flasiński, 2016; Min, 2010; Oke, 2008; Russell & Norvig, 2010; Tecuci, 2012)
Genetic algorithms	(Bai, 2011; Brunette et al., 2009; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Russell & Norvig, 2010; Tecuci, 2012)
Knowledge representation	(Buchanan, 2005; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Oke, 2008; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012)
Fuzzy logic	(Bai, 2011; Brunette et al., 2009; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012)
Learning	(Bai, 2011; Buchanan, 2005; Cheng & Wang, 2012; Flasiński, 2016; Min, 2010; Russell & Norvig, 2010; Tecuci, 2012)
Speech recognition	(Bai, 2011; Brunette et al., 2009; Flasiński, 2016; X. Li & Jiang, 2017; Pfeifer & Iida, 2004; Russell & Norvig, 2010)
Gaming	(Bai, 2011; Cheng & Wang, 2012; Flasiński, 2016; Min, 2010; Russell & Norvig, 2010; Tecuci, 2012)
Expert systems	(Cheng & Wang, 2012; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Oke, 2008; Tecuci, 2012)
Pattern recognition	(Bai, 2011; Flasiński, 2016; X. Li & Jiang, 2017; Min, 2010; Pan, 2016; Russell & Norvig, 2010)
Knowledge acquisition	(Flasiński, 2016; X. Li & Jiang, 2017; Pan, 2016; Russell & Norvig, 2010; Tecuci, 2012)
Constraint satisfaction	(Brunette et al., 2009; Flasiński, 2016; Oke, 2008; Russell & Norvig, 2010; Tecuci, 2012)
Machine vision	(X. Li & Jiang, 2017; Pfeifer & Iida, 2004; Russell & Norvig, 2010; Tecuci, 2012)
Knowledge-based systems	(Buchanan, 2005; Flasiński, 2016; Russell & Norvig, 2010; Tecuci, 2012)
Data mining	(Bai, 2011; Oke, 2008; Pfeifer & Iida, 2004; Russell & Norvig, 2010)
Decision making	(Bai, 2011; Flasiński, 2016; Russell & Norvig, 2010)

One of the problems in AI research is that different terms and fields are often discussed without providing an organized view. Few authors have suggested models or frameworks to deal with this issue. Flasiński (2016) organizes subfields to methods and application areas. Methods, such as algorithms focus on achieving the intelligent computing. Application areas, such as natural language processing and pattern recognition are the outcomes of intelligent computing. Classification to only either one is not mandatory, as some fields, such as reasoning, is both a method and application. (Flasiński, 2016.)

X. Li and Jiang (2017) propose a four-layer framework to organize the research of AI. Authors acknowledge that this illustration is not adequate enough to describe all fields in AI research, but is helpful in providing an overview (Li & Jiang, 2017). While AI lacks a well-established definition, spans to multiple different fields of sciences and consists of numerous individual subfields, AI calls for a framework to categorize the research.

Framework by X. Li and Jiang (2017) is complemented with recommendation systems on the application technique layer. It has to be noted that in reality the boundaries of fields are not as strict as one could derive from the illustration, as application areas can embody characteristics from other areas. Framework categorizing AI fields is illustrated in FIGURE 1.

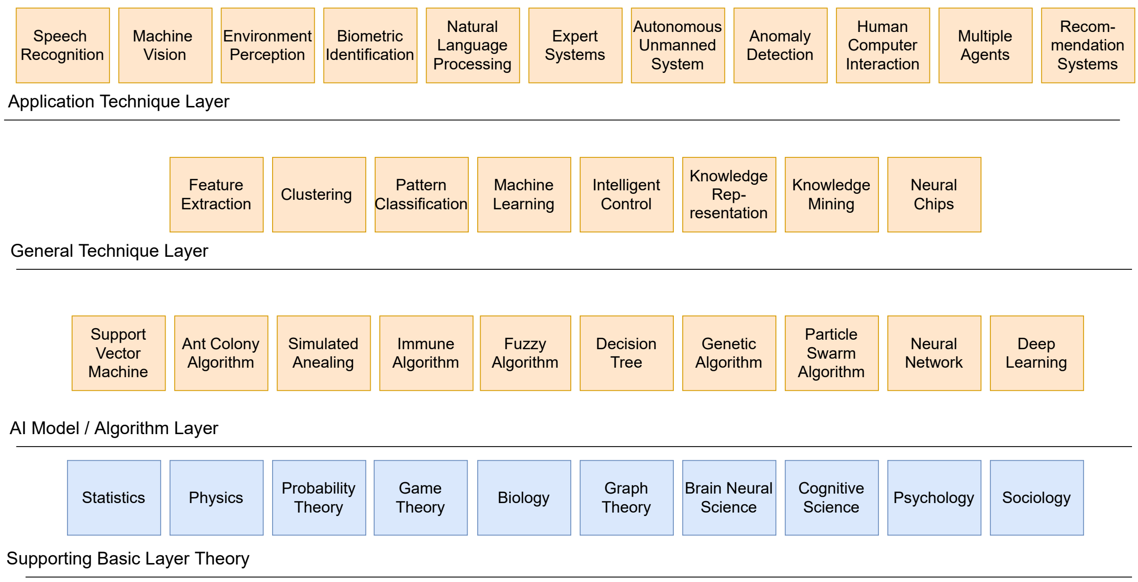

FIGURE 1 Framework of AI fields, adapted from X. Li and Jiang (2017)

To form a framework depicting system features and associated value propositions, four subfields were chosen to be continued with to the empirical part of the Thesis. Subfields were synthesized from FIGURE 1 and TABLE 2.

These four fields were chosen due to particular reasons. They represent entities from application technique layer, which we are interested in. Machine vision, expert systems, speech recognition and natural language processing represent most active subfields identified from the literature, despite some entities from other layers have had more research interest.

Additionally, it can be argued that chosen subfields are most relevant for eCommerce. As Song, Yang, Huang & Huang (2019) describe, applications of AI on eCommerce are culminated to following aspects: chatbots, recommendation engines, applications for intelligent logistics and pricing. Selected subfields are concerned with previously mentioned aspects. In the following TABLE 3 we capture the AI attributes the subfields of AI, and present the perceived benefits related to each attribute. Recommendation systems will be introduced on next chapter, thus not added to this table.

TABLE 3 AI values mapped to AI features

Subfield	**AI feature**	**Value**
Speech Recognition	verbal communication between humans and computers / robots (Bai, 2011; Flasiński, 2016)	have computers understand us, natural use of computers (Bai, 2011), non-human conversant assistants (Bruderer, 2016)
	automatic translation (Brunette et al., 2009; Flasiński, 2016)	automating a routine task (Brunette et al., 2009; Russell & Norvig, 2010)
	recognizing features of speech (Flasiński, 2016)	recognizing human mood (Flasiński, 2016)
	speech to text conversion (X. Li & Jiang, 2017)	improves human-computer interaction (X. Li & Jiang, 2017)
	speech system as an interface to IS (Pfeifer & Iida, 2004; Russell & Norvig, 2010))	interacting without the need of hands (Russell & Norvig, 2010)
	single word commands (Pfeifer & Iida, 2004)	producing text rapidly without the need to type (Pfeifer & Iida, 2004)
Machine Vision	recognize elements from image and video (X. Li & Jiang, 2017)	optical character recognition, optical quality control, analysis of images, understand elements (Flasiński, 2016)
	ability to percept the environment (Flasiński, 2016)	
Natural Language Processing	understand semantic meanings from natural language such as text (Li & Jiang, 2017)	ability for machines to communicate with humans, answer questions and learn (X. Li & Jiang, 2017)
	chatbot simulating a human (Flasiński, 2016)	simulate intelligent conversation (Flasiński, 2016)
Expert System	system possessing the same information that humans have in the field (Flasiński, 2016)	support decision-making process (Flasiński, 2016)
	integrate interrelated decision-making processes and form a knowledge base (Min, 2010)	select optimal warehouse picking order, predict end customer demand, manage logistics, inventory and purchasing more efficiently (Min, 2010)
	use human-like reasoning and information techniques (Oke, 2008)	solve a narrow set of problems, optimize production level automatically (Oke, 2008)
	human expertise in problem solving (Flasiński, 2016; X. Li & Jiang, 2017; Tecuci, 2012)	theorem proving, medical diagnosis (X. Li & Jiang, 2017), solve problems in specific area (Tecuci, 2012)
	system with even small amount of knowledge (Buchanan, 2005)	enables intelligent decision-making (Buchanan, 2005)

3 RECOMMENDATION SYSTEMS

This chapter discusses recommendation systems. Relationship of AI and recommendation systems is described to connect two stems of research together. Definition of recommendation systems will be given, following with an introduction of different types. Recommendation process will be described by three step process introduced by Adomavicius and Tuzhilin (2006). Last, firm-level impact of recommendation systems is discussed.

3.1 Relationship of recommendation systems and AI

Recommendation systems are fundamentally applications of AI due to two particular reasons. First, recommendation system research has confluences with AI research. According to Ricci & Werthner (2006) recommendation systems are intelligent applications assisting in decision-making process, where users do not have enough experience to choose items from a large set of similar or alternative items. Research has typically overlapped numerous topics, but initially research initiated from information retrieval and AI (Ricci & Werthner, 2006). In the past, AI community has had great effort trying and solve decision-making issues with AI through personalization, intelligent agents and recommendation systems (Montaner, López & De La Rosa, 2003).

Second, recommendation systems utilize algorithms from the general technique layer of AI. According to Portugal, Alencar & Cowan (2018) recommendation systems use more and more AI methods to provide recommendations. Especially machine learning algorithms are responsible of the great progressive step recommendation systems have made (Portugal et al., 2018).

Zhang, Lu & Lian (2021) identify two application areas – machine vision and natural language processing to be present in recommendation systems. These application areas combined with deep learning have produced outstanding performance for recommendation systems. With natural language processing it is possible to benefit from text information of the items. Machine vision has been valuable in areas such as fashion, where items are highly linked with their visual appearance. AI techniques have enabled recommendations to have higher quality than conventionally, propelling a new era for recommendation systems (Zhang et al., 2021.)

3.2 Definitions for recommendation systems

Recommendation systems are a multi-disciplinary effort, which is tied to various computer science fields (Ricci, Rokach & Shapira, 2011). As with AI, also research of recommendation system is fragmented. Terms used to describe recommendation system research are not formalized.

Sometimes recommendation systems are referred to as being personalized systems. Picault, Ribière, Bonnefoy and Mercer (2011) discuss personalized systems and state that such system consists of multiple interacting parts, data processing methods, algorithms, user models, filtering techniques and metrics, which result in different personalization levels. In short, the personalized system ingests data and then presents results to the end users. In a real-world such a system can be a recommender, that is a piece of some larger and more complex environment. (Picault et al., 2011.) When referring to recommendation systems, terms such as personalization systems or recommender systems can be used. In this Thesis the term recommendation system is used.

According to Ricci et al. (2011) recommendation systems consist of software tools and techniques which provide useful suggestions to users. Suggestions are ultimately aids for decision making process – suggestion can be music to listen, online news to read or an item to buy (Ricci et al., 2011). Pu, Chen and Hu (2012) describe recommendation systems to be interactive and adaptive, which often are crucial components of any online service. Recommendation systems can provide decision support for users, such as recommend a book of interest. This way, recommendation systems are ultimately personalization technologies. (Pu et al., 2012; S. S. Li & Karahanna, 2015.)

According to Burke (2002), recommendation systems provide recommendations for users when the space of options is large. Recommendation systems are valuable when the amount of information is outstanding to users capability to process it. (Burke, 2002.) One environment where recommendation systems are fundamental parts is eCommerce (Burke, 2002). Amazon.com and eBay are examples of eCommerce sites utilizing recommendation systems (Schafer et al., 1999). For eCommerce recommendation systems are not novelties, but business tools which are reshaping the field of electric business (Schafer et al., 1999).

Recommendation systems collect preferences and recommend tailored products or services (S. S. Li & Karahanna, 2015). On eCommerce they help customers find relevant products to purchase by recommending them (Burke, 2002; S. S. Li & Karahanna, 2015; Matt, Hess & Weiß, 2013; Schafer et al., 1999). They can base recommendations to overall sellers on a site, demographics of a customer, or by analyzing buying behavior of customer (Schafer et al., 1999). They use algorithms to recommend selected relevant items to customers from a large inventory of products (Matt et al., 2013). Distinguishment of recommendation systems is usually approached by dividing methods to content-based filtering, collaborative filtering and hybrid filtering (Adomavicius & Tuzhilin, 2006).

3.3 Types of recommendation systems

In content-based filtering, user is recommended products which are similar to those the user has preferred earlier (Adomavicius & Tuzhilin, 2006). To gain information earlier users ratings are used (Adomavicius & Tuzhilin, 2006; Burke, 2002). Items which have similarities with items which user has preferred earlier are recommended (Adomavicius & Tuzhilin, 2006). Nowadays content-based approach is the most widely adopted method since customers transaction information can be collected effortlessly (S. S. Li & Karahanna, 2015).

There are some problems and pitfalls with content-based approach. Using content-based approach requires well-structured data in high quality and quantity. According to Picault et al. (2011) ability to distinguish items from another depicts the data quality. Quantity of data requires balancing – too few leads to inaccurate recommendations and too great requires additional processing (Picault et al., 2011). Matt et al. (2013) mention characteristics of products which are hard to classify or describe as one challenge with content-based approach.

Content-based approach is not that powerful in making cross-sell recommendations. (Matt et al., 2013.) Burke (2002) discusses cold start problem, which can only be avoided by having enough ratings before making recommendations. Portfolio effect, meaning that already bought items are recommended, is apparent. Ramp-up problem can be painstaking too, as once the user profile is built, changing preferences can be hard. (Burke, 2002.)

Collaborative filtering is the second most discussed approach. Adomavicius and Tuzhilin (2006) describe that with this approach items are recommended to customer based on preferences with people of same taste. Collaborative filtering relies on the closest persons, those that have the highest similarity of preferences. Once closest persons have been established, collaborative approach recommends items that are most liked among them. Collaborative approach uses also ratings as a feedback. Some techniques only rely on ratings, whereas more advanced techniques rely also on the demographic attributes of the customers, for example age or gender. (Adomavicius & Tuzhilin, 2006.)

According to X. Li and Jiang (2017) collaborative filtering bases recommendations on three assumptions: people having preferences that can be compared, preferences are stable, and choice of these people can be concluded from their past preferences. For a customer, closest persons with similar preferences are called neighbors. By past behavior of neighbors, we can conclude recommendations for this customer for the future. Amazon is famous for successfully applying collaborative filtering for their recommendations. (X. Li & Jiang, 2017.)

X. Li and Jiang (2017) state that collaborative filtering has been developing rapidly, and the improved algorithms provide nowadays accurate recommendations. These algorithms can be divided to user-based and item-based. User-based approach supports the neighbor-mindset. When we compare users, we can find groups of similar preferences, called neighborhoods. From the neighborhood, closest neighbor is used to provide accurate recommendations. It's possible, however, to select an insufficient neighborhood. It will result in inaccurate recommendations. Item-based has the opposite approach, as it first analysis relationships between users and items. It then compares features, attributes and items, ending up calculating recommendations for users based on the similarities between items. (X. Li & Jiang, 2017.)

X. Li and Jiang (2017) point out that collaborative filtering suffers from fake ratings which exist in large counts on eCommerce. Cold-start problem is also evident. If user has not rated anything, collaborative filtering does not have any input for preferences. (X. Li & Jiang, 2017.) If the quality of item data is lacking, collaborative approach can provide accurate recommendations as ratings are used (Pu et al., 2012).

According to Adomavicius and Tuzhilin (2006) hybrid approach combines collaborative and content-based approaches. Hybridization can be achieved in two ways, either have both collaborative and content-based approaches implemented and combine the resulted recommendations. Another way is to have one recommendation model, that uses both of these techniques. Despite hybrid being more advanced recommendation technique, it uses the same data to recommend items. This data can consist from demographic attributes and ratings of the customer and product data, such as keywords. (Adomavicius & Tuzhilin, 2006.)

Konstan and Riedl (2012) point out that hybrid approach could, for example, recommend items which have high ratings but are also popular. This approach would combine best of both worlds, as popularity alone does not reflect individual user's preferences well enough and individual ratings can result in obscure recommendations. (Konstan & Riedl, 2012.) Picault et al. (2011) argue that the use of hybrid methods can be powerful, but at the same time emphasize quality of data – poor quality can lead to medium recommendations, even though algorithms would be well over sufficient.

3.4 Recommendation process

Adomavicius and Tuzhilin (2006) describe personalization process and divide it into a cycle of three steps consisting of six different stages. Steps are understanding the consumer, delivering personalized offerings and measuring the impact of personalization. This forms personalization process cycle (Adomavicius & Tuzhilin, 2006.)

According to Adomavicius and Tuzhilin (2006) understanding the consumers requires gathering data and turning data into actions of knowledge. Deliver personalized offerings refers to the process of finding the relevant items, and then presenting them to customers. Measuring the impact means measuring how satisfied the customer is with the personalized items. By measuring satisfaction, it is possible to collect more information from the customers and then enhance the personalization even more. (Adomavicius & Tuzhilin, 2006.)

Adomavicius and Tuzhilin (2006) point out that measuring the satisfaction usually happens through gathering feedback, which serves as an additional information to provide possible improvements for different delivered personalized components. Different stages in personalization process are data collection, build consumer profiles, matchmaking, delivery and presentation, measuring personalization impact and adjusting personalization strategy. (Adomavicius & Tuzhilin, 2006.)

Adomavicius & Tuzhilin (2006) state data collection as the step where the process begins. Here information is gathered from the customer across various possible streams. This data can be collected either explicitly with surveys, or implicitly through the consumers past behavior, purchase history or searching activity. This implicitly collected information also contains demographic or psychographic data about the customer. (Adomavicius & Tuzhilin, 2006.)

According to Picault et al. (2011) possibilities for implicitly collected data are almost limitless – for example geographic location data can be used to recommend items from local area of customer. Temporal factors, such as timing is one type of implicitly collected information, there is a lot of potential in understanding the correct timing of the recommendations. For example a customer can watch news on a train to work, and something else such as comedy on the way home. (Picault et al., 2011.)

S. S. Li and Karahanna (2015) mention that social network information can utilized when recommending products, as for example Amazon has a page that recommends products based on customers' Facebook friends. The foundation for such recommendations is on the social profiles of the friends, which presumably are similar to the profile of the customer. (S. S. Li & Karahanna, 2015.)

In reality, the availability of information is so large in quantity, that it is not realistic to use all that to build profiles. Merchants need to select the most relevant sources of data, that in suitable level enable them to understand the customers. (S. S. Li & Karahanna, 2015). Collected data is processed so that it is made heterogenous for processing, and a model from the consumer is built. This is also called building consumer profiles. (Adomavicius & Tuzhilin, 2006.) Data collection in the personalization process cycle is on the bottom, as illustrated in FIGURE 2.

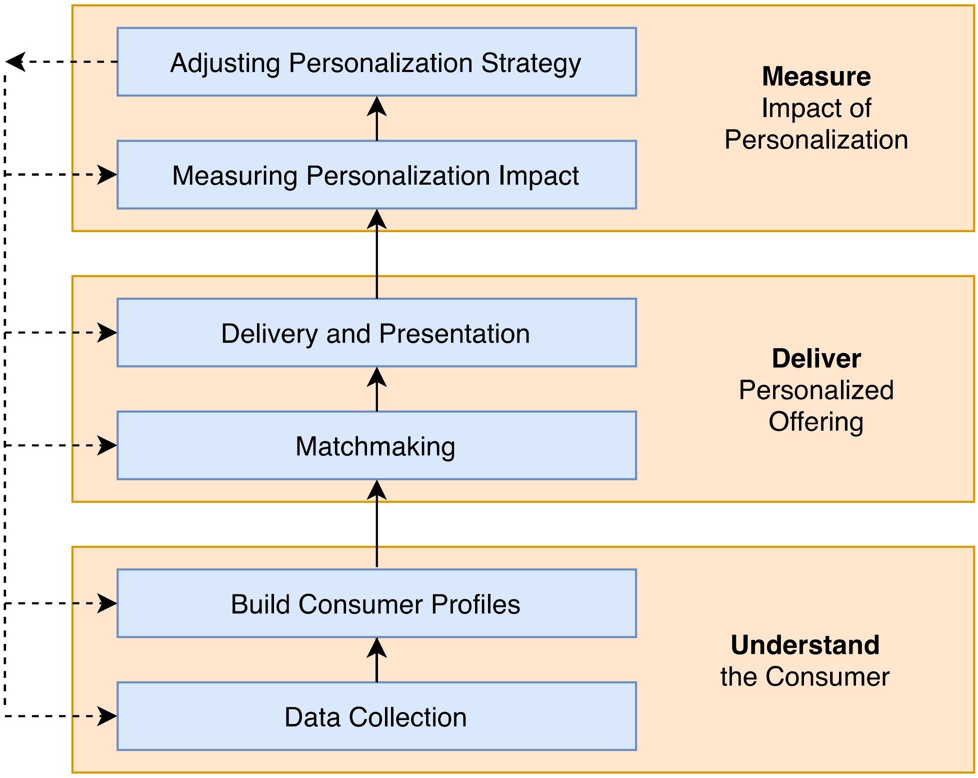

FIGURE 2 Personalization process, by Adomavicius and Tuzhilin (2006)

Building consumer profiles is about creating comprehensive model about the customer. Adomavicius and Tuzhilin (2006) propose three techniques to build profiles – rules, sequences and signatures. Rule is something that is known about the customer – for example that the customer enjoys certain types of products. Sequences are series of actions carried by the customer, for example customer purchasing certain types of products during some period of time in the year. Signature is about enhancing the profile built from the customer, for example listing five favorite products of this customer during some period of time in the year. (Adomavicius & Tuzhilin, 2006).

Pu et al. (2012) describe this process as preference elicitation, which is combination of data collection and model building. It consists of making predictions of the customers' interests by observing the customer (implicit mode) and customers rating, purchasing, selecting and rating behaviors. In explicit mode preferences are elicited through customers stated preferences. (Pu et al., 2012.)

Matchmaking enables systems to provide relevant content or offerings to customers. For matchmaking different techniques are available. According to Adomavicius and Tuzhilin (2006) some of these techniques can are user-specified rule-based content delivery systems, statistic-based approaches and recommender systems. Authors focus on recommendation systems, and divide different approaches to previously introduced content-based, collaborative and hybrid recommendation approaches. (Adomavicius & Tuzhilin, 2006.)

Adomavicius and Tuzhilin (2006) classify delivery and presentation of personalized offerings to pull, push and passive methods. On top-level, be the classification of delivery any of the presented, end result is that customer is offered offerings in various different forms of visualization, such as a list ordered by relevance. (Adomavicius & Tuzhilin, 2006.)

According to Pu et al. (2012) layout of recommender systems is relative to computer screen, where on the right-hand side a longitudinal list of recommendations is presented, such as in YouTube, or a vertical latitudinal list on the bottom of the screen, such as in Amazon. Sometimes lists can be presented together with the item of interest that the user is currently inspecting, but not always. This is called a grid-view, that is adopted by some commercial websites such as Asos. (Pu et al., 2012.)

In the central focus of research on delivering recommendations is to understand and design a system, that presents offerings in a way that enables customers to understand and perceive the recommendations with ease (S. S. Li & Karahanna, 2015). According to Pu et al. (2012) usually this is aided by labels, such as "recommendation for you", "customers who bought this also bought", or "customers who viewed this also viewed". Another factor is to introduce transparency to explain why the offerings are recommended, such as "because you purchased". Merchants should also consider a balance on the saturation of the recommended items, so that at least some items are familiar, while also keeping a diversity in the recommendations. There is a need for balancing the size of recommendations – some studies indicate that one item is too less, whereas more than five can increase the customer's choice difficulty. It's not that simple though, as showing more can positively affect to perception of diversity. (Pu et al., 2012.)

Various metrics should be used in measuring personalization impact. Metrics can measure accuracy of recommendations, or measure the impact to consumers value, loyalty and experience (Adomavicius & Tuzhilin, 2006). In the past correctness metrics, which measure how precise and accurate recommendations are, were used to technically evaluate algorithms (Konstan & Riedl, 2012).

Jiang et al. (2019) discuss algorithm evaluation metrics and point out that there are many indications for them. Most classical and well-adapted metric is mean absolute error (MAE), that measures the average error of actual rating and the predicted rating. Smaller MAE would mean more accurate predictions. (Jiang et al., 2019.)

According to Konstan and Riedl (2012) the emergence of business applications shifted evaluation and measuring recommender systems towards more business-oriented perspective. Metrics measuring MAE alone were not in the interest of research projects of business applications. What was more interesting, was the response for the business through the recommender systems – how much recommender systems were able to convert recommendations into sales, for example. This more human-centered approach did not however remove the concern regarding prediction, and for example Netflix still brought data scientists, researches and machine learning experts into the field to focus solely on the prediction accuracy. (Konstan & Riedl, 2012.) According to Chen & Pu (2009) researchers have recently turned their focus on to perceived accuracy, which is claimed to have more influence on the customers' trust and intention to return to the system.

Presented lifecycle as described by Adomavicius and Tuzhilin (2006) ends to adjusting personalization strategy. On this step, in ideal state a virtuous cycle of personalization is achieved. Feedback gathered from previous measurement step is properly integrated into the process to provide improvements for the recommendations. This improvement happens through deciding how the recommendations can be developed to be better – it could be achieved for example through building better profile, gathering more data, switching the matchmaking algorithm or by paying attention to the delivery of the personalized offerings. If feedback is not integrated properly, a de-personalization can happen. Trust in the system decreases and in the worst case customers stop using it. (Adomavicius & Tuzhilin, 2006.)

3.5 Firm-level impact of recommendation systems

In an extensive literature review S. S. Li and Karahanna (2015) conclude that numerous studies have been conducted about understanding how recommendation systems affect consumers focus, beliefs and behavior. Some studies carefully take into account different types and features of recommendation systems, while some studies consider recommendation systems as a black box, meaning it either exists or not. A limited number of studies examine the market-level impacts of recommendation systems, and the findings are yet debatable. All in all, impacts of recommendation systems has gained a lot of interest on the literature, but some areas are yet missing, such as the firm-level impact. (S. S. Li & Karahanna, 2015.)

Despite the firm-level not having a thorough exploration on the literature, there are benefits why eCommerce businesses provide recommendations for their customers, such as increased customer loyalty, increased financial revenues and sales (S. S. Li & Karahanna, 2015). Ricci et al. (2011) identify four different reasons, why eCommerce businesses should be offering personalized recommendations. They are following: increase the number of sold items, diversifying sold items, increase user satisfaction, increase user fidelity and gain better understanding what the consumer wants. (Ricci et al., 2011.)

Ricci et al. (2011) argue that increasing sold items is one of the most obvious and important factors on why recommendation systems are used. By recommending personalized products eCommerce sites suit better customer's needs compared to situation where there would be no recommendations at all. For businesses utilizing a recommendation system is a way to increase conversion rate. Improved conversion rate practically means that more users are buying items rather than just browsing the site. (Ricci et al., 2011.)

Diversifying sold items is an interesting and studied factor on recommendation systems research. Matt et al. (2013) found in their study that both content-based and collaborative filtering techniques increase sales diversity of items. Since products can be recommended not only by their popularity but the similarity of product characteristics, less likely purchased niche products can be recommended increasing the products effectiveness. (Matt et al., 2013.) These items can also be hard to find if they are not precisely recommended (Ricci et al., 2011). So called "long tail" items can be in the heart of many eCommerce companies business models, and recommendation systems can make these hard to find, lesser known items easily accessed for each customer in a tailored recommendation (Picault et al., 2011).

According to Ricci et al. (2011) user satisfaction is widely acknowledged benefit of recommendation systems. When users find recommendations interesting and relevant, they enjoy using the site. Precise, relevant and usable recommendations will positively affect to the evaluation of the system (Ricci et al., 2011). Positive evaluation of the system contributes to the customers' readiness of accepting recommended products (Konstan & Riedl, 2012; Ricci et al., 2011). Even though inaccurate recommendations lower customers' perception of the effectiveness of the system, customers might not be able to identify the reason (Konstan & Riedl, 2012). The goal that matters in the end is the user satisfaction (Picault et al., 2011).

Ricci et al. (2011) discuss that users are more loyal to sites that treat them as valuable visitors. Customers return to those services, which they find match best their needs (Picault et al., 2011). According to Ricci et al. (2011) when a site provides personalized recommendations to users, users tend to spend more time on the site and become more loyal. Increased fidelity leads to increased time in interacting with the site. User model will be refined the more user spends time on the site. Refining leads to more accurate personalized recommendations. (Ricci et al., 2011.) Understandably, loyal users are valuable to businesses.

Last, Ricci et al. (2011) point out understanding customers and their needs. Some businesses, by leveraging recommendation systems, are able to collect preferences from their customers. By understanding their customers, businesses can use this knowledge in their aid in other areas. (Ricci et al., 2011.)

4 CREATING AND PROPOSING VALUE

In this chapter we define value, value creation, value propositions and value co-creation. These terms are described in information systems context. Value itself is at the very core of economic exchange, but the definition of the term can be rather elusive (Vargo, Maglio & Akaka, 2008).

4.1 Value, value creation and value propositions

It can be argued that the main function of the businesses today is to create value. The term has ancient roots, dating back to 4th century BC, when Aristotle first considered the meaning of value (Vargo et al., 2008). Core construct of value has remained same, but alternative views have been proposed. Alternative views have made the term problematic as it is used to refer to different phenomena (Bowman & Ambrosini, 2000).

It was Aristotle who made the effort to distinguish its two meanings, value in-use and value in-exchange (Vargo et al., 2008). Many authors have later accepted the same distinguishment (Bowman & Ambrosini, 2000; Grönroos & Gummerus, 2014; Kowalkowski, 2011; Lusch & Vargo, 2006; Vargo et al., 2008). There can be multiple approaches when discussing value, but value distinction to in-use and in-exchange is commonly used to clarify the subject in hand.

According to Vargo et al. (2008) value in-exchange (or exchange value) represents more traditional view on value. It is related to the goods-dominant (G-D) logic, where value is seen as something that the manufacturer creates and then distributes to the market, or customers. Value is then exchanged to something, which usually is money. (Vargo et al., 2008.) Bowman and Ambrosini (2000) explain value in-exchange to refer to money, more specifically to the price of the goods. Exchange-value is realized when the goods are sold. Amount of exchange value is the amount of the money paid by the customer. (Bowman & Ambrosini, 2000.)

The amount paid is reflected from the value in-use (or use value), which is also called the perceived value (Bowman & Ambrosini, 2000). It refers to qualities, quantities and relationships of the goods, or services, that are exchanged (Vargo et al., 2008). Qualities are always subjective to individual customer, they are specific features which are related to the need customer need (Bowman & Ambrosini, 2000; Vargo et al., 2008). Vargo et al. (2008) explain that cars, for example, have different qualities, such as the color or sportiness and relationships, such as owning or leasing the car. These features are perceived by the customer, and different customers value, or need different qualities (Vargo et al., 2008).

Like value, also the term value creation is used in a way which frequently causes misunderstandings. Grönroos and Ravald (2011) state that the term is used to refer to the process of creating value from customers perspective, leading to the interpretation that the customer is the only one creating value. Often customer is seen as the co-creator of value, so that the value is created by the customer, but arising from the processes (e.g., developing or manufacturing) of the supplier. It is safe to say that value creation isn't heterogenous and when describing value creation the individual setting must be taken into account. (Grönroos & Ravald, 2011.)

According to Bowman & Ambrosini (2000) value creation from supplier's side refers to processes which turn resources into value. Individual resource, such as machine, computer, or information itself, is considered to be nothing but what it fundamentally is. These resources turn into use value when work is put on them. However, when the resources turn into use value, it is possible that there is no added exchange value. Exchange value is realized only when the consumer exchanges the goods or service to money. (Bowman & Ambrosini, 2000.)

Ambiguity of the terms continues to value proposition. Term can be seen in various ways, but ultimately value proposition is a promise made by the supplier that the customer is able to obtain value from the offering (Grönroos & Voima, 2013). According to Ordanini and Parasuraman (2011), value propositions are the only things firms can offer. This implies that customer is always the value creator (Ordanini & Parasuraman, 2011). Grönroos & Voima (2013) argue that based on service logic, firms can go beyond making value propositions. Firms aren't bound to it, as they can also influence the customers' value creation actively and directly (Grönroos & Voima, 2013).

Peffers et al. (2003) have argued a theoretical basis for the linkage between values and system features. It follows personal construct theory developed by George Kelly (Kelly, 1955). Personal construct theory has relationship of attributes, consequences and values. Personal construct theory applied to information systems essentially denotes that system has features and attributes, which in turn have consequences. Consequences always have some values for the assessor. (Peffers et al., 2003.) Practically, this view enables to derive value propositions from system features.

4.2 Co-creation of value

According to Vargo et al. (2008) service-dominant (S-D) logic, which refers to value in-use, captures a common view on value co-creation. Value is co-created mutually through the relationship between firm and customer. Take for example a car, it would have no value if people did not have access to resources necessary for operating a car, such as gas, or simply did not know how to drive. In this scenario, manufacturers are actively applying their resources on creating the car valuable, for example offering service. Meanwhile customers apply their knowledge on using the car on their daily lives. (Vargo et al., 2008.)

Vargo and Lusch (2004) argue that value is the result of application of resources, which are transmitted to customers through operand resources or goods. This view implies that co-creation is a joint effort of companies, employees, customers and all other relevant stakeholders related to the exchange. To take a step further, authors argue that customer is the always the one that determines the value. (Vargo & Lusch, 2004.) Vargo et al. (2008) later argue, that value does not exists until the value offering is used. Using value offering is tied into experiences and perception, that determines how customer assesses the value. (Vargo et al., 2008.)

Prahalad & Ramaswamy (2004) have a similar approach on value co-creation. They take the example of a video game. A video game could not exist without active consumers who co-create the value. A more classical example can be found from agriculture and in John Deere's network, which calls farmers to share experiences and to open up a dialogue with the company. It is believed to increase productivity of the company. eBay and Amazon are examples of companies co-creating value by offering personalized offerings, involving customers and facilitating conversation. (Prahalad & Ramaswamy, 2004.)

Prahalad & Ramaswamy (2004) argue that value co-creation is a whole new notion. It's a shift from firm-centric view to a more holistic idea of value creation. It's not about pleasing customers, having a customer-centric attitude or involving customers to activities by outsourcing or transferring tasks to them. Co-creation as a holistic idea emphasizes co-creation of value through the interaction between firm and the customer. Interaction needs to be personalized to suit each individual's wants and needs on the interaction with the company. Each and every interaction point between the company and customer is a critical point in co-creation of value. (Prahalad & Ramaswamy, 2004.)

According to Vargo et al. (2008) for service systems value creation happens through proposing, accepting and evaluating value. Value propositions made by firms can be either accepted or rejected. Propositions can also go unnoticed. Services can be provided directly or indirectly, depending on the nature of the service. Take for example a tax service, where preparing a tax return is direct and offering a software related to taxes is indirect. Proposed value can then be assessed by customers – some customers go for direct service and some opt for indirect service. Ultimately, firm proposing the value has applied competence and resources before customer is able to realize the value from the proposition. (Vargo et al., 2008.)

4.3 Conceptualizing value co-creation

S-D logic differs from G-D logic. According to Payne, Storbacka and Frow (2008) S-D logic suggests that products are not organizers of new opportunities, but rather the experiences of the customer are. Customers experiences suggest relevant meanings over the period of time. This difference can be seen in marketing where focus has turned from designing meaningful products to emphasizing the relationship between the customer and the supplier. In S-D logic customers are the ones that can co-develop and be active players. Customers are able to have an effect on their relationships with suppliers. (Payne et al., 2008.)

Shift to S-D logic has resulted in various efforts on conceptualizing value. Payne et al. (2008) approach value creation through three main components: customer and value-creating processes, supplier value-creating processes and encounter processes. Customer value-creating processes refer to practices, resources and processes, which are used by customers to manage activities of value-creation. On business-to-business context these are carried by customer organization in order to manage relationship and do business with the supplier organization. (Payne et al., 2008.)

According to Payne et al. (2008) supplier-value creating processes aim to achieve same goal as the customer processes, but they are additionally targeted towards other relevant stakeholders. Encounter processes are in-between. Interaction and exchange of two organizations embody in these processes. They are managed by both of the companies for developing prolific value co-creation opportunities. (Payne et al., 2008.) FIGURE 3 illustrates this conceptualized framework for value co-creation.

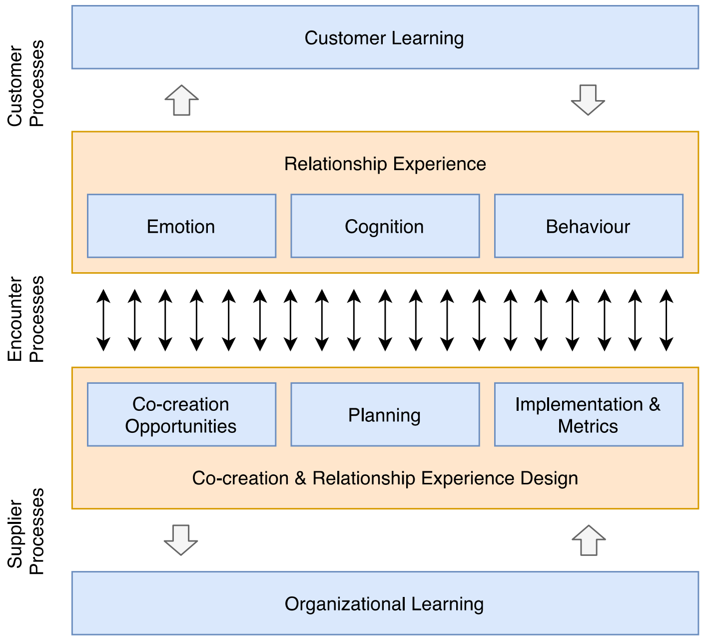

FIGURE 3 Framework for value co-creation as Payne et al. (2008)

Payne et al. (2008) describe that the set of processes on the framework are connected, and co-creation is recursive in the nature. In the middle of the figure, there are arrows which are encounter processes. Encounters are interactive, this is represented by arrows pointing in both directions. On both sides arrows between relationship and learning indicate that these two subjects are tied together – both parties are actively learning from the relationship experiences. By learning supplier is able to offer improved experiences in the relationship, thus enhancing co-creation. Meanwhile customer learning impacts on how customer engages with co-creation activities. (Payne et al., 2008.)

Payne et al. (2008) remind that this framework can be seen in both theoretical and practical perspective. From theoretical point of view this framework integrates multiple key areas of work from S-D logic. It contributes to the roles of supplier and customer by highlighting how value is created together and what the core factors are. This framework highlights the importance of relationship experience. (Payne et al., 2008.)

Grönroos and Voima (2013) approach value and co-creation in order to provide a theoretically sound foundation for them. Authors analyze nature, scope, and locus. Grönroos and Voima (2013) proceed to identify roles for both service providers and customers, and interestingly to great lengths, their approach identifies similar components as the framework by Payne et al. (2008).

Grönroos and Voima (2013) define value creation solely as customer's actions of creating value in-use, while co-creation is the interaction in-between. The interaction in-between can be either direct or indirect. The interaction happens between three spheres, that are provider, joint and customer, illustrated in FIGURE 4. Their conceptualization emphasizes interactions in the value co-creation opportunities, and suggest managerial implications for value co-creation. (Grönroos & Voima, 2013.)

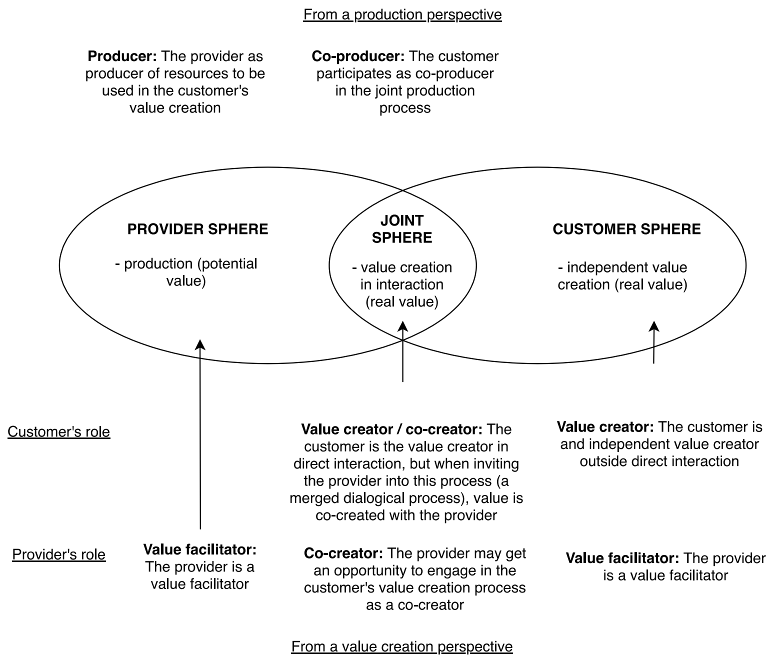

FIGURE 4 Value creation spheres as Grönroos and Voima (2013)

Grönroos and Voima (2013) describe that spheres are to illustrate different varying roles of customer and supplier. On a top-level, firm is responsible of the production processes, and on its sphere, as a provider, produces resources and processes for the customer. This way, firm is the facilitator of customer's value co-creation. In the middle, on the joint sphere, customer plays greater role than the firm, but this sphere is not restricted from the provider. Here provider may have the ability to engage in the customer's value creation processes, thus take also the role of the co-creator. On the joint sphere, customer is both the co-producer of resources and processes, and also a value creator. Customer sphere is something that is tightly proprietary for the customer – this is where no interactions nor co-creation exists. On this sphere, customer creates value by in-use. (Grönroos & Voima, 2013.)

According to Grönroos and Voima (2013) it's important to notice, that the joint sphere is something that can widen and the process is not as linear, as this figure implies. Customer is able to be the co-designer, co-developer or co-manufacturer, where customer actively takes on the role of the value facilitator (Grönroos & Voima, 2013).

Grönroos and Voima (2013) argue that provider sphere is where potential value is generated. Value is facilitated for the customer for turning it into realized value in-use. Provider performs actions and utilizes resources to facilitate value in physical and virtual forms. Facilitation of value is not counted as a part of value in-use. (Grönroos & Voima, 2013.)

On joint sphere, Grönroos and Voima (2013) argue that through interactions customers can be in charge of the value creation, but provider is able to influence it and serve as a co-creator to some extent. Co-creation is only happening through these interactions, and nothing else. Without direct interactions there can't be co-creation. (Grönroos & Voima, 2013.)

This emphasizes similar actions as in the relationship-view proposed by Payne et al. (2008). Interactions are not a road to co-creation, but a platform for it. On the joint sphere, customers value-creation can be affected either positively or negatively, but in can also have no effect at all. There is a risk for value destruction, because provider is never able to have a holistic view of customers mental state or the situation customer is at a specific moment. (Grönroos & Voima, 2013.)

Joint sphere according to Grönroos and Voima (2013) is by far the most widest sphere of them all. Both customer and firm are able to move closer towards each other, as provider can ask the customer to be more active in the provider sphere actions. Customer can also cross boundaries without asking, which leads to a broadened sphere. Customer can contact for example contact providers management regarding service failures, where the actions carried by the provider can go both favorable and in-favorable directions in regard to customer's value creation. Also, provider is able to expand the sphere by proposing possibilities for the customer to contact the provider. Typically, though, joint sphere is dominated by the customer, but direct interactions can enable provider to influence value creation that is happening in the customer sphere. Joint sphere is dynamic and not at all fixed. (Grönroos & Voima, 2013.)

G-D logic according to Grönroos and Voima (2013) has traditionally emphasized the provider sphere and ignore customer sphere. S-D logic has brought a change to this, as customer sphere is seen to be sole independent sphere where value in-use is realized. Customer makes value creation possible by combining their resources and carrying out actions, to reach their individual, relational and collective objectives. Provider is able to indirectly affect the realization of value in-use, but the sphere itself is closed to the customer, and customer creates real value through the experiences, resources and processes. (Grönroos & Voima, 2013.)

4.4 Conclusion of the literature review

There are three parts in the literature review. This chapter discussed value, value co-creation and value propositions. Value typically has distinction of use value and exchange value (Vargo et al., 2008). Use value represents more abstract view on value. Use value is sometimes discussed as perceived value (Bowman & Ambrosini, 2000). Use value can refer to the quantities of goods and quality of services, which are always subjective to individual customer (Bowman & Ambrosini, 2000; Vargo et al., 2008).

Perceived quality of services is central sentiment to this study. In the digitizing world services are more frequently objects of exchange. Value is not typically realized on the moment goods are exchanged, but rather central in the relationship of the supplier and customer. This idea is also present in the case setting of this study.

It's important to understand how value is created and that it's not heterogeneous in all settings. Value is created mutually through the relationship of the supplier and customer (Vargo et al., 2008) and each relationship has specific premises which make it unique. This is called value co-creation. Value co-creation can be portrayed by three spheres – customer, provider and joint sphere (Grönroos & Voima, 2013). Boundaries for spheres are not explicit, but essentially each sphere has responsibilities and actions.

Value creation has three processes: proposing, evaluating and accepting value (Vargo et al., 2008). Value proposition is a promise for the customer that value can be obtained from the offering (Grönroos & Voima, 2013). Value is something that the supplier proposes, customer evaluates and either accepts or discards. Personal constructs theory is applied to explain the relationship between system features and value propositions. As Peffers et al. (2003) have indicated, value propositions can be led from system features. This study adopts the same view, thus enables us to investigate value propositions through the features of AI and recommendation systems.

Recommendation systems provide suggestions for users (Ricci et al., 2011). On eCommerce recommendation systems can provide personalized content, but more often they are used to recommend relevant products for customers. Recommendation systems can recommend products based on customers demographics, overall sellers on the site or by analyzing the behavior of the customer (Schafer et al., 1999). Aim of recommendation systems is to enable customers to find items to buy from a large catalog (Matt et al., 2013).

Literature body discussing value propositions of recommendation systems is thin. Recommendation systems have gained research attention, but research identifying the added value for eCommerce merchants is lacking. S. S. Li and Karahanna (2015) describe the firm-level impact of recommendation systems to be missing.

Literature review aimed to identify value propositions of recommendation systems by inspecting why and how eCommerce merchants should offer recommendation systems and how businesses benefit from utilizing them. In addition to increase in financial revenues (S. S. Li & Karahanna, 2015), literature review indicated that recommendation systems increase amount of sold items, increase user fidelity and user satisfaction (Ricci et al., 2011). According to Ricci et al. (2011) with recommendation systems businesses can gain data of what customers actually want. Recommendation systems optimize conversion rate and make niche products easier to find. (Ricci et al., 2011.) Matt et al. (2013) found out recommendation systems to increase sales diversity of items.

First part discussed AI. It went briefly through the history of the field, handed out key definitions for AI and formulated a framework depicting AI features and value propositions. Literature review identified most relevant subfields of AI for merchants to be speech recognition, machine vision, natural language processing and expert systems. Recommendation systems were not discussed together with AI as they are, in a sense, proprietary research area of its own. AI and recommendation systems research does still overlap. Despite recommendation systems to be own research area, it does not indicate recommendation systems to not be AI applications. Recommendation systems use technologies from general technique layer of AI, thus indicating the artificially intelligent nature of them.

AI chapter included a table, which maps AI features to AI values. This table was gathered as a result of the literature review. It aims to encapsulate features and associated values of different areas of AI. This framework is carried on to the empirical part of the research, where aim is to test if findings indicated by the literature review are present in the case setting. Empirical research tries to strengthen, discard and identify new relevant features and associated values of AI for eCommerce merchants.

5 METHODOLOGY

In this chapter research methodology is introduced. First research goal and method are presented. Chapter introduces case companies and continues to data acquisition and analysis.

5.1 Research goal

There are two research goals. First goal is to explore how AI applications create value for eCommerce merchants. Question is answered by identifying value creation elements and gathering features and values of AI applications. Second aim is to identify value propositions of recommendation systems. This issue is investigated by understanding how recommendation systems can successfully be implemented, what is the firm-level impact and how is it measured. By taking these goals into account, following research questions are formed:

- How artificial intelligence applications create value for eCommerce merchants?
- What are the value propositions of recommendation systems for eCommerce merchants?

It is in the interest to study the subject as firms offering services for eCommerce customers can gain competitive advantage by understanding how AI applications and recommendation systems create value for merchants. Subject is important theoretically too, as the firm-level impact of recommendation systems has not been widely studied. With AI little is known about the actual valuable features for eCommerce merchants.

5.2 Research method

To conduct the empirical part of the Thesis, qualitative case study was chosen as a research method. According to VanWynsberghe and Khan (2007) case study is often poorly defined despite being regularly invoked in many different areas of research. VanWynsberghe and Khan (2007) suggest that case study is ultimately a heuristic which includes careful selection of the phenomena for which evidence is collected. Case study does not have disciplinary orientation – it can be used in various different areas of research. (VanWynsberghe & Khan, 2007.)

Qualitative case study encompasses features from qualitative research method, but what differs is the approach to the research subject. On detailed level qualitative case study investigates one or more organizations or groups, and focuses to provide an analysis of the context and processes involved in the study, but without any specific requirements guiding it (Meyer, 2001).

In order to refer work as case study chosen method should be qualitative and small and research clinical, participant-observation or "in the field" (Yin, 1994). Gerring (2004) mentions that commonly a case study investigates single phenomenon but it has so many profound meanings, proponents and opponents that researchers do not have a coherent view. For this reason, Gerring (2004) argues that ultimately case study is intensive study, which focuses on one single unit for the sake of understanding a variety of similar units. Unit itself is a bounded phenomenon, observed for some period of time (Gerring, 2004).

Meyer (2001) stresses that case is a loose design, which includes numerous design choices including selection of cases, sampling time, areas of business and selection of data collection procedures. Gerring (2004) establishes and defines relationship of his definition to other definitions on the crowded semantic field. According to Gerring (2004), population consists of samples, referring to studied and unstudied cases. A sample consists of units that are observed. Observing a sample results to comprising a case. Case consists of dimensions, or variables, that are built from the observations. What is common for all these terms, is that they can be defined only when referenced to a particular research design. This implies that country can be case, unit, population or study. (Gerring, 2004.)

Qualitative nature of case study can be examined and explained through qualitative research method. According to Hirsjärvi, Remes and Sajavaara (2009) qualitative research method is often described by comparing it to quantitative research method. This is likely due to the fact that these two methods are often seen as opposite to each other. It is argued that this confrontation between the terms isn't advantageous, as it doesn't illustrate the continuum between the two. (Hirsjärvi, Remes and Sajavaara, 2009.) While the differences between them can be illustrated by comparing it should be done without pitting one against other (Hirsjärvi & Hurme, 2000). It should also be noted that even though the methods are seen as opposite, it is possible to integrate them and there is no need to draw a clear line between the two (Hirsjärvi & Hurme, 2000).

Qualitative research tries to understand the meaning, nature, and features of the research subject (Lähdesmäki, Hurme, Koskimaa, Mikkola & Himberg, 2009). The name of the method is sometimes criticized, as it can imply that the research is quality-wise stronger than quantitative. It is important to understand that no research can completely understand the subject despite the applied method (Saaranen-Kauppinen & Puusniekka, 2016).

According to Hirsjärvi & Hurme (2000) the emphasis in qualitative research is on the relationships between causes and effects, which are universal. Qualitative research aims to make generalizations, predict and give causal explanations about the subject. (Hirsjärvi & Hurme, 2000). Qualitative research is based on induction, meaning that conclusions are drawn from individual to general (Hirsjärvi & Hurme, 2000; Saaranen-Kauppinen & Puusniekka, 2016).

5.3 Case companies

Two case companies are studied. Supplier company is a Nordic IT service provider focusing on digital business solutions. Supplier has over 600 employees and offices located in six countries. Supplier has various service offerings, from which one is offering solutions for eCommerce, product information management and order & supply chain management. Clients of the supplier are mainly located in Nordic countries.

Customer company is one of the leading department store chains in Finland. Customer company has strong growth, over 30 stores in Finland and an online store utilizing recommendation system. Customer company's product offerings consists of building materials, electrical accessories and animal products to name few. Customer company is well-known for affordable prices for do-it-yourself customers. Supplier is the service provider of the customer company's online store.

5.4 Data acquisition and analysis

According to Hirsjärvi & Hurme (2000) choosing a research method usually influences the selection of the data acquisition method. One of the most popular ways to acquire data are interviews. Interviews are rather adaptive methods, as they fit many different research purposes. There are also multiple different ways to conduct interviews, which all have their own rules and assumptions. (Hirsjärvi & Hurme, 2000.)

Due to the qualitative nature of the study, interviews were chosen as the data acquisition method. In qualitative studies, interviews are considered to be the most popular methods of acquiring data (Hirsjärvi & Hurme, 2000). The particular interview method chosen for this study was theme interview. Theme interview is also referred to as theme-centered interview or theme-oriented interview. Theme-centered interview was something developed in the Bremen Institute for Psychology and Social Research (Schorn, 2000). Theme-centered interview has a discussion leader, who is not a neutral observer, and who takes part in the discussion process (Schorn, 2000). According to Schorn (2000) in this type of interview, open conversation needs to be established. Interviews regularly open up with short introduction about the topic, explanation of the study and giving information about the interview frame, referring to duration, confidentiality and any other relevant clarification (Schorn, 2000).

Saaranen-Kauppinen & Puusniekka (2016) describe theme interview to formally locate between structured interview and open question interview. Theme interview consists of loosely identified themes. Interviewer is able to proceed with any route interviewer wishes, but as opposed to open question interview, previously prepared themes are the same for each participant. It's important to pay attention to the individual interpretations of the interviewees on the subject. Interviewer is free to explore the themes in any order. Some interviews can contain more attention to some theme. There is no need to go into equal depths on each theme with each interview. Strenght of theme interview is that it opens up space for interviewees and their speech. As interviews are thematically organized, it's also relatively easy analyze this data thematically. (Saaranen-Kauppinen & Puusniekka, 2016.)

As interviews were conducted as theme interviews, it's was natural to also analyze data thematically. Saaranen-Kauppinen & Puusniekka (2016) discuss thematical data analysis. Process starts by forming themes and often this begins from the interview data, but also analysis based on theoretical framework is possible. Themes that were discussed with interviewees are often reflected and found in each interview, but in varying amounts (Saaranen-Kauppinen & Puusniekka, 2016).

Interviews were recorded and then transcribed to 81 pages of text format. Data was organized under themes. For each theme, interview data was analyzed and then coded to find similarities and differencies between interviewees on this specific theme. An inductive approach was used to draw themes from interviews. Interviewees are listed in TABLE 4. Interviewees are coded with "S" and "M". "S" refers to supplier organization and "M" to customer organization.

TABLE 4 Interviewee roles and experience

Interviewee	Role	eCommerce experience
S1	eCommerce Consultant	8 years
S2	Director	15 years
S3	Technology Director	14 years
S4	Consultant	17 years
S5	Director	13 years
M1	Chief Information Officer	5 years
M2	eCommerce Manager	10 years
M3	Customer Service Manager	5 years
M4	Senior Digital Marketing Specialist	2,5 years
M5	Chief Marketing Officer	5 years

6 FINDINGS

Findings from the theme interviews are presented thematically. Main themes drawn from the interviews are applications of AI on eCommerce, how AI creates value and the paradigm of AI. For recommendation systems themes comprise three topics – how to create value with recommendation systems, what is the firm-level impact and how the value can be measured.

6.1 Applications of AI on eCommerce

To understand possible applications of AI on eCommerce, interviewees were asked to answer which type of applications or features of AI they see valuable in eCommerce. During the interviews it was clearly established that there is no deficiency of potential ideas. Few main areas were regularly identified from the interviews, both from the suppliers and the merchant's side.

Supplier was able to view possibilities of AI broadly compared to the merchant. Supplier interviewees reflected on the recent eCommerce trends and identified areas that could be valuable for any eCommerce merchant. One interviewee mentioned that stated ideas and applications do not directly imply they would necessarily be relevant for one or multiple customers of the supplier. Stated ideas are rather general trends of eCommerce AI.

> I'm unable to talk about this in great depths, I think about this more through the common eCommerce trends, and through the meaning of eCommerce – – I think about this in a greater context. -S5, 1

From supplier's side it was possible to identify main themes, from which one was dynamic pricing. Dynamic pricing was seen to help merchants automatically adjust correct price points for end customers. Ideally dynamic pricing would work by setting the lowest possible price point, and having AI take care of the rest. Dynamic pricing is something that is frequently seen in ticket and flight sales, but not too many retailers yet take advantage of such possibility. Pricing could be dynamic based on demand or based on competitors' pricing. If it would be possible to adjust price real time, or near real time, it would enable setting price depending how some items are sold in other stores. Take for example an item that is out of stock from other merchants. In such scenario it would be possible to even have a higher price point, if the product would have high demand.

> Product pricing would somehow be AI-based, to take into account how it's sold elsewhere and so on. -S2, 2

> Dynamic pricing, which is commonly nowadays used in ticket sales, on flight carrier business and in hotel room pricing, but not much on retail business with products. Automated pricing based on demand or alternatively competitors pricing. -S3, 3

If pricing is not dynamic, merchants need to adjust price points manually. Adjusting price points manually requires great effort from merchants in order to try and stay competitive. Merchant would need to see how competitors are selling items, then calculate sales margins and come up with own pricing strategy. Amount of work is huge, so in reality it would not even be possible to achieve this manually in large scale. AI would enable merchants achieve something that would not otherwise be possible. Song et al. (2019) describe similar situation, where adjusting prices continuously long-term has turned out to be a great challenge for merchants.

> Manually spying and trying to follow prices of other stores, and to do so in order to stay competitive, calculate own sales margins and think about own pricing strategies. Automating all of that which is a huge amount of work. It's a competitive factor, so that it's possible to carry out actions that would practically be impossible due to the amount of manual work. -S4, 4

Dynamic pricing is also related to segmentation and campaign tools. With AI it would be possible first profile customers, then assign customers to segments and then set correct price points. AI-driven campaign tools were seen important for merchants. Especially AI was seen to be helpful in simulating different scenarios of campaigns.

> Identify customer through profile and segment, based on the behavior of the customer assign a price which we think that the customer would be able to pay. -S5, 5

> Campaign tools, which somehow have AI included. For example, to create different scenarios of some campaign and then be able to run different scenarios about how this campaign would succeed, and then utilize AI to calculate these scenarios. Solutions like that could be really helpful for merchants. -S3, 6

As campaigns are complicated, measuring how they perform is not straightforward. AI could assist merchants in creating more performant campaigns. If AI would have suggestions of products for campaigns, price points and segments, it would be a powerful set of features.

Sometimes seeing how campaign performs is only about seeing what the sales are. Additionally, it would be really important to see how the sales are after the campaign. AI could reduce merchants "campaign hangover" and enable merchants learn what type of campaigns actually work. Performant campaigns lead to better end results.

> AI could recommend that you should add these products to a campaign, price point should be here, and this is your campaign segment and so on. Such recommendations would be really powerful. And you could learn for the next campaign that which things work, and it would also decrease the campaign hangover. Many times, attention is only paid to how well did the campaign sell, but not to how the sales are after the campaign, which can be lacking. It's complicated, how it affects to the end result. -S2, 7

Profiling customers, assigning customers to segment and offering relevant products with correct price points could result as something that is described as journey optimization. Journey optimization can take advantage of multiple features of AI and be implemented in multiple steps along the customer path. Journey optimization refers to the ability to appreciate each customer based on the customers purchase and behavior patterns.

> Journey optimization. This is a bigger theme. I mean that when I now go to see contact lenses, my journey is optimized just for me, so that this guy usually orders once in every half year these contact lenses, is not interested in anything else. And show appreciation to such customer by recommending particular things. -S5, 8

Search was considered to be in great importance in journey optimization too. Search was identified as an area where AI, or machine learning, is already present. With intelligent search it is possible to offer the most relevant and correct products for end customers.

> Search is something where the aim is to try understanding when customers search something, what are the correct products at that given time. -S1, 9

> Mainly product search is the place where nowadays continuously in increasing amount could be described to utilize AI or machine learning. -S4, 10

One particularly interesting and rising feature of AI benefiting from natural language processing and speech recognition would be conversational commerce. Conversational commerce refers to the ability to purchase using natural language. It could also mean a virtual assistant, something like chatbot. According to Song et al. (2019) chatbots or AI assistants are seen valuable for merchants as they can reduce labor costs and optimize user experience by responding to simple questions.

Conversational commerce is more than chatbots or virtual assistants, though. Conversational commerce refers to the ability to fully understand customer and based on this, steer the customer towards the correct path. In the future, conversational commerce would not only be restricted to speech, as it could also understand human's natural behavior, such as facial expressions and gestures. Movement towards understanding human's natural behavior is important, as slowly we are drifting away from typical point and click user interfaces.

> Natural language processing and what results is conversational commerce. And then virtual assistants, as in any situation you can ask virtual assistant to gather information, choose things, find correct categories – at some point it can be gestures and facial expressions that are used to control, but still though we are moving away from typical point and click, or text-based interfaces, when understanding natural language is important. -S5, 11

> Conversational commerce, meaning controlling by speech or text. Behind it, AI-based solutions could interpret the customer need and steer customer towards correct path – – to put it bluntly, chatbot 2.0 type of thing – – this speech recognition is coming from home devices of Google, Amazon and Apple, so that purchasing can be steered towards speech recognition, is interesting area. -S3, 12

Aside from mentioned features, supplier saw the use of AI to help in product data enrichment. AI could help enriching product data mainly through two features of AI, image recognition and natural language processing. With image recognition AI could identify products of same design and identify the color of a shirt. Merchant would not need to manually update the color.

> Would it be possible with AI and images to recognize products of same design, or something similar. - S3, 13

> Why would some person need to manually tell product information management system that this woolen shirt is blue, when from the image we can obtain information with image recognition software that this woolen shirt is actually blue. -S3, 14

With natural language processing, it would be possible to identify shortcomings in the product data. Deficiency in the product data could be identified by AI through recognizing semantic meanings. Fixing deficiencies in product data could be raised to manual process.

> Then the product data enrichment process could use AI – – the data could be processed, some things could be identified and raised to manual process – – that this might not have been correct here or – – this is missing. -S5, 15

Regarding product information, translation is something that is naturally associated to AI. Automatic translation of language is one example where AI can assist merchants.

> Product data enrichment and translating text for example. -S3, 16

Merchants usually reflected the possible applications through their individual line of work. AI solutions were identified to help controlling packaging or picking. Similarly Min (2010) has identified AI to be able to select optimal warehouse picking order. Song et al. (2019) describe more advanced intelligent logistic application, that could forecast inventory turnover and improve logistics through real-time RFID sensors for example.

> Replace manual processes or overall actions that eCommerce includes, talk about picking or packing or controlling it. -M2, 17

Merchant interviewees considered customer service to be in great interest with AI solutions. Using natural language processing, a customer service chatbot was seen as a valuable assistant for merchant. Merchant viewed that such chatbots would be used even more in the future. Chatbot could also assist in sales promotion.

> Customer service bot or sales promotion bot is something that can be seen and used more in the future. -M2, 18

> – – computationally communicate to customer, AI can ask easy questions for that dialogue and customer answers yes or no and that continus how the dialogue continues. -M3, 19

Merchant identified AI applications to be valuable in two main issues, marketing and sales. Merchant described that the use of AI culminates to two factors, solutions that aid merchants to target marketing more accurately and solutions that enable merchant gain more sales.

> Of course applications that help aim marketing or close the deal. That's where it encapsulates, something that can be used to obtain customers and something that can help generate sales. -M1, 20

Gaining more sales was seen to happen through relevant product recommendations. With product recommendations, customer service view was clearly present. AI-driven product recommendations were seen valuable as they enable merchant to gain more sales, and relevant recommendations were seen to be linked with great customer service.

> AI could offer relevant products for customers – – so scaling sale up in practicality. That's something I see maybe as the most important. -M5, 21

> What can be taken into use are related to product recommendations and somehow joined together with customer service, I atleast feel that they will go hand to hand in the future. -M2, 22

In conclusion, merchant identified applications related to content personalization including product recommendations, tools for marketing, AI to help with sales promotion, controlling packaging or picking and processing natural language, in terms for customer service or sales promotion bots. From supplier's side the main themes arising were dynamic pricing, enrichment of product data, conversational commerce, campaign tools, journey optimization, genuinely learning search and personalization.

Mainly the differences between the views of the supplier and merchants are visible in the detail of the identified applications. Supplier is able to identify different application areas of AI, but merchants are able to describe potential applications in more detail and how they see these applications beneficial. Based on these findings, it seems that applications for logistics, intelligent pricing and virtual assistants are relevant trends for eCommerce merchants, as argued by Song et al. (2019).

6.2 How AI creates value on eCommerce

To understand why AI is valuable, interviewees were asked how they feel AI is creating value for eCommerce merchants. As financial revenues should naturally be in heart of any business, interviewees were asked to focus on intangible values, that eventually lead to tangible and financial values.

One of the key value propositions of any AI solution was to reduce manual work. Manual work conducted by humans could be assigned to AI, which would free up time for merchants. AI was seen as an enabler, as some things would be impossible for us humans to conduct. Those tasks that humans are able to conduct, AI would be able to optimize. Oke (2008) has a similar view arguing that AI can solve a narrow set of problems, for example optimize activities like production level automatically.

> First and foremost enable things that would not otherwise be possible. And then also optimize what is possible without AI. -S5, 23

Reducing manual work means saving time. There are tasks that AI can conduct in more time-efficient manner than humans. It's fundamentally the same principle as in optimizing activities. As Brunette et al. (2009) and Russell & Norvig (2010) mention, AI can can automate routine tasks. Such ability will inevitably save time.

> It would noticeably save time. -S2, 24

To dig deeper, AI was seen to have positive effect on customer relationships. Using AI-driven solutions can improve customer experience, have positive effect on the brand image and result in longer relationships.

> There are other measuring instruments, maybe additional sales or improvement of the sales is most important, but then indirect benefits, increase of brand image, improvement of customer experience and longer customer relationships. -S5, 25

Regarding financial values, gaining more sales is important. It's the outcome of better conversion rate. Reducing manual work, gaining more sales and offering relevant personalized content were all seen to positively affect conversion rate.

> Reducing manual work – – additional sales – – personalization – – they are things which affect conversion. -S3, 26

In short, the main value propositions of AI are to create more sales, increase conversion and reduce the amount of manual work. These propositions were acknowledged from both supplier's and merchant's perspective.

Supplier considered AI as an enabler and identified AI to impact positively to customer loyalty, brand image and customer relationships. Merchant inspected the value of AI through financial outcomes, thus not identifying the intangible values of AI as clearly.

6.3 Paradigm of AI

When interviewees were asked to define AI or describe what AI means, saturation of answers was high. Depending on the background, technical knowledge or the role of the interviewee, different descriptions were given. Interviewees considered defining AI difficult.

Learning and machine learning were common themes when describing AI. Interviewees described AI to usually have some sort of ability to learn. This ability to learn was described through human's natural behavior. AI is seen to imitate humans and as a result, AI is something that can be characterized as a technology that learns through imitating. Cheng & Wang (2012) have adopted similar view describing AI to imitate behavior of humans.

> Intelligence which simulates actions of humans. And behavior. And technology that learns. -M5, 27

Most technical views considered AI to be explicitly machine learning. Technical views discarded the natural characteristics of AI, and saw AI to be computational, referring to "matching and joining things that we know beforehand". AI was not associated to human's natural behavior and was not seen to have any natural capabilities. This definition is aligned mostly with definition by Russell & Norvig (2010), who describe AI to be an agent that maps sequences to actions.

> – – AI is computatinal, so to say, it refers to things we know beforehand and to matching and joining them – – I feel that it's more machine learning. -M1, 28

Algorithmic views emphasized that AI should always adapt to new environments and new data. Interviewees considered AI to be greatly linked with data. One algorithm shouldn't always produce the same result and the result of the algorithm should always depend on the amount of data. This type of view is in line with the view of Halevy et al. (2009) who argue that the intelligence we pursue lies in data, not in algorithms.

> – – computer program which can adapt to new environment and new data – – it's not an algorithm that always produces the same end result, as the result of algorithm depends on how much it data is available – – that's how I see it – – and you can say that it's able to learn. -S2, 29

Similar algorithmic view identified ability to adjust actions. Based on data and actions done with it, AI should be able to learn reach better outcomes than before. Actions are identified by Russell & Norvig (2010), as they define AI agents to percept environment and perform actions based on it.

> – – data which is used to make actions – – when actions have been made – – AI is the one that can change it's behavior for the next time so that end results would be better. -S3, 30

Technical and algorithmic views were also able to take the human-factor of AI into account. Whereas algorithms have always some pre-defined rules how to act, AI has rules which make it behave similarly than humans. So, in a sense, AI is an algorithm that simulates the cognitive processes of humans. This type of view is most aligned with definitions from literature. Many authors such as Bai (2011), Cheng & Wang (2012,) X. Li and Jiang (2017), Min, (2010), Ning and Yan (2010), Pan (2016) and Tecuci (2012) define AI by taking into account the aim to simulate human intelligence.

> The difference for other algorithms is that algorithms have some specific set of rules and a model which guides their behavior. And AI tries to behave similarly than thinking humans or the cognitive processes of humans. -S5, 31

Philosophically, AI was seen as something that human teaches, but something that also imitates humans. AI was seen to be helpful in conducting some tasks, that have routines. For routine tasks, humans can teach AI and AI can imitate humans. It results as an AI that learns and repeats.

> – – human teaches machine how to act – – take for example a job task, if it has a recurring model, machine – – can learn by imitating and then will repeat it. -M3, 32

Amount of data and algorithms result in applications that we can associate to natural human behavior. Applications can be used in various different tasks, which either enable or optimize activities. As an end result, AI is data, and this data is a tool for businesses.

> It's data that steers business – –it's a business tool. - M2, 33

6.4 Creating value with recommendation systems

Recommendation systems were seen as the one major AI application that eCommerce merchants can benefit from. Interviewees were asked how recommendation systems can be utilized, so that they create most value. Main factors contributing to the successful utilization of recommendation systems were relevancy and correct timing of the recommendations. These factors were identified by both from suppliers and merchant's perspective.

Recommended products should be relevant for the customer. Relevancy alone was not considered to be the most important factor, but relevancy accompanied with the correct timing was seen to contribute most to the successfulness of the recommendation. Main function for recommendation systems is to help customers find relevant products (Burke, 2002; S. S. Li & Karahanna, 2015; Matt et al., 2013; Schafer et al., 1999), but only Picault et al. (2011) have emphasized the importance of temporal factors, such as timing to be important for the successfulness of recommendations.

> One of the most important criteria, at least in the top three, is correct timing. I have to say that correct, or relevant content too. These are maybe two things, which correlate most to what is called successfulness. -S5, 34

Correct timing was seen to be a factor of multiple things. First of all, merchant described correct timing related to the weather conditions and selling a snow plough. A concern is whether a snow plough should be marketed before, during or after there's snow.

> Correctness is something I would emphasize as the most important. That the product is correct, but also that timing is correct. Take for example a snow plough, it can be really important but when should it be marketed. Is it bought when it has snowed, snow is coming or when there should be no more be snow? This I think has even more significance. -M1, 35

Correct timing was also inspected through the customer journey on the website. Interviewees agreed that once customer is on the checkout, there should not be product recommendations as they can be interrupting.

> And then maybe at that point when we have gotten the customer, for example add products to cart, then calm down and start to steer customer towards conversion. No more interrupting product recommendations during the checkout process, as the focus needs to be on ensuring that the order is completed. -S3, 36

Correct timing is one of the most important factors to take into account when utilizing recommendations. Correct timing was also seen as the factor that usually goes wrong. If timing is not correct and recommended products are not relevant, recommendations were seen to be irritating.

> How it goes with me, is the correct timing. And the relevancy, I mean it's really irritating if it recommends something that I would not be less interested in. -M3, 37

It was identified that some merchants get the timing of the recommendations wrong, which leads to similar irritation that customers can experience if the recommendations are not relevant. Getting timing wrong can be easy. As Picault et al. (2011) describe, a user can watch news on the way to work and comedy on the way back. It illustrates just how much timing can and should be refined.

One example of invalid timing was described through a classical error in retargeting, where customer is being recommended a product that the customer has already bought. This issue seems to be clearly identified, but it still is an existing one with many merchants and recommendations.

> Correct-timing, I mean – – classical regargeting nowadays is – – that it will continue to recommend me the same system that I have already bought. -S5, 38

> Two weeks after that exactly the same deals are shown for the same shoes that I have already bought, or something similar. -S2, 39

Merchant identified that this problem exists also when a customer has bought the recommended item from the physical store or from a different store. This issue has been acknowledged, and it has seen as a valuable feature to invest to.

> Purchase history of one eCommerce store can be quite limited. So how would it be possible to utilize data which would be combined from the behavior of the customer all around the web. In product recommendations. And that has been an area, which has been seen as something that should be invested to. -S4, 40

> It could be that the customer has already got the item from us but from some other channel, and still, we are waking the customer up online with adverts. -M2, 41

With a feature like this, to some extent it would be possible to tackle the classical error of retargeting with products that the customer has already bought. If data could be pieced together from multiple different sources, it would have a great impact on reducing the error in retargeting, which Burke (2002) calls portfolio effect. This also promotes the idea that one service provider could share data about customers to all merchants.

> If as a service provider you would have the information that customer has bought shoes from somewhere else, the information could be shared to everyone, as it would benefit each party to focus on the next customer. Or recommend shoe care products for this customer, as the shoes are already bought. -M1, 42

6.5 Firm-level impact of recommendation systems

Interviewees were asked how they see successful implementation of recommendation systems to be valuable for the merchants. Added value for the merchants were inspected through intangible and tangible factors. Merchant saw recommendation systems to increase brand image which in turn creates sales, provides data about popular products, makes products visible for the customers through personalization, reduces amount of manual work and overall provides great customer service for end customers.

Increasing brand image was one of the main themes arising from the interviews. Increasing brand image was seen as an intangible value, that in the long run contributes to tangible, financial benefits.

> Be it either building of the brand image or increasing the recognizability, maybe they are intangible benefits, that will generate, when sales are made online or somewhere else, those tangible benefits. -M2, 43

Recommendation systems were seen to provide data about popular products. For merchants, this can be seen as a valuable feature. For merchant's sales and purchase departments it is important to have data about which products are popular. This data can even be used in steering the business. Ricci et al. (2011) point out that by understanding customers businesses can improve other business areas, such as improve management of item's stock. Steering business based on the recommendation systems data is a step further though.

> For us salespeople, support people for the chain, purchase department and each and every one inhouse, is really important to acquire clear data, and particularly popular products, they can be used to even slightly steer the business. -M2, 44

If merchant would not have a recommendation system, the customer experience would not be personalized. Greatest impact of the personalized content for the customer was seen to embody in greater product visibility for the customers. Long tail and hard to find products might not be visible for customers without recommendations (Ricci et al., 2011).

> If option is that we would not have recommendations in use at all, then the customer experience would not be personalized at all. And with product recommendations the products can be offered to customers. -M4, 45

In addition to greater product visibility for the customers, using product recommendations was seen to reduce manual work, thus increasing the productivity of the merchants. Using product recommendations enables the merchant to focus on other important tasks in conducting their business.

> Greatest value is that it doubles the effectiveness, as maybe even humans could not do something at specific times during the day. And that is all the time present for each different customer segment. In a way, financial benefit is great, but then time and prioritizing it will free up time to create and build something new. -M3, 46

Merchant also saw a link between recommendations systems and customer service. By providing relevant recommendations customers get the feeling they are being provided great service.

> Offers me correct products, knows me and provides great service, too. So, I see it like that also. That is the biggest thing. -M5, 47

An interesting idea about combining recommendation systems and customer service with some AI-solution such as chatbot, was seen as a valuable idea for the merchants. Firm-level impact for such a solution would mean a way to remove barriers from making a successful transaction.

> What will be seen and used more in the future is to combine product recommendations and customer service, so begin to remove those barriers from making successful purchases with automation or AI. -M2, 48

From suppliers' side this type of customer service view did not emerge so clearly, but supplier identified providing great customer experience as one of the key value propositions of recommendation systems. Customer experience builds trust and enhances the brand image of the merchant. Other firm-level value propositions of were increasing sales by increasing average order value and increasing conversion, optimizing rate of inventory turnover, and reducing the amount of manual work, that can reflect through for example reduced amount of refunds.

Using recommendation system was seen as a cornerstone of an eCommerce website. By providing great customer experience through recommendation systems, merchant can positively affect the brand image.

> Well-functioning store and product recommendation are part of the basic principles of eCommerce. Well-functioning store makes customer experience better and eases customer's judgement towards the brand. -S5, 49

Tangible benefits were financial outcomes, culminating to increased sales. Increased sales consist of increased average order value and increased conversion through relevant recommendations. Indeed, Ricci et al. (2011) have argued in their study that recommendations do increase conversion. Conversion and average order value are considered to be key factors in eCommerce. Number of users and conversion rate form the net revenue. Past studies have not been able to identify average order value to be important for eCommerce merchants nor has there been any scientific evidence to back up that recommendations actually increase it.

> Tangible benefit is that these systems have been proved to increase the average order value and on the other hand relevancy can improve conversion too. Those are the basic principles in eCommerce business, that number of users, average order value and conversion forms basically the net revenue. -S3, 50

One thing that can be overlooked is recommending products due to business reasons. Optimizing the rate of inventory turnover is a factor which is not always thought about, or at least end customer do not think about. For merchant, at times it can be more cost-beneficial to sell cheaper products which take out complete storage locations, than just selling products which have high sales volume.

> Inventory turnover is something that is not thought about, or at least the customer does not think about it. But for eCommerce merchants these can be things that are not solely thought of. It can be more cost-efficient to sell cheaper product, when you think about logistics or stock values, so sometimes even product recommendation based downscaling of order value can be more profitable in the end, if other benefits can be achieved. -S4, 51

As with AI-solutions, the recommendation systems are seen to reduce the amount of manual work. Reducing the manual work can concretize through reducing the amount of refunds, that can originate through offering more relevant products for the customers. Also, similarly like merchant identified, the data about popularity of products was also seen from the supplier's side, but through another example. More intelligent the product recommendation system is, it could also identify products that are not selling enough or products that are seen, but seldom sold.

> Regarding tangible benefits, most evident is that hopefully it increases net revenue and decreases number of returns. So, to have more precise purchases. And if intelligent product recommendation works well, it also reduces amount of own work. The more intelligent it is, it could also recommend things that should be removed. Okay, these have not been bought by anyone, that can be seen from ERP or some other system, but these are not even being watched, or these are being watched but it's only a couple of seconds and then away, so there must be something wrong in this. Benefits like that could also be achieved. -S2, 52

Both supplier and merchant views on value creation have some differences. Supplier identifies that recommendation systems can create value through business reasons, whereas merchant sees that recommendation systems create value through providing great customer services.

6.6 Measuring value

Interviewees were asked if the created value of recommendation system is measured, and if it is, how is it measured? Both supplier and merchant had coherent views regarding the question – value is measured but measuring has shortcomings.

Added value of recommendation system can be measured through sales, as recommendation system should be increasing merchants net revenue or average order value. One way to measure is to use A/B testing, which would include a phase when recommendation system is in use and a phase, when it would not be in use. Theoretically, A/B testing could be done concurrently, where one group would see recommendations and another group would not. This way, in theory, it would be possible to find out which group creates more sales for the merchant or which group has higher average order value. Concurrent measuring is something that can create the last drops of the efficiency but is not too commonly adopted.

In addition to using financial measuring instruments, the performance of the recommendation system can be partly measured through the data the recommendation system provides. From the provided data, it is possible to see how individual recommendation elements perform. Data will tell for example how many times products are viewed or bought.

Interviewees identified shortcomings regarding measurements. Merchant emphasized that the overall performance of the recommendation system is not analyzed well enough. Financial measuring instruments are not enough, as it would be more important to measure the customer satisfaction associated with recommendation systems.

Konstan and Riedl (2012) argue that the emergence of business applications has shifted evaluation from algorithms to business metrics. This seems to be true, as little to no attention is paid to algorithm performance. According Adomavicius and Tuzhilin (2006) impact to consumer loyalty, experience and value can be measured. Despite more emphasis is paid to business metrics, it seems that in reality the most important view of customer satisfaction is still left out.

> In my opinion it's not measured enough. And if it is measured, it's measured by euros, and in my opinion, it alone is wrong measuring instrument, how much it generates additional sales. -M3, 53

> See how much recommendation channel has generated sales or monthly reporting. But that's basically everything you can data-wise get. How could you otherwise measure, as somehow it should contain the comprehensive customer satisfaction. That is some instrument, that you are not able to get to the report. -M2, 54

Konstan and Riedl (2012) argue that one way to measure performance of recommendation system is to see how much it can generate sales from recommendations. Supplier emphasized that measuring the created value is problematic due to difficulty of ruling out factors affecting to the measured outcome. You can measure the net revenue of the merchant once a recommendation system has been in use for a while and you could even see a positive increase. Identifying if it's due to the recommendation system performing well, or is it caused by some other, non-relevant factor, is hard.

> When product recommendation system gets better, you can see that net revenue has increased a bit, but you might not be able to associate it directly if it is due to the recommendation system or is it because it has been raining today. There are so many factors contributing to how much people are ordering from the Internet. I believe, that measuring one particular system is not really mature yet. -S2, 55

Similarly, we can measure how a recommendation system performs or what kind of an impact it has to customer loyalty, but it's hard to identify to which extent the recommendation system has affected to it.

> Measuring like this is done to some extent. If you bought something recommended for you, are those people more loyal? But there's the issue to determine what actually contributes to the loyalty. So, what has the value of recommendations been there. I argue that measuring these is not adequate enough. -S4, 56

Value can be measured, but according to supplier and merchant it's not measured adequately. Measuring value would need to be holistic – financial measurements are not alone enough. Measuring added value is problematic, as it's hard to rule out other factors and actually determine to which extend recommendation system has had the impact.

7 DISCUSSION

This chapter discusses the study. Managerial and theoretical implications are presented, and research questions are answered. Chapter also includes discussion of reliability, validity and limitations of the study. Further research topics are presented.

7.1 AI and recommendation systems creating value

Aim of this study is to answer how AI applications create value for eCommerce merchants and what are the value propositions of recommendation systems. AI is vast and multidisciplinary field. No prior research addressing value creation for eCommerce merchants has been conducted, or at least papers were not found. For this reason, literature review provided an effort to answer research question by identifying most important subfields, features and values. Literature review indicated most active subfields to be machine vision, natural language processing, speech recognition and expert systems.

Natural language processing and speech recognition as subfields enable features such as automatic translation of language, verbal communication between humans and computers and speech to text conversion. Features enable computers to be conversant assistants and help automate routine tasks like translating text.

Natural language processing tries to understand ideas and semantic meanings from text, which mean that machines can communicate with humans, answer questions and learn. For example, a chatbot can simulate intelligent conversation. Song et al. (2019) identified AI assistants or chatbots to be relevant in today's eCommerce. Empirical research complemented this view, but additional view of conversational commerce was established. One interviewee characterized conversational commerce as the next generation of chatbots.

This chapter has tables, which illustrate findings both from literature review and empirical research. Tables are laid out so that each row should explain same feature identified from literature review and empirical research. There are some exceptions, as identified features are not always identical.

Found features and values from both literature and empirical part of the Thesis are illustrated below in TABLE 5. This table presents natural language processing and speech recognition.

TABLE 5 Features and values of natural language processing and speech recognition

Literature review		Empirical research	
Feature	**Value**	**Feature**	**Value**
translation (Brunette et al., 2009; Flasiński, 2016)	automating routine task (Brunette et al., 2009; Russell & Norvig, 2010)	translation	automating routine tasks
			saving time
			reducing manual work
verbal communication between humans and computers (Bai, 2011; Flasiński, 2016)	improve human-computer interaction (X. Li & Jiang, 2017)	conversational commerce	assist customer in shopping
		virtual assistants	
		customer service bot	assist in customer service
		computer to communicate with customer	
		sales promotion bot	increase conversion
understand ideas or semantic meanings from natural language (X. Li & Jiang, 2017)	machines to communicate, answer questions and learn (X. Li & Jiang, 2017)	process product information data to identify issues	raise issues to fixing to manual process

Literature review indicated that with machine vision it's possible recognize elements from image and video. It can result in recognizing characters, analysis of images and understanding elements from images.

Interviewees saw machine vision to help in analyzing product images. Machine vision could be used in making product information more accurate, which is thought to contribute to better conversion rate.

Machine vision can reduce amount of manual work. It can help enriching product data by recognizing valuable information from the product image. An AI solution with machine vision could fill some product data attributes, such as color, automatically. Machine vision could also enable recognizing same line of products by the design.

Despite machine vision being an active subfield of AI, practical applications for eCommerce remain thin. TABLE 6 illustrates features and values of machine vision found from literature review and empirical research.

TABLE 6 Features and values of machine vision

Literature review		**Empirical research**	
Feature	**Value**	**Feature**	**Value**
recognize elements from image and video (X. Li & Jiang, 2017)	optical character recognition (Flasiński, 2016)	recognize elements from product images	make product information more accurate
	optical quality control (Flasiński, 2016)		better conversion
	analysis of images (Flasiński, 2016)		reduce manual work
	understanding elements (Flasiński, 2016)		recognize same line of products by design

Expert systems as one major AI subfield encapsulates variety of different features and benefits. Expert systems ultimately are systems that focus on one well-defined area, and these systems can have the same knowledge that humans have (Flasiński, 2016). With expert systems companies can have support with decision-making processes (Flasiński, 2016), select optimal warehouse picking order, predict customer demand, manage logistics, inventory and purchasing in an efficient manner (Min, 2010).

Applications categorizable to expert systems have a lot of potential in eCommerce. Great number of applications were identified by interviewees. On a general level, applications for personalization were identified, in addition with applications for dynamic pricing, journey optimization and campaign tools. Search was seen as an area, where machine learning can be utilized to achieve great opportunities.

Commonly merchant's views on such expert system applications were identified via the interviewees line of work. For example, a system aiding in packaging or picking was seen to be valuable time-saver, in addition with the ability to personalize and target marketing more efficiently.

Below TABLE 7 illustrates both features and values found from literature, and findings from empirical research. On TABLE 7 each row does not comprise same identical feature due the nature and wide spanning features of expert systems.

TABLE 7 Features and values of expert systems

Literature review		**Empirical research**	
Feature	**Value**	**Feature**	**Value**
focus on well-defined area (Flasiński, 2016)	support decision-making process (Flasiński, 2016)	segmentation	accurate marketing for better conversion
	enables intelligent decision making (Buchanan, 2005)	intelligent search	find the right products
human-like reasoning and information techniques (Oke, 2008)	solve a narrow set of problems (Oke, 2008)	personalization	offering relevant products
	optimize production level (Oke, 2008)	journey optimization	ability to show appreciation for different types of customers
problem solving (Flasiński, 2016; X. Li & Jiang, 2017)	intelligent analysis (Tecuci, 2012)	dynamic pricing	achieve correct price points for customers
integrate interrelated decision-making processes (Min, 2010)	select optimal warehouse picking order (Min, 2010)	controlling packaging or picking	reducing manual work
	manage purchasing more efficiently (Min, 2010)		
	predict end customer demand (Min, 2010)	campaign tools	access to accurate insights based on data

Findings from the empirical part suggest that in the context of eCommerce, most valuable features of natural language processing are to assist customer in shopping, assist merchant in customer service and increase conversion. These values can be achieved with conversational commerce, virtual assistants, customer service or sales promotion bots.

Literature saw translation as an area where natural language processing can automate routine tasks (Brunette et al., 2009; Russell & Norvig, 2010). Empirical research supported this view. Automation was seen to save merchants time and reduce the amount of manual work. By understanding ideas or semantic meanings from the text, merchants can raise issues in product information data to manual process. Understanding semantic meanings from text is something that natural language processing as an AI subfield is focusing to achieve (X. Li & Jiang, 2017).

Recommendation systems consists of tools and techniques, that enable providing useful suggestions for end users (S. S. Li & Karahanna, 2015).

Recommendation systems for eCommerce merchants are fundamental parts of eCommerce websites (Burke, 2002). By utilizing recommendation systems eCommerce merchants can help customers to find relevant products to purchase (Matt et al., 2013).

Firm-level impact of recommendation systems has been left almost unexplored in the past studies. Despite narrow body of literature, literature review was able to identify and name firm-level impacts such as financial revenues and gaining more sales (S. S. Li & Karahanna, 2015). Firms offering personalized recommendations can benefit through selling more items, diversifying sold items, increasing customer satisfaction and increase customer fidelity. Through recommending products, firms can also gain better understanding on what the end customers want. (Ricci et al., 2011.)

Recommending personalized products mean that eCommerce site can suit better users need. This results in increase in the amount of sold items (Matt et al., 2013). Diversifying the sold items means that niche products, that are not bought so often, can be recommended to customers. Customers can find these "long tail" items much easier with recommendation systems (Ricci et al., 2011).

User satisfaction is the goal that matters in the end (Picault et al., 2011). When customers evaluate eCommerce system positively, it affects their perception of the effectiveness of the systems. When customers perceive the eCommerce website effective, they are also more ready to accept recommended products (Konstan & Riedl, 2012; Ricci et al., 2011). Customer loyalty goes hand-to-hand with user satisfaction – customers are more loyal to website that treat customers as valuable visitors. Loyal customers are valuable to eCommerce businesses.

Personalization with recommendation systems was a common theme. Empirical research revealed multiple reasons why companies should and are offering personalized recommendations. Empirical research identified tangible and intangible factors, that contribute to the added value of recommendation systems.

Recommendation systems were seen to increase brand image, provide data about popular products for the merchants, make products visible for the customers through personalization and reduce amount of manual work. Recommendation systems provide great customer service. Personalized recommendations were also seen to have a great impact to the customer experience and customer loyalty.

Increasing sales was seen to happen through building the brand of the eCommerce website. Increasing the sales was seen to result from increasing the average order value and optimizing conversion rate. Financial outcomes are aligned with findings by S. S. Li & Karahanna (2015) and Ricci et al. (2011), but past literature has not been able to identify average order value as a measuring instrument.

Recommendation systems can also be utilized for other than financial reasons. For merchants it can be valuable to recommend products due to business reasons, such as optimizing the rate of inventory turnover. Sometimes for merchants it can be more financially beneficial to recommend and sell cheaper products that for example take a lot of space in the storage location.

Recommendation systems were seen to provide important data for the eCommerce merchants in steering their business. Gathering data about popular products sales and purchase departments can access valuable data for conducting their business. Ricci et al. (2011) mention recommendation systems to help in managing items stock, for example.

Interestingly, recommendation systems were seen to contribute to the customer service. When customers are provided personalized products, they can feel excellent customer service. Combining recommendation systems and chatbots is a way to remove barriers from making successful transaction was seen as a valuable feature for the merchants in the future.

Reducing manual work will enable the merchant to focus on other tasks in conducting their business. It would be impossible for the merchant to offer personalized products without the automation of recommendation systems. When recommendation systems take care of the personalization of the eCommerce website, merchant can utilize time to focus on creating new.

Value propositions of recommendation systems are illustrated in TABLE 8. This table compares findings from literature review to findings from empirical research. Empirical research was able to strengthen argued value propositions while also identifying new value propositions.

TABLE 8 Value propositions of recommendation systems

<table>
<tr><th>Literature review</th><th>Empirical research</th></tr>
<tr><td>Make hard to find products visible (Ricci et al., 2011)</td><td rowspan="2">Make products visible for customer</td></tr>
<tr><td>Diversify sold items (Ricci et al., 2011)</td></tr>
<tr><td>Increase customer loyalty (Ricci et al., 2011)</td><td>Increase customer loyalty</td></tr>
<tr><td>Increase in financial revenues (S. S. Li & Karahanna, 2015)</td><td rowspan="2">Gain more sales</td></tr>
<tr><td>Sell more items (Ricci et al., 2011)</td></tr>
<tr><td>Gain better understanding what the end customer wants (Ricci et al., 2011)</td><td>Provide data about popular products for steering business</td></tr>
<tr><td>Increase conversion rate (Ricci et al., 2011)</td><td>Increase conversion rate</td></tr>
<tr><td>Increase customer satisfaction (Konstan & Riedl, 2012; Ricci et al., 2011)</td><td>Increased customer satisfaction</td></tr>
<tr><td></td><td>Personalize shopping experience</td></tr>
<tr><td></td><td>Remove barriers from making transactions</td></tr>
<tr><td></td><td>Reduce amount of manual work</td></tr>
<tr><td></td><td>Increase brand image</td></tr>
<tr><td></td><td>Optimize rate of inventory turnover</td></tr>
<tr><td></td><td>Increase in average order value</td></tr>
<tr><td></td><td>Provide great customer service</td></tr>
<tr><td>Diversify sold items (Matt et al., 2013)</td><td></td></tr>
</table>

7.2 Theoretical and managerial implications

Aim of this study was to explore how AI applications create value for eCommerce merchants and what are the value propositions of recommendation systems. Prior literature body discussing AI creating value on eCommerce is scarce, and there has not been real effort in tying these two subjects together. This Thesis aims to settle this issue. Recommendation system was chosen as an example of AI application, whose value propositions were investigated in more detail.

Aim of this research was not to test any existing theory, but to explore value creation elements of AI applications on eCommerce and identify value propositions of recommendation systems. Issues were investigated in one well-restricted setting of two case companies.

This Thesis has two important implications for research. One of them is strengthening the framework depicting AI subfields, associated features and values. This research identifies relevant AI subfields for eCommerce and provides concrete examples of different applications and features. This Thesis also describes why features of AI are considered valuable.

Second implication is the identification of recommendation system's value proposition. This research strengthened identified firm-level impacts of recommendation systems and shed light on how recommendation systems should be utilized to maximize created value. This research was also able to identify several unidentified value propositions of recommendation systems. As expected, findings of this study did not contradict with prior studies, which are limited in number.

There are two managerial implications of this study. First, generated ideas for many potential applications of AI can be managerially valuable for any supplier or merchant in the field. This Thesis was also able to depict the relationship between features and values. Findings of this study can be particularly valuable for supplier organizations offering AI solutions for eCommerce merchants. This Thesis pinpoints current expectations of AI and in addition presents why and how AI features create value.

Second, this Thesis enables to understand firm-level impact of recommendation systems by identifying key value propositions. This is important both managerially and theoretically. Managerially, this information can be beneficial for supplier organization offering recommendation system solutions for customers. This Thesis also grasps the subject on how the impact of recommendation systems should be measured. Theoretically, it can be argued that this Thesis lays groundwork for inspecting value propositions of recommendation systems in more detail.

7.3 Reliability, validity and limitations of the study

With every study, it's important to carefully examine and discuss the success. Success is usually measured and examined by discussing reliability and validity. According to Golafshani (2003) reliability has traditionally been used to test or evaluate quantitative research, but the idea behind reliability can be implemented in many often types of research. Reliability is not the silver bullet criterion of qualitative research, though. Stenbacka (2001) argues that reliability as a concept is misleading in qualitative research, and that a good qualitative study should never be discussed through reliability. Reliability and validity go hand-to-hand, and there never can be validity without reliability (Golafshani, 2003). Patton (2002) argues that in qualitative research reliability consequences from the validity of the study. For this reason, demonstrating validity for qualitative research is enough to establish the reliability of the study.

According to Golafshani (2003) the construct of validity is discussed with many different terms in qualitative studies. Many researchers have taken individual views when discussing validity of qualitative study and adopted terms such as quality, trustworthiness and rigor (Patton, 2002). Golafshani (2003) once again refers to Stenbacka (2001) and points out that Stenbacka (2001) has not ruled out validity as a construct of discussing the success of qualitative study.

Creswell & Miller (2000) state that there is a need for qualitative researchers to demonstrate their credibility. There are multiple different ways to achieve this. Ultimately Creswell & Miller (2000) "define validity as how accurately the account represents participant's realities of the social phenomena and is credible to the interpretations accurately represent them."

For defining validity of the study, it is important to reflect on how the research was carried out. Chosen research method was a case study. Choosing the research method was straightforward, as the goal of the study was to answer the research questions in one specific, well-restricted setting within two case companies representing both supplier and customer views. Case study can also be considered as a fruitful approach for due to both the theoretical and managerial implications, from which the latter in this setting play key role for many organizations.

Data collection method chosen for the study was theme interview. Theme interview was chosen as it enables interviewees freely open up about the themes chosen for investigation. Theme interview covers topics, not rigorously formed questions. For the interview a set of themes and questions were formed. Questions were discussed in an open conversation. Not every question was consistently asked from each interviewee. Aim of this was to leave space for open discussion. Interviewees were triangulated as much as possible from the two case companies, to get enough saturation for the answers.

During interviews it was clearly emphasized that there is no need to share confidential secrets – personal experiences were enough. This aimed to motivate interviewees answer truthfully how they felt about the subject at hand.

Amount of prior literature covering the subject can be seen as a major limitation. AI the research is lacking a consensus on how the subject should be described and organized. One major limitation is the fact that the researchers covering the subject have differing views on what AI is and what it aims to achieve as a research area. There is a great contradiction on the term, as some researchers imply that AI is yet to be achieved, whereas different businesses marketing for solutions are describing applications as "AI-driven".

Lack of well-organized literature covering AI also shadowed gathering literature for the value creation of AI applications withing eCommerce. This poses great limitations for this study, as prior literature has not formulated any viable ways how to approach this type of subject.

It has to be noted that the research is only an explorative study aiming to grasp the subject that has not yet had great research interest. For this reason, the study aims to explore and acquire knowledge about the phenomena. For acquiring knowledge, a rather closed setting of two case companies was chosen. For this reason, the results of this study are ultimately true in the setting of these two companies, and one might argue that results cannot be generalized to great extent. Despite concerns, results of this study are generalizable, and the results could be verified in some other setting within similar case companies operating in similar business environments.

Inexperience of the researcher is also a major limitation. This was the first empirical research conducted by the researcher, and this might have led to some unsatisfactory design choices to study the topic. It is not definite that researcher has been able to gather and process all related prior studies. Limitation arising from the inexperience was mitigated by consulting supervisor and studying the topic as widely as possible.

7.4 Further research

Research aiming to understand how portfolio effect can be mitigated would be welcomed. Technical research could identify possibilities in combining data from multiple sources to provide great recommendations. Research could find out how customers and merchants deal with sharing data within multiple merchants, not just one eCommerce site. Initial results from this research are promising as they suggest that merchants might be willing to share such data, as each merchant would benefit.

Further research would be welcomed to form a profound definition of AI and the different features. In such study it would be important to focus on those applications and features that can be achieved with current technology and the state of AI. It would defragment AI research and bring an effort to normalizing the arguably too high expectations. One step further, it would be possible to tie value propositions to different applications more rigorously in order to form value chains. Large-scale study could test which are the most valuable ones. Such study could provide important insights for companies offering AI solutions.

8 CONCLUSION

This Thesis aimed to answer questions on how AI applications create value for eCommerce merchants and what are the value propositions of recommendation systems. On this Thesis a framework depicting AI subfields, features and values was created. This framework indicated that most active subfields of AI research are expert systems, natural language processing, speech recognition and machine vision. Each of these subfields have individual features and values, but ultimately, they aim for the same objective – to develop a system that exhibits those natural characteristics we associate to intelligent human behavior

To examine the subject in more detail, recommendation system was chosen as an application of AI. Numerous studies have been conducted about the impacts of recommendation systems, but in the past, firm-level impact has not been thoroughly explored. Narrow body of literature indicated that firms utilizing recommendation systems can have benefits such as increased customer satisfaction, fidelity and loyalty. Financially, firms can achieve better conversion rate, that inevitably relates to financial benefits, such as increased sales, selling more and diversifying sold items.

On the empirical part of the Thesis the objective was to confirm, complement or discard findings identified from the literature. Empirical part of the research was conducted as a qualitative case study. Case organizations were two Finnish companies, from which the supplier is responsible of delivering eCommerce solution to the customer organization. Five interviewees were chosen from both organizations. This resulted in total ten interviews, which were conducted as theme interviews. Data was analyzed thematically.

Findings from empirical research completed findings from literature review. Most active subfields of AI research are relevant in eCommerce, and the empirical research was able to identify features and values in more detail. Empirical research identified natural language processing to assist in translating and identifying issues in product data, help achieving conversational commerce and have chatbots for customer service or sales promotion. These features are valuable for eCommerce merchants as they automate tasks, reduce manual work and assist both customer in shopping and merchant with customer service.

Machine vision can recognize elements from product images. It could help in making product information more accurate and recognize same line of products by design. Essentially, but indirectly, they are means to increase the conversion rate.

With expert systems, the landscape of potential features is extensive. Expert systems encapsulate features related to personalization, campaign tools, dynamic pricing, intelligent search, segmentation, journey optimization and controlling packaging or picking. Offering relevant products, gaining access to accurate insights, achieving correct price point for each customer, help customers finding right products, increase accuracy of marketing, ability to appreciate each customer and reduce manual work are fundamental values.

With recommendation systems the identified value propositions found from the literature review were strengthened. Additionally, empirical research was able to identify new value propositions such as ability to personalize shopping experience, remove barriers from making transactions, reduce amount of manual work, enable automated recommendation of products and increase the brand image.

To conclude, AI has great potential for both eCommerce merchants and suppliers offering solutions. This research provided an effort to bring together these three entities – AI, recommendation systems and value creation. This effort led to the identification of AI subfields, features and values, with a case study of two organizations. Additionally, this study strengthened and complemented the theoretical implications of value propositions of recommendation systems. Managerially, this research was able to generate potential and valuable applications of AI for eCommerce merchants. These efforts stand as the main implications of this Thesis, and as such, they pave the way for further research addressing this subject.

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APPENDIX 1 THEME INTERVIEW FORM IN FINNISH

Esittely
Nauhoitus

Taustakysymykset
Rooli
Kokemus verkkoliiketoiminnasta vuosissa

Teemat

1. Mitkä tekoälyn sovellukset koet luovan arvoa eniten verkkokauppiaille?
2. Koetko tekoälyn tarjoavan hyötyä verkkokauppiaille, jos koet, millä tavoin?
3. Miten määrittelisit käsitteen tekoäly, mitä tekoäly mielestäsi on?
4. Mitkä tekijät vaikuttavat eniten tuotesuosittelujärjestelmien onnistuvuuteen?
    a. Suositteluiden osuvuus, suositteluiden sijainti, suositteluiden esittäminen ostoprosessin vaiheissa (aikainen, myöhäinen)
5. Mitkä eri tuotesuosittelun tyypit koet tärkeimpinä ja miksi?
    a. Kontekstuaaliset eli esimerkiksi suosituimmat tuotteet, tuotteeseen liittyvät (osti tämän, osti myös tämän), asiakkaan aikaisempaan käytökseen perustuvat suositukset
6. Miten näet älykkäiden tuotesuosittelujärjestelmien luovan arvoa eli hyötyä verkkokauppiaalle?
    a. Aineettomat ja aineelliset hyödyt
7. Kuinka tuotesuosittelujärjestelmien luomaa arvoa eli hyötyä verkkokauppiaalle voidaan mitata, ja mitataanko sitä?
8. Millaisena näet verkkokauppiaan sekä palveluntarjoajan roolin tuotesuosittelujärjestelmien hyödyntämisessä?

Haluatko lisätä vielä jotain?

APPENDIX 2 THEME INTERVIEW FORM IN ENGLISH

Introduction
Recording

Background questions
Role
Experience of eCommerce in years

Themes

1. Which AI applications do you think creates most value for eCommerce merchants?
2. Do you think that AI offers value for eCommerce merchants and if you do, in which ways?
3. How do you define AI, what do you consider AI to be?
4. Which factors affect most in successful utilization of recommendation systems?
    a. Relevance of recommendations, position of recommendations, timing of recommendations during purchase process (early, late)
5. Which types of recommendations do you consider to be most important and why?
    a. Contextual meaning for example most popular products, recommendations related to products (bought this, bought that), recommendations based on customers past behavior
6. How do you see recommendation systems create value for eCommerce merchants?
    a. Intangible and tangible values
7. How do you feel value created by recommendation systems can be measured, and is it measured?
8. How do you see the roles of eCommerce merchant and supplier on the utilization of recommendation systems?

Do you wish to add something?

APPENDIX 3 FINNISH INTERVIEW CITATIONS

Mä en osaa sanoa tästä vielä kovin syvällisesti, mä ajattelen tätä niinkun yleisesti verkkokauppatrendien ja verkkokaupan merkityksen kautta – – mä aattelen tätä niinkun isommassa kontekstissa. -S5, 1

Tuotteen hinnoittelu ois jotenkin tekoälypohjaista, että ottais huomioon vaikka miten sitä on muualla myynnissä tai niin edelleen. -S2, 2

Dynaaminen hinnoittelu mitä käytetään tänä päivänä laajasti tuolla lippumyynnissä, lentoyhtiöiden liiketoiminnassa ja hotellien hinnoittelussa mutta aika vähän sitten taas tuolla retail-puolella vielä tuotteissa. Eli kysynnän tai sitten vaihtoehtoisesti kilpailijan hinnoittelun perusteella tehtävää, jopa automatisoiduksi asti vietyä hinnoittelua. -S3, 3

Manuaalisesti vakoilet ja yrität seurata muiden kauppojen hintoja, pysyä sillä tavoin kilpailykykysenä ja laskeskella omat kateprosentit ja miettiä omia hinnoittelustrategioita. Kaiken ton automatisoiminen, onhan se ihan valtava, niinkun siis työmäärä. Se on oikeastaan sellanen kilpailutekijä, että pystytään toteuttamaan asioita jotka käytännössä olis mahdottomia niiden manuaalisen työmäärän johdosta -S4, 4

Tunnistetaan asiakas profiilin ja segmentin kautta, käyttäytymisen perusteella räppästään sellanen hinta millä me luullaan, että se asiakas vois sen ostaa -S5, 5

Kampanjanhallintatyökalut, joihin on jollain tavalla tekoälyä tuotu sisään. Esimerkiks tehdään skenaarioita jostain kampanjasta ja sitten pystytään ajamaan useita eri skenaarioita siitä, miten se tulis menestymään ja hyödyntämään siinä tekoälyä laskemaan niitä skenaarioita. Sen tyyppisiä ratkaisuja vois olla tosi hyödyllisiä verkkokauppiaille. -S3, 6

Tekoäly pystyis suosittelemaan, että sun kannattais laittaa nää tuotteet kampanjaan ja se kampanjan hinta pitäs olla tässä hintapisteessä ja tässä on sun kampanjasegmentti ja näin. Tälläsiä ehdotuksia tulis aina, niin se olis todella voimakas setti. Siitä aina seuraavaan kamppikseen opittais mikä toimii ja pystyttäis laskee sitä kampanjakrapulaakin vähän. Monta kertaa mietitään vaan, että miten se kampanja möi, mutta ei oteta huomioon sitä että itseasiassa ku se kampanja möi paljo ni meidän normaali myynti kampanjan jälkeen sakkaa pikkusen. Se on niin monimutkaista kuitenkin se, että miten se vaikuttaa loppujen lopuksi siihen sun tulokseen. -S2, 7

Journey optimization. Tää on isompi teema. Tarkotan sitä, et kun mä nyt käyn piilareita kattomassa, mun journey optimoidaan juuri mulle, että tää tyyppi tyypillisesti ostaa kerran puolessa vuodessa nuo linssit, ei oo kiinnostunu mistään muusta. Ja arvostetaan sitä, sen kaltasta asiakkuutta suosittelemalla tiettyjä juttuja. -S5, 8

Haku on semmonen missä pyrittäs ymmärtämään sitä, kun asiakkaat hakee jotakin, niin mitkä tuotteet sitten sillä hetkellä olis niitä oikeita tuotteita. -S1, 9

Lähinnä se on tuotehaku, jossa nykyisin jatkuvasti kasvavissa määrin voisi jo luonnehtia, että on tekoälyä tai koneoppimista hyödynnetty. -S4, 10

Luonnollisen kielen ymmärtäminen ja mitä siitä seuraa, on conversational commerce. Sitten virtuaaliset avustajat, eli missä tahansa tilanteessa voit pyytää virtuaalisen avustajan hankkimaan lisätietoa, valitsemaan asioita, löytämään oikeita kategorioita – – se voi jossakin vaiheessa olla sitten eleitä tai ilmeitä millä ohjataan, mutta kuitenkin me mennään pois siitä point and click, tai tekstipohjaisesta käyttöliittymästä, jolloin se luonnollisen ihmisen ymmärtäminen on tärkeää. -S5, 11

Conversational commerce, eli joko puheella tai tekstillä ohjattuna. Siellä taustalla AI-pohjaiset ratkaisut pystyy tulkitsemaan asiakkaan tarvetta ja ohjaamaan oikeeseen suuntaan – – jos niinku tylsästi sanoo, sellanen chatbot 2.0 tyyppinen juttu – – tää puheohjaus tulee tuolta Googlen, Amazonin ja Applen kotilaitteitten kautta, että saadaan vietyä ostamista ja verkkomyyntiä puheohjaukseen, niin on mielenkiintoinen alue. -S3, 12

Pystyiskö sitten tekoälyn kanssa jopa kuvien perusteella tunnistamaan näitä saman sarjan tuotteita, tai kuoseja, tai jotain tämmöstä. - S3, 13

Miksi jonku henkilön pitäis manuaalisesti käydä kertomassa tuotetietojärjestelmässä, että tämä villapaita on sininen, kun sen villapaidan kuvan perusteella me saadaan tieto jo pihalle tämmösellä kuvantunnistushärvelillä, että kyseessä on sininen villapaita. -S3, 14

Sitten tuotetiedon rikastusprosessissa voisi olla tekoälyä ihan paikallaan – – sitä dataa vois prosessoida, tunnistaa sieltä tiettyjä asioita ja nostaa sitten ihan manuaaliseen prosessiin – – että, toi nyt ei kyl ehkä tainnut olla ihan oikein tässä tai että – – tämä puuttuu. -S5, 15

Tuotetiedon rikastaminen ja sitten siellä käännöstyön tekeminen vaikkapa. -S3, 16

Korvaamaan niinku manuaalisii prosesseja tai ylipäätänsä toimenpiteitä mitä verkkoliiketoiminnassa tehää, puhutaa sitte iha niiku keräilystä tai pakkaamisesta tai sen ohjauksesta. -M2, 17

Aspabotti tai myynninedistämisbotti on varmaa se mitä niiku tullaa tulevaisuudessa niinku näkee ja käyttää enemmä.-M2, 18

– – koneellisesti viestimään asiakkaalle, niin tekoäly pystyy kysymään siihen dialogiin liittyviä tosi helppoja kysymyksiä, asiakas vastaa siihen kyllä tai ei ja se määrittelee, miten se dialogi jatkuu. -M3, 19

Tietysti sellaiset sovellukset mitkä auttas kohdentaan mainontaa tai sitten clousaamaan sitä kauppaa. Siihen kai se kiteytyy, jollain millä saadaan niitä asiakkaita ja joillain millä saadaan tehtyä sitä kauppaa. -M1, 20

Tekoälyllä pystys tarjoamaan asiakkaalle relevantimpia tuotteita – – eli vähän tällästä ylösmyyntiä käytännössä. Sen mä nään ehkä kaikista tärkeimpänä. -M5, 21

Semmoisia mitä pystyy ottamaan käyttöön nii liittyy ehkä nimenomaan tuotesuosituksiin ja siihen sitte yhdistettynä jollain tavalla asiakaspalveluun, että ite ainakin koen että ne tulee jatkossa menee aika käsikädessä. -M2, 22

Ennenkaikkea niinkun enabloida tiettyjä asioita mitkä ei ole mahdollisia. Ja sitten myös tavallaan tehostaa sitä toimintaa niiltä osin mitkä on mahdollisia ilman sitä tekoälyä. -S5, 23

Kyllä siitä olis huomattavaa ajansäästöä. -S2, 24

Onhan siellä siis muita mittareita, et ehkä se lisämyynti tai myynnin kehittäminen on se tärkein, mut sit – – välillisiä hyötyjä, brändin imagon parantuminen, asiakaskokemuksen parantuminen ja pidemmät asiakassuhteet. -S5, 25

Manuaalisen työn väheneminen – – lisämyynti ja – –personointi – – ne on konversioon vaikuttavia asioita. -S3, 26

Älyä joka imitoi pitkälti myös ihmisen toimintaa. Ja niinkun käyttäytymistä. Ja oppivaa teknologiaa. -M5, 27

– –tekoäly kuitenkin on niin sanotusti laskentaa, et se on niinkun ennalta, ennalta tiedettyjä asioita ja niiden niinkun mätsäämistä tai yhdistelemistä – – että enemmänkin sitä niinkun machine learningia siinä niinkun miellän. -M1, 28

– – tietokoneella suoritettava ohjelma mikä pystyy mukautumaan ympäristöön ja uuteen dataan – – se ei oo algoritmi mikä tuottaa aina saman lopputuloksen vaan algoritmin lopputulos riippuu siitä miten paljon dataa sillä on käytettävissä– – silleen mä sen niinkun näkisin ja – – voidaan sanoa että se on oppivaa. -S2, 29

– – data pohjalla jonka perusteella tehdään actioneita – – kun on tehty actioneita – – niin sit se tekoäly on se joka pystyy muuttamaan sitä toimintaa seuraavaa kertaa varten että ne lopputulokset olis parempia kuin aikasemmin. -S3, 30

Se ero nimenomaan muihin algoritmeihin on se, että algortimeilla on tietty säännöstö ja tietty malli mitenkä ne toimii. Ja tekoäly pyrkii nimenomaan toimimaan samoin kuin ihmisajattelu tai ihmisen kognitiiviset prosessit. -S5, 31

– – ihminen opettaa koneelle miten toimia – – esimerkiksi jos otetaan työtehtävä, niin jos siinä on aina toistuva malli, niin konehan – –matkimalla oppii, ja sitten toistaa sitä. -M3, 32

Se on liiketoimintaa ohjaavaa dataa – – se on liiketoiminnan työkalu.- M2, 33

Yks ehkä tärkein kriteeri, ainakin top kolmosessa on oikea-aikaisuus. Pakko sanoa myös niinku oikea, tai relevantti sisältö. Nää on ehkä kaks sellasta, jotka mun mielestä korreloi kaikkein eniten siihen mikä on onnistuvuutta. -S5, 34

Osuvuuden alleviivaisin niinkun kaikessa tärkeimmäksi, ennen kaikkea että se osuu se tuote, että se on tarpeellinen. Mutta sitten aikataulullisesti, et jos otetaan esimerkkinä vaikka lumikola, niin sehän voi olla hyvinkin tarpeellinen mutta millon sitä markkinoidaan, että otetaanko sitä sillon kun on lumisateet tullu vai tulossa vai menny, niin sillä on ehkä vielä suurempi merkitys. -M1, 35

Ja sitte ehkä vasta siinä vaiheessa ku on saatu se asiakas, esimerkiksi lisäämään asioita tarpeeksi sinne ostoskoriin, niin sit rauhotetaan se et lähetään ajamaan asiakasta kohti konversiota. Ei häiritä enää esimerkiksi sen checkout prosessin aikana tuotesuosituksilla vaan sitten sen focuksen pitää olla siinä et se tilaus viedään maaliin. -S3, 36

Miten se itellä menee, niin se on ajallisesti se oikea kohta. Ja sitten oikeasti se osuvuus, että niinku kyllähän siinä hermo menee jos ehdottaa ihan jotain muuta mahdollista joka ei vois vähempää kiinnostaa. -M3, 37

Oikea-aikaisuus, eli – – tällänen klassinen retargeting tällä hetkellä – – tulee edelleen suosittelemaan mulle sitä samaa systeemiä jonka mä oon ostanu. -S5, 38

2 viikkoa sen jälkeen netissä näytetään tismalleen samoja tarjouksia niistä kengistä mitkä mä oon jo hankkinut tai muuta vastaavaa. -S2, 39

Yksittäisen verkkokauppiaan ostohistoria voi olla aika rajallinen tekijä. Elikkä miten sen kuluttajan niinkun oikeastaan verkkokäyttäytymiseen, myös muilla sivustoilla liittyvää dataa voidaan hyödyntää. Noissa tuotesuosituksissa. Ja se on niinkun tainnu olla sellanen osa-alue, mihin on nähty, että kannattaa panostaa. -S4, 40

Se on ehkä meilläkin voinu jopa toisesta kanavasta hankkia sen meillä mutta silti me herätellään sitä verkosta mainoksen avulla. -M2, 41

Jos ois paveluntarjoajana tieto, että asiakas on ostanut kenkänsä jostain muualta, niin jakais sen tiedon jopa kaikille, koska se hyödyntäis kaikkia keskittämään sen panoksen ehkä seuraavaan asiakkaaseen. Tai tälle kyseiselle asiakkaalle kengänhoitotuotteita, kun se on ostanu kengät. -M1, 42

On sitten tavotteena brändin rakentaminen tai tunnettavuuden lisääminen, niin ehkä se on aineettomat hyödyt -osioo, joka sitten generoi, sitä kauppaa joko siellä verkossa tai muualla, niin sitten niitä aineellisia hyötyjä. -M2, 43

Meille niinku myyjille, ketjun tuelle, ostajille ja kaikille oikeastaan talon sisällä on todella tärkeätä saada sitä dataa selkeästi esille, ja nimenomaan suosituimmat tuotteet, pystytään vähän niinkun ohjaa jopa niinku liiketoimintaaki noitten pohjalta. -M2, 44

Jos vaihtoehtona on se että meillä ei olis ollenkaan minkäännäköistä tuotesuosittelujärjestelmää käytössä, niin sillonhan se ostokokemus ei ole ollenkaan personoitu. Tuotesuosituksilla voidaan suositella asiakkaille just niitä tuotteita. -M4, 45

Suurin arvo on varmaan et se tuplaa niinsanotun tehon mitä ei välttämättä ihminenkään pysty tekemään tiettyinä vuorokauden aikoina. Ja se on niinku kokoajan siellä eri asiakasryhmille. Tavallaan rahallinen hyöty on suuri, mut sit taas se oma aika ja sen priorisointi vapauttaa sitä uuden uuden luomista, tekemistä ja tuottamista. -M3, 46

Tarjoaa minulle sopivia tuotteita, tuntee minut ja tarjoaa hyvää palvelua myöskin. Et kyl mä näkisin sen sellaisenakin asiana. Et se on se isoin juttu. -M5, 47

Se mitä tullaan tulevaisuudessa näkee ja käyttää enemmä et yhdistetää tuotesuositukset ja sitte asiakaspalvelu, eli ruvetaa blokkaa niitä ostamisesteitä automaation tai tekoälyn avulla. -M2, 48

Hyvin toimiva verkkokauppa ja tuotesuosittelu on osa hyvin toimivan verkkokaupan perusrakenteita. Hyvin toimiva verkkokauppa parantaa asiakaskokemusta ja asiakkaan suhtautumista siihen brändiin. -S5, 49

Aineellinen höyty, niin kylhän nää tutkitusti ja todistetusti nostaa muun muassa keskiostosta ja sitten toisaalta sillä relevanttiudella voidaan päästä siihen, että myös konversio kasvaa. Ne nyt kumminkin on niitä perustekijöitä siellä verkkoliiketoiminnassa, että kävijämäärä, keskiostos ja konversio muodostaa käytännössä sen liikevaihdon. -S3, 50

Varastonkiertonopeus on myös sellanen yks kulma jota ei ajatella, jota se ostaja ei ainakaan ajattele. Mutta myös verkkokauppiaalla nää voi olla asioita, että ei ajatella puhtaasti sitä. Voi olla edullisempaa myydä vaikka halvempi tuote, kun ajatellaan vaikka niinku logistiikkaa tai varasto-arvoja, eli joskus semmonen tuotesuosittelujärjestelmäpohjainen ostoskorin alas-skaalaaminenki voi olla kuitenkin loppupeleissä kannattavampaa, jos sillä saavutetaan muita hyötyjä. -S4, 51

Aineellisista hyödyistä selkeintä on, että toivottavasti lisää liikevaihtoa, vähemmän palautuksia. Elikkä olis enemmän osuvia ostoksia. Ja sitten jos toimii hienosti älykäs tuotesuosittelujärjestelmä, on myös se oman työmäärän vähentäminen. Mitä älykkäämpi se olis, se vois myöskin ehdotella sellasia mitkä hommat kannattaa poistaa. Että okei näitä ei oo kukaan ostanu, sen nyt näkee varmaan ihan ERPistäkin tai muusta järjestelmästä mutta näitä ei kukaan edes katso, tai näitä tuotteita joku katsoo mutta se on samantien muutama sekunti ja pois että tota tässä on jotain vikaa, niin tälläisiä hyötyjä vois tulla kanssa. -S2, 52

Mun mielestä ei ei sitä mitata tarpeeksi. Jos sitä mitataan jollain ni sitä mitataan eurojen kautta, ja se on mun mielestä yksinään tosi väärä mittari et miten paljo se tuo lisämyyntiä. -M3, 53

Kuinka paljon on myyntiä tullut mistäki tuotesuosituskanavasta tai ylipäätänsä kuukaustason raportointi. Mutta se on oikeastan siinä, mitä sä niinkun datan osalta saat. Miten muuten sä niinku mittaat, jollain tavalla tohon pitäs liittää se kokonaisvaltainen asiakastyytyväisyys. Se on kuitenki joku mittari siinä, mitä ei raportille asti saa. -M2, 54

Ku tuotesuosittelujärjestelmä paranee ni voidaan nähdä että pikkusen liikevaihto paranee kanssa, mutta siinä on se, että ei voida suoraan välttämättä yhdistääettä johtuuko se tästä vai johtuuko se siitä, että tänään sataa. Oniin monia vaikuttajia siihen, että miten paljo sieltä verkosta ostetaan. Uskoisin, että tuollasen yksittäisen systeemin mittaaminen on aika lapsenkengissä vielä tällä hetkellä. -S2, 55

Kyllähän tämmöstäkin mittarointia ehkä jollain tasolla tehdään. Että jos ostit tuotesuosittelujen kautta niin onko tälläset käyttäjät sitoutuneempia, mut niissä ehkä se kohdistusongelma, että mistä se sitoutuminen oikeasti tulee. Että mikä juuri se tuotesuosittelun arvo siinä on ollu. Väitän, että aika puutteellisesti näitä kuitenkin mitataan. -S4, 56