Lund University
School of Economics and Management

Department of Informatics

Adopting AI in Organizational Decision Making

A qualitative study

Master thesis 15 HEC, course INFM10 in Information Systems

Authors: Ludwig Entzenberg
Erik Söderqvist

Supervisor: Christina Keller

Correcting Teachers: Miranda Kajtazi
Osama Mansour

Adopting AI in Organizational Decision Making: A qualitative study

AUTHORS: Ludwig Entzenberg and Erik Söderqvist

PUBLISHER: Department of Informatics, Lund School of Economics and Management, Lund University

PRESENTED: May, 2020

DOCUMENT TYPE: Master Thesis

FORMAL EXAMINER: Christina Keller, Professor

NUMBER OF PAGES: 168

KEY WORDS: Artificial Intelligence, organizational decision making, TOE framework, technology adoption

ABSTRACT (MAX. 200 WORDS):
Organizational decision making is a challenging task that tends to be impactful. Decision-makers have for more than 50 years been using different types of computational support to enable for more accurate and faster decision. In today's business context, there is an increasing volume of data available for the decision-maker. However, humans are limited in their capacity to consume and manage data and information. In addition, humans possess biases and can be considered as unreliable decision makers. Hence, AI-enabled systems have intelligence capabilities that require some sort of such as problem solving or communicating, assisting organizations to overcome potential biases that could affect the decision. However, there is a lacking understanding of what factors influences the organizational adoption of AI-enabled system in decision making. Therefore, a qualitative investigation using six semi-structured interviews with organizational decision makers were conducted through the lens of an adapted TOE-framework. The conclusion shows that amount of data, perceived direct and indirect benefits, perceived technical competence, top management support and competitive pressure were factors perceived to be influential in the adoption. These initial insights may serve as further guidance for more research of this phenomenon.

Content

Figures

Tables

1 Introduction

Organizational decisions are a challenging task tending to be impactful, therefore it requires knowledge and wisdom (Zins, 2007). However, research have shown that humans are unreliable decision makers, where judgements are influenced by noises such as current mood, the weather, and time since their last meal (Kahneman et al., 2016). In addition, professionals often make deviate decisions if compared to their own prior decisions, their peers, and the rules they have claimed to follow. Thus, such noise becomes an invisible tax for companies to pay (Kahneman et al., 2016).

Nevertheless, organizations and decision makers have for more than 50 years been using different types of decision support systems (Power, 2007; Watson, 2017). Decision support systems (DSS) are applications that help managers to make more accurate and faster decisions (Clark, Jones & Armstrong, 2007; Power, 2007; Arnott & Pervan, 2008). DSS is also used to describe an academic discipline (Watson, 2014). DSS have ever since evolved into terms such as business intelligence and analytics, which is an umbrella term for data analysis applications (Watson, 2014). Despite researchers having shown the rational usefulness of DSS applications and the ever increasing ease of use, prior studies have identified resistance to pursue the recommendations produced by the DSS (Snead & Harrell, 1994; Fisher & Howell, 2004; Giboney et al., 2015).

Similar to DSS, Artificial Intelligence (AI) has been around for many years but have recently gained a lot of attention both within organizations and academia (Russell & Norvig, 2016). AI can be treated as an umbrella term for “The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision making, and translation between languages.” n.p (Oxford Dictionary, 2020).

AI has been applied throughout the years in several domains which has resulted diverse in descriptions of AI-enabled systems, especially for decision making, such as expert systems, knowledge-based systems and intelligent decision support systems (Duan, Edwards & Dwivedi, 2019). It can therefore be argued that defining AI and its related terms has become a moving target (Duan et al., 2019). Nevertheless, according to Gartner's 2018 Technology trend survey, AI is listed as the No. 1 strategic technology for organizations. The Gartner survey also showed that 59% of the organizations are still gathering information on how to build their AI strategies, while the other 41% have already made progress in adopting AI solutions (Panetta, 2017).

AI-enabled systems have capabilities that require some sort of intelligence such as problem solving or communicating (Russell & Norvig, 2016; Brynjolfsson & Mcafee, 2017; Rzepka & Berger, 2018). AI-based elements have been incorporated and used for data analytics for many years (Gill, 1995). The usage of AI-enabled systems such as DSS, helps organizations and decision-makers to overcome any potential bias that could affect the decision (Ocasio, 2011; Russell & Norvig, 2016). In addition to potential biases in judgement, noise also exist, possibly more than one can imagine (Kahneman et al., 2016). In addition, when collecting relevant inputs and making a decision, humans tend to lack the ability of appropriately weighing or combining them consistently (Harrell, 2016). As a rule, Kahneman et al. (2016) argue that managers and professionals cannot assess their own reliability of judgment. Therefore, AI has become increasingly more important for organizations regarding decision making (Parry, Cohen & Bhattacharya, 2016; Leyer & Schneider, 2019b).

1.1 Problem

In today's business context, there is an increasing volume of data available for the decision-maker (Hilbert & López, 2011; George, Haas & Pentland, 2014). Humans are limited in their capacity to consume and deal with data and information (Zahra & George, 2002; Hoffman, 2016). Thus, this could result in information overload (Hilbert & López, 2011; Stenzelius, Morey & Boström, 2019). Hence, when relying on human judgment in collecting relevant inputs and making a decision, humans tend to lack the ability of appropriately weighing or combining them consistently (Harrell, 2016). Therefore, AI among other digital technologies could help assist the human in processing the information and data (Russell & Norvig, 2016).

However, Keding (2020) state in a literature review that: "Despite the alleged maturity of the research field and the growing stream of literature on the business potential of AI, very little is known about what encompasses the concept within strategic management."(p.3). Interestingly, former CEO of IBM Ginni Rometty argued in 2016 that all major business decision within five years will be improved by cognitive technology (Rometty, 2016). Nevertheless, when receiving forecasters from AI to use in decision making, researchers have found both appreciation (Logg, Minson & Moore, 2019), and aversion of AI-advice (Dietvorst, Simmons & Massey, 2015; Prahl & Van Swol, 2017). Consequently, human distrust in algorithmic forecaster (Dietvorst et al., 2015) and resistance in using them (Davenport & Harris, 2007b), becomes a costly phenomenon.

Still, there is a tremendous potential of AI-enabled applications, yet there is a lacking in-depth exploration in managerial adoption of an AI-enabled system in the decision making context (Leyer & Schneider, 2019b). Furthermore, Kahneman et al. (2016) provide evidence that in many decision-making situations algorithms outperform humans. Hence, this could result in an improvement of the decision making, given that the organizational managers are keen to adopt AI in decision-making contexts (Leyer & Schneider, 2019a). However, Gaines-Ross (2016); Marler, Fisher and Ke (2009) offer insights into the reasons of managerial hesitation to adopt algorithm-based decision making. This includes fear of being replaced and of job losses, concerns about privacy infringements, overconfidence in their own abilities, and group pressure. Still, there is a lack of understanding of what factors influences the organizational adoption of AI-enabled system in decision making. Therefore, by identifying influential factors, valuable insights can be derived. Thus, generating leveraging factors, could be beneficial for the understanding of decision makers in the modern IS context.

1.2 Research question

AI has proven its significance and is expected to influence the decision making context in organizations. Therefore, the intended knowledge contribution of this study is to describe the influential factors in adoption of AI-enabled systems in decisions. Hence, this study aims to answer the following research question:

- What factors were perceived to influence organizational adoption of AI-enabled systems in organizational decision making from a qualitative perspective?

1.3 Purpose

The purpose of this master thesis is that through an interview study describe perceived factors in organizational adoption of AI-enabled systems in organizational decision making as perceived by decision makers, from a qualitative perspective. This contribute to a recognition of factors in the technological, organizational, and environmental context of an organization. Thus, this study aims to provide an initial insight to fellow academics regarding AI-enabled system adoption for organizational decision making.

1.4 Delimitation

Thoroughly studying the entire adoption process would possibly generate rewarding insights. However, contemplating the time restraints of this thesis, focus had to be directed to a part of the adoption. Hence, this thesis will primarily focus on the technological adoption prior to the decision of implementing AI in organizational decision making. Consequently, the interviews have emphasized on the early stages of the adoption. Therefore, the potentially influential factors presented in the literature review are mostly concentrated on prior to the adoption. In addition, this thesis narrows the focus towards the organizational decision making context, which enabled for possibly well-suited factors for this study.

Nevertheless, considering earlier research that has applied Technology-Organization-Environment (TOE) framework to study technology adoption, a vast number of potential factors are investigated as influential through quantitative methodology. Thus, since this thesis are of qualitative nature, investigation will not cover causality effect nor interrelationships among the selected factors. Instead, the examination will be directed towards how decision makers perceives the selected factors. This have been done previously in other qualitative research work investigating technology adoption through various adoption models such as TOE, Technology Acceptance Model, Diffusion of Innovation theory, for the beneficial aspect of gaining a rich description of the selected factors in specific contexts (Alshamaila, Papagiannidis & Li, 2013; Mallat, 2007; Kurnia, Karnali & Rahim, 2015; Vogelsang, Steinhüser & Hoppe, 2013; Black et al., 2001; Chan & Ngai, 2007).

2 Literature review

2.1 Organizational Decision Making

The Cambridge dictionary defines a decision as "a choice that you make about something after thinking about several possibilities " n.p (Cambridge Dictionary, 2020a). On the other hand, decision making is "the process of making choices, esp. important choices" n.p (Cambridge Dictionary, 2020b). Nevertheless, everyone makes decisions and are consequently a decision maker. However, the decision can be of various importance and be impactful for the individual or an entire organization. In this thesis, investigation covers the organizational decision making.

In organizational decision making there is usually not one single manager taking the decisions. Instead, decision making is a social process that occurs between people rather than within a person (Vroom & Yetton, 1973). To develop good judgement in decision making, we gather information about the occurrence to make the decision (Saaty, 2008), which was illustrated as crucial in early research on decision making (Cyert, Simon & Trow, 1956).

On organizational level, managers make decisions using both intuitive and analytical practices in information processing (Dane, Rockmann & Pratt, 2012). Intuition is sometimes referred to as gut feeling (Hayashi, 2001), but the intuitive process is somewhat more complex. Dane and Pratt (2007) defines it as "affectively charged judgments that arise through rapid, nonconscious, and holistic associations" p.40. In contrast to intuition, the analytical practices often entail examining information through logical reflection and conscious reasoning (Jarrahi, 2018). As scholars have theorized, analytical decision making includes a procedure that individuals knowingly attend to and then systematically and sequentially use symbolically encoded rules (Alter et al., 2007). These are fundamental to the rational decision making process.

There are two types of organizational decisions: programmed or structured decisions, which are well defined and repetitive, thus procedures already exist to solve the problem (Soelberg, 1966; Cyert et al., 1956). On the other hand, there is nonprogrammed or unstructured decisions where the problems have not been encountered in the same way before, therefore lacking a clear set of planned responses existing in the organization (Mintzberg, Raisinghani & Theoret, 1976; Cyert et al., 1956). The alternatives in nonprogrammed decisions are ambiguous and unsure to actually solving the problem (Soelberg, 1966; Mintzberg et al., 1976). Therefore, in unstructured situations the decision maker creates situational factors into familiar structural elements already experienced (Newell & Simon, 1972).

The Incremental Decision Process Model, developed by Mintzberg et al. (1976), was created to gain structure to unstructured decisions following three phases: identification, development of solutions, selection of solutions. However, Mintzberg et al. (1976) acknowledge that organization might hit barriers along the decision process, called decision interrupts. That means that the organization must cycle back to a previous decision made and make another choice (Mintzberg et al., 1976). Therefore, the paths are not as sequentially as presented, since research indicates that different paths repeats, iteration occurs, and various paths follows

(Eisenhardt & Zbaracki, 1992). Still, it is through these decision loops that organization understand what works (Mintzberg et al., 1976).

Furthermore, research shows that decision makers satisfice instead of optimizing (Eisenhardt & Zbaracki, 1992), meaning that the optimal solution is wanted, but because bounded rationality and limited information, acceptance of a “good enough” solution is chosen. Moreover, decision makers rarely engage in comprehensive research and discover goals during the search process (Eisenhardt & Zbaracki, 1992). In addition, the decision maker may face several obstacles to deal with, examples of these are equivocality, complexity, and uncertainty.

2.1.1 Equivocality in Organizational Decision Making

Why do organizations process information? According to Daft and Lengel (1986), organization theory suggest that it is to reduce uncertainty and equivocality. However, the larger the quantity of information, does not necessarily mean that we have a better understanding and our judgment have been improved (Saaty, 2008). This is because, the problem identification and development of solutions can involve multiple departments, thus generating multiple viewpoints of what a problem is (Daft, Murphy & Willmott, 2017). As there are conflicting interests, the decision must please different stakeholders within and outside the organization (Saaty, 2008; Jarrahi, 2018), leaving the decision maker to do trade-offs. According to the Eisenhardt and Zbaracki (1992) literature review on strategic decisions, this holds true by most scholars based on that organizations consist of people with contradicting preferences. This is because of conflicting interpretations about the organizational situation, thus having an existing equivocality. Daft and Macintosh (1981) explains the equivocality as “…the multiplicity of meaning conveyed by information about organizational activities” (p.211). Hence, when information is clear and specific, leading to a general interpretation by the people involved, unequivocally exists (Daft & Macintosh, 1981). Still, if the information is unequivocal, there is a danger that ill-defined events have been oversimplified (Daft & Macintosh, 1981). Misrepresentation can also occur where ill-defined information about clear unequivocal events leads to decision errors (Daft & Macintosh, 1981). Therefore, it is important that organizations fit the equivocality of the information processing to the extent of equivocality of the task (Daft & Macintosh, 1981).

2.1.2 Uncertainty in Organizational Decision Making

Furthermore, there is an assumption of literature that the amount of information and task uncertainty is closely related (Daft & Macintosh, 1981). As a result, when organizations face problems with high uncertainty, the information process within the organization increase (Daft & Macintosh, 1981). Still, this is based on the assumption that organizations and the managers work in an environment where asked questions receive answers (Daft & Lengel, 1986). If organization faces work-related uncertainty, a crucial mission is to facilitate the collection, gathering, and processing of information (Tushman & Nadler, 1978). This is important for internal sources of uncertainty e.g. how various parts of the organization are functioning, and level of quality of outputs (Tushman & Nadler, 1978). But also, about external uncertainty e.g. conditions in external technological and market domains (Tushman & Nadler, 1978). Hence, the assumption in organizational theory is that when new data are obtained, tasks are carried out under a reduced level of uncertainty (Daft & Lengel, 1986).

However, when managers are confronted with a complex environment, the perceived uncertainty will be greater and enhance the requirements of information processing in contrast to a simple environment (Duncan, 1972; Tung, 1979). Duncan (1972) conducted a study to identify the characteristics in the environment that contributes to members of the organization experiencing uncertainty in decision making. Two dimensions of environmental uncertainty was detected. First, simple-complex, characterized by the number of factors taken into consideration when making decisions (Duncan, 1972). Second, static-dynamic, defined by the extent of these factors' persistence over time in the decision making units, or if the factors change.

Based on the work of Duncan (1972), the greatest degree of uncertainty in decision making was experienced by the individuals in decision units that experienced environments with dynamic complexity. The results also indicated that the most significant contributor to uncertainty is the static-dynamic dimension. Between decision making units in complex and simple environments the difference is not significant, unless the environment of the units is also dynamic (Duncan, 1972). Hence, a dynamic environment in decision making being either simple or complex, significantly influences the perceived uncertainty. Still, as Duncan (1972) points out, this is based on the perceived uncertainty of the individual, and not to be considered as a constant feature of the organization, as the individual perception and tolerance for ambiguity might differ (Duncan, 1972).

2.1.3 Complexity in Organizational Decision Making

Complex situations in organizational decision making are often characterized by an abundance of elements or variables (Jarrahi, 2018). These characteristics demand processing of a lot of information or data, preferably at high speed to gain a competitive advantage (Jarrahi, 2018). Complex decision making is by its nature - motivated by a cognitive process especially in organizational environments (Wood & Bandura, 1989). Making decisions in complex environments is an ongoing process that requires integration of multiple sources of information to produce distal, socially mediated outcomes (Mintzberg, 1973; Stewart, 1988). In these kinds of environments, appropriate decision rules are discovered through systematic application of analytical strategies (Wood & Bandura, 1989). Despite the information complexity facing organizations, organizations have boundaries of dealing with information (March & Simon, 1958; Simon, 1960; Cyert & March, 1963). It is impossible for an organization and human to interpret and process all available information in the world, thus creating an uncertain environment (Daft & Lengel, 1986). To deal with complex environments, managers try to find decision rules, information sources and structural designs that provide an understanding to cope with complex and uncertain environments (Daft & Lengel, 1986).

2.1.4 Computational Support in Organizational Decision Making

Decision making is a core managerial activity for both the individual and collective decision makers (Bonczek, Holsapple & Whinston, 1979). In the decision making, Bonczek et al. (1979) argued that computers were seen as supportive tools, regardless of the decision makers area of application. This was seen as something new, thus Bonczek et al. (1979) argued to view their work as an initial effort pointing out directions for future enhancement of computer-based support of decision makers. Furthermore, Bonczek, Holsapple and Whinston (1980b) provided an early description of a decision support system (DSS) and its components language system, knowledge system and problem-processing system. It was argued that these concepts and techniques within these systems would make an important contribution to business oriented DSS, and emergence of more powerful systems. Moreover, Bonczek, Holsapple and Whinston (1980a) emphasised on the business community's incorporation of DSS information handling capabilities as an important system characteristic. In general, these works highlighted how the technology may help decision making, but also the need for further development of DSS (Bonczek et al., 1979; Bonczek et al., 1980a; Bonczek et al., 1980b).

An empirical investigation by Sabherwal and Grover (1989) following the decision phases of Mintzberg et al. (1976) provides an early understanding of computer support systems applicability through the different phases. However, the prominent feature of what-if analysis, has been found to establish an "illusion of control", causing overestimation of the DSS effectiveness (Davis & Kottemann, 1994; Kottemann, Davis & Remus, 1994). A what if analysis is a method used for manipulating a quantitative model of a business situation, where the decision maker must specify alternative values of the variables of the decision and environmental assumptions (Davis & Kottemann, 1994). Then the computer solves the model and displays predicted results (Davis & Kottemann, 1994). This is done in an attempt to make better decisions (Kottemann et al., 1994).

Nevertheless, when organization grow larger and diversification increases, the information's complexity for managers does so too, creating a need for technology that can improve the managing of executive information (Rai & Bajwa, 1997). Likewise, when the uncertainty of the organizational environment rises, that means the complexity, ambiguity, variety of managerial information rises too (Rai & Bajwa, 1997). Moreover, Rai and Bajwa (1997) investigated the adoption of a DSS labelled executive information systems (EIS). The availability of internal IS resources were found to be more likely to enable consideration of EIS for decision support (Rai & Bajwa, 1997). Additionally, IS support becomes important in spreading the level of EIS adoption across executives and problem context (Rai & Bajwa, 1997). However, top management was of paramount significance in propagating the decision support and collaboration support capabilities internally (Rai & Bajwa, 1997).

Early discussions on how AI could improve DSS was agent enabled DSS (Hess, Rees & Rakes, 2000). An autonomous software agent was defined as a software implementation of a task in a specific domain, empowering the DSS with mobility, intelligence, and interactivity, by having the essential features of persistence, reactivity, and homeostatic goals (Hess et al., 2000). Based on criteria specified by the user, the autonomous agent seeks to accomplish the goal and sustain that state for as long as the user wants (Hess et al., 2000).

In addition to the practical improvement of DSS, acknowledgements were also made of AI as a new reference discipline to DSS research representing a new DSS era (Goul, Henderson & Tonge, 1992). Now, the research field has progressed. Therefore, an examination of artificial intelligence follows.

2.2 Artificial Intelligence

Several definitions of artificial intelligence have been proposed over the years (Rzepka & Berger, 2018; Russell & Norvig, 2016). In 1955, McCarthy and his colleagues offered the first definition of the term: "For the present purpose the artificial intelligence problem is taken to be that of making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy et al., 1955, p.11). The proposed definitions of AI over the years have been similar to McCarthy et al. (1955), which Russell and Norvig (2010) categorized into four categories: AI as systems that think like humans, AI as systems that act like humans, AI as systems that think rationally, and AI as systems that act rationally. These definitions are more focused on what AI research seeks to achieve rather than to conclusively determine what AI is (Rzepka & Berger, 2018). To the best of our knowledge, there is not yet a commonly accepted definition of AI, thus this thesis will follow the Oxford Dictionary's definition of AI "The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision making, and translation between languages" n.p (Oxford Dictionary, 2020).

Nevertheless, in 1943 Warren McCulloch and Walter Pitts presented a paper that is now generally recognized as the first work in artificial intelligence (McCulloch & Pitts, 1943; Piccinini, 2004; Russell & Norvig, 2016). In the paper the authors proposed a model of artificial neurons in which each neuron is characterized as being either "on" of "off" (McCulloch & Pitts, 1943). If a sufficient number of neighbouring neurons is responding to the stimulation, the switch turns "on" (McCulloch & Pitts, 1943). The authors conceived the state of the neuron to be "factually equivalent to a proposition which proposed its adequate stimulus" p.117 (McCulloch & Pitts, 1943). Finally, McCulloch and Pitts (1943) suggested that suitably defined networks could learn.

The term of Artificial Intelligence was however established in 1955 workshop in Dartmouth where scholars and practitioners gathered (Russell & Norvig, 2016; Brynjolfsson & Mcafee, 2017). This workshop was a springboard for the phenomenon of AI where it received a lot of attention from scholars and advanced in complexity swiftly (Russell & Norvig, 2016). There was what we consider today, basic computers during that time, which had limited functionalities and the introduction of AI disproved what many scientists thought was impossible for a machine to accomplish (Russell & Norvig, 2016). However, the development speed of AI decreased as scientists found limitations to the technology, such as that the machine could not understand the context it was operating in (Russell & Norvig, 2016). This led to a shift in the 1980's where expert systems instead were given attention which at the time was considered powerful and allowed larger reasoning steps with the limitation of only being applicable to narrow areas of expertise (Russell & Norvig, 2016). Today, most practitioners are using expert systems which both the scientific and practicing AI-community are not content with as expert systems are completely rule-based which hinders the development of trying to create a machine which can replicate a human-level intelligence (Russell & Norvig, 2016; Burgess, 2018).

2.2.1 Advancements of Artificial Intelligence

As explained above, AI has been recognized and studied for years, yet it has only recently gained a lot of attention and quickly become a buzzword for the general public (Brynjolfsson & Mcafee, 2017; Duan et al., 2019). This is due to the development of data generation which has resulted in another buzzword called "big data" (Brynjolfsson & Mcafee, 2017; Duan et al., 2019). In short, big data is not only about the volume. It is also about the velocity - real time, near time etc. - , and variety - structured, unstructured etc. - of the data (Russom, 2011; McAfee et al., 2012).

There has been a lot of emphasis on trying to create the perfect algorithms within AI, which was then tested with simple data (Yarowsky, 1995). However, Yarowsky (1995) identified issues with this methodology. He claimed that this issue should and could be solved with accessing multiple data sources. Yarowsky (1995) used the word “plant” as an example, which could mean both factory and flora. Early machine learning techniques enforced human-labelled examples on how to understand which of the meanings the word “plant” was referring to (Yarowsky, 1995). In Yarowsky’s (1995) findings, by switching methodology to larger data sources, the machine’s accuracy of applying the word “plant” in the correct context increased and showed an accuracy of 96% with far less human intervention than previously needed. In conclusion, the findings of Yarowsky (1995) showcased the importance of accessing large volumes of data and multiple sources for the AI-community.

The findings of Yarowsky brought attention to dealing with large quantities of data instead of emphasising on creating the perfect algorithm among scholars (Banko & Brill, 2001; Criminisi, Pérez & Toyama, 2004; Russell & Norvig, 2016). To continue, Banko and Brill (2001) investigated the phenomenon of perfecting algorithms versus acquiring large quantities of data in the context of word processing. The authors concluded that a machine who had large quantities of data but a worse performing algorithm still outperformed a better designed algorithm with less quantities of data (Banko & Brill, 2001). Criminisi et al. (2004) also studied the same phenomena but focused on photographs instead of words in their data. Their result supported Yarowsky (1995); Banko and Brill (2001) findings that the larger the data set, the better performance of the AI-machine (Criminisi et al., 2004).

The field of AI attempts to understand intelligence entities (Russell & Norvig, 2016). Thus, Russell and Norvig (2016) thinks it is important to study AI to learn more about ourselves. However, AI as a phenomenon can be seen differently depending on the philosophical stance one has regarding the intelligence that machines can exhibit (Russell & Norvig, 2016). John Searle, a philosopher, described AI as either “strong AI” or “weak AI”. A strong AI machine can think by itself and have a mind, whereas a weak AI system only acts like it can think by itself and has a mind (Searle, 1990). Andrew Burgess (2018), a practitioner, somewhat agreed to Searle but used the terms “general AI” and “narrow AI”. Burgess (2018) defines the concept of “general AI” as the machine understanding why something is happening, which AI cannot do yet. Artificial general intelligence is according to Burgess (2018) “the holy grail of researchers but is still very theoretical at this stage” (p.4). “Narrow AI” on the other hand is what is being used today by practitioners (Burgess, 2018). It is the ability of a machine to excel at thousands of relatively narrow tasks such as playing Go or looking for fraudulent transactions (Burgess, 2018). To test whether a machine is capable of “strong AI” or “general AI” several tests have been conducted, and still are today, such as “The Coffee Test” by Steve Wozniak, “The Employment Test” by John Nilsson and perhaps the most famous one, “The Turing Test” by Alan Turing (Burgess, 2018; Russell & Norvig, 2016). The Turing Test involves a human having conversations on a computer via text messages for a couple of minutes with both humans and computers and after the test is finished tells which conversation was with a computer and which was with a human (Burgess, 2018). If the human cannot tell, the machine has passed the test. No machine has yet passed The Turing Test and thus have not reached “General AI” or “Strong AI” capabilities (Burgess, 2018). The Turing Test has however been considered insufficient to determine whether or not the machine has reached “General AI” (Shieber, 1994).

The phenomenon of AI is broad and has surprised scholars and practitioners throughout the years with its possibilities. As mentioned earlier, there are different approaches to problem solving in AI research which raises the question as to which systems can be considered intelligent. There is also to the best of our knowledge no commonly accepted definition of AI - nor, therefore of intelligent systems. Researchers have, however, come to a consensus that certain capabilities require intelligence (Rzepka & Berger, 2018; Russell & Norvig, 2010). These include problem solving, reasoning, planning, learning, natural language processing and knowledge representation (Russell & Norvig, 2010). Therefore, we will refer to AI-enabled systems that possess at least one of these capabilities and are relevant to the research question "What factors were perceived to influence organizational adoption of AI-enabled systems in organizational decision making from a qualitative perspective?" and the respondents. Following, some of the AI-capabilities are presented with explanations and motivations.

2.2.2 Natural Language Processing

Natural Language Processing (NLP) is used to acquire the data of the written language, processing of it and presenting it to the user or system for example (Russell & Norvig, 2016). This is useful since there are millions of web pages of information available, and most of the presented information on the web pages are written in natural language (Russell & Norvig, 2016). The NLP capability sends out an AI-agent which acquires the information on the web pages, for example, and tries to understand the language that is presented (Russell & Norvig, 2016). This capability is useful for decision-makers when trying to gather as much data as possible and as fast as possible to make a decision. NLP is used in several ways by organizations, such as information retrieval, an information extraction which looks for specific relationships between objects in the text or spam detection (Russell & Norvig, 2016; Burgess, 2018). Finally, NLP is also considered as a possibility for machines to communicate with humans among researchers (Russell & Norvig, 2016; Young et al., 2017).

2.2.3 Machine Learning

AI can be utilized to learn how to do certain things such as performing a task or optimizing a process, which is quite difficult to achieve since there is no easy way for a programmer to explain how to recognize a picture or how to swim for example to a machine (Brynjolfsson & Mcafee, 2017). There are three different approaches to making a machine learn: supervised learning, unsupervised learning and reinforcement learning (Mello & Ponti, 2018; Russell & Norvig, 2016; Brynjolfsson & Mcafee, 2017). Supervised learning is when a machine is presented with labelled input examples with the aim of being able to label unclassified examples (Brynjolfsson & Mcafee, 2017). Unsupervised learning is when a machine tries to understand and find relations and similarities among the data that is being input, similar to the NLP process (Mello & Ponti, 2018). Reinforcement learning is when the programmer introduces several restrictions to the machine and presents it with either a reward or a punishment based on the result (Brynjolfsson & Mcafee, 2017; Russell & Norvig, 2016). A famous example is the AI-machine that was programmed to play the board game of Go. If the machine won, it was provided with a reward and a loss generated a punishment which was forcing the machine to learn how to win through trial and error to eventually learn the best available move (Russell & Norvig, 2016; Brynjolfsson & Mcafee, 2017). Machine learning can be considered an important foundation of AI in general (Brynjolfsson & Mcafee, 2017).

2.2.4 AI in Decision Making

The resurgence of AI and other cognitive technologies has led believers to think that machines will soon outthink humans and replace them in the workplace, especially within decision making contexts (Jarrahi, 2018). Such inflated arguments are not entirely new. Celebrated cognitive scientist Herbert Simon (1965) predicted that AI-machines would be capable of achieving any work that a human can do by 1985. Marvin Minsky, founder of MIT's AI Lab argued in the 1970's that in 3 to 8 years, there will be a machine with general intelligence of an average human being (King & Grudin, 2016). These arguments have been proven wrong by other scientists and scholars as mentioned before. Instead, AI-capabilities, especially within decision support systems, have been used for more than 30 years by decision makers (Goul et al., 1992).

Organizational decision making is often challenged with uncertainty, complexity, and equivocality (Simon, 1972; Choo, 1991). Complex situations are characterized by abundance of elements or variables (Jarrahi, 2018). This requires the decision maker to process masses of information at a high speed which can be troublesome for the decision maker. AI has superior quantitative, computational, and analytical capabilities that has surpassed humans in solving complex tasks (Tshilidzi, 2015). AI can therefore help to reduce the complexity of a problem by for example identifying causal relationships among actors (Tshilidzi, 2015). However, decision makers are more capable of understanding common-sense situations and understanding novel situations where there are barely or no data to be found for the AI-machine (Jarrahi, 2018).

The recent attention to AI has been surrounded with the discussion of how the unique strengths of humans and AI can act synergistically, instead of primarily focusing on making the machine smarter or equally smart as a human (Jarrahi, 2018). In figure 1, decision situations of uncertainty, complexity, and equivocality shows how human-AI collaboration can work. The speed of collecting and analysing data of AI combined with human's superior intuitive judgement and insight opens up possibilities for better decisions (Jarrahi, 2018). The synergic partnership between AI and humans can be observed in many disciplines (McAfee et al., 2012). A cancer detection study from Wang et al. (2016) showed that an AI-exclusive approach in decision making had a 7.5% error rate, while pathologists had a 3.5% error rate, however when combining the inputs from both the machine and the human, results showed an error rate of 0.5%.

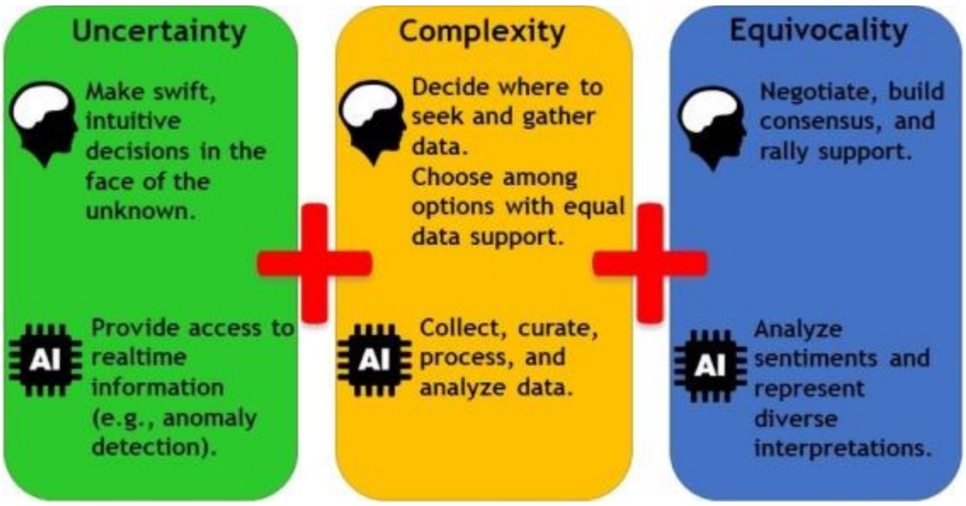

Figure 1: Human-AI in decision making situations (Jarrahi, 2018)

2.3 Technology Adoption

Technology adoption has been an important research subject in the IS field (Liu, Min & Ji, 2008). Significant achievements have been made in the 1980's with several new theoretical models being introduced (Liu et al., 2008). Since the context of technology and the nature of the technology keep changing (Benbasat & Barki, 2007), the view on IT adoption and its studies have changed focus and objectives (Liu et al., 2008). Nevertheless, Khasawneh (2008) defines technology adoption as "[...] the first use or acceptance of a new technology or new product." (p.2). Moreover, Musawa and Wahab (2012) argue that technology adoption is about voluntary behavior in regard to technology. These views are focused on the user acceptance, while there are more stakeholders that could potentially be influenced by the adoption of technology. Liu et al. (2008) categorized adoption at three levels: individual, group/team and organization. Looking at the theories being used to examine IT adoption within the IS field, Liu et al. (2008)'s view will be used throughout this thesis.

The adoption of technology is usually not a linear process within organizations (Karahanna, Straub & Chervany, 1999). Nevertheless, to dissect the process of technology adoption, Rogers (1995) proposed a model of five stages in the innovation-decision process (see Figure 2). In short, the innovation-decision process refers to the process an individual (or other decision making unit) goes through when deciding to adopt an innovation (Rogers, 1995). It starts according to Rogers (1995) with knowledge about an innovation or technology when the individual is exposed to the innovation's existence and gains a general understanding of how it works, which then forms an attitude toward the innovation. The attitude could be favorable or unfavorable which affects the decision to adopt or reject the innovation (Rogers, 1995). If the adoption is accepted, it gets implemented and confirmed (Rogers, 1995). Confirmation refers to when an individual seeks reinforcement for an innovation-decision that was done earlier (Rogers, 1995).

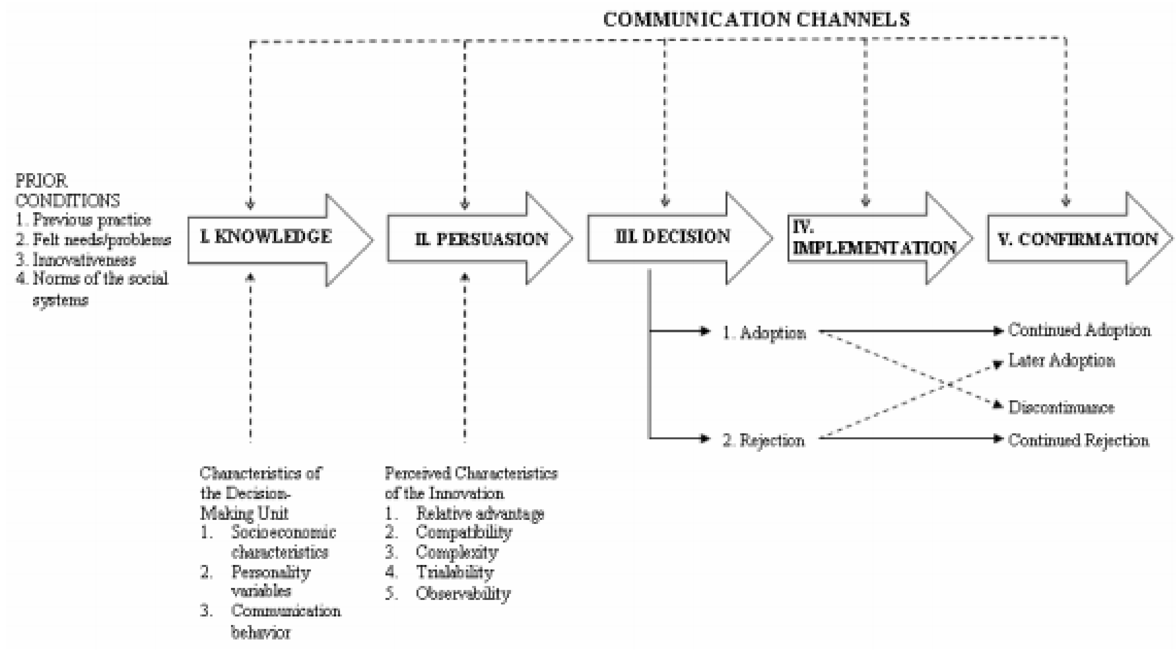

Figure 2: A model of five stages in the innovation-decision process (Rogers,1995)

Nevertheless, as mentioned earlier, there are several theories being used in IS research to study IT adoption (Liu et al., 2008; Oliveira & Martins, 2011; Wade & Hulland, 2004). The most used theory within the IS discipline to study IT adoption is the Technology Acceptance Model (TAM) (Davis, 1985; Davis, 1989; Davis, Bagozzi & Warshaw, 1989). Theory of Planned Behaviour (TPB) by Ajzen (1985; 1991), Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), Diffusion of Innovation Theory (DOI) by Rogers (1995), and the Technology-Organization-Environment framework (TOE) by Tornatzky and Fleischer (1990) are other popular theories being used when studying IT adoption within the IS discipline. However, TAM, TPB and UTAUT are models focusing on the individual level of IT adoption which is not applicable to our research focus since we are studying an organizational context with managers in the focus (Oliveira & Martins, 2011). TOE on the other hand is widely used for studying technology adoption at an organizational level (Oliveira & Martins, 2011; Williams et al., 2009; Liu et al., 2008; Gangwar, Date & Raoot, 2014). Therefore, this study will use the TOE framework as a theoretical lens when studying the adoption of AI-enabled systems.

2.4 TOE Framework

The TOE framework was developed by Tornatzky and Fleisher in the 1990's to examine organizations adoption of various IT artefacts and services on an organizational level (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011; Gangwar et al., 2014; Baker, 2012). The framework identifies three aspects of an organization's context that influence the process by which it implements and adopts a technological innovation, the technological, organizational and environmental context (Tornatzky & Fleischer, 1990). The original book where the TOE framework is presented by Tornatzky and Fleischer (1990) concerns the entire process of innovation, however the TOE framework only represents one segment of this process; the organizational adoption. Nevertheless, the three aspects influence the decision making of the organization in terms of adopting and implementing the technological innovations (Zhu, Kraemer & Dedrick, 2004).

The TOE framework is grounded on a theoretical basis, consisting of empirical support to explain several innovations such as ERP-systems (Pan & Jang, 2008), E-businesses (Zhu, Kraemer & Xu, 2003) and open systems (Chau & Tam, 1997). The inclusion of technological, organizational and environmental variables has made the TOE framework advantageous over previously mentioned IT adoption models when studying technology adoption, technology use and value creation from technology innovations (Hossain & Quaddus, 2011; Oliveira & Martins, 2011; Zhu & Kraemer, 2005). It is also not restricted by the firm-size of the companies being studied nor is it industry restricted (Wen & Chen, 2010). Thus, it provides a holistic view of user organizations adopting new technology (Wang, Wang & Yang, 2010; Zhu et al., 2004; Gangwar et al., 2014). What is common among the empirical studies that use the TOE framework as a theoretical lens is that the factors among the three different contexts are used differently because of the nature of the technology and the context that the study examines (Oliveira & Martins, 2011).

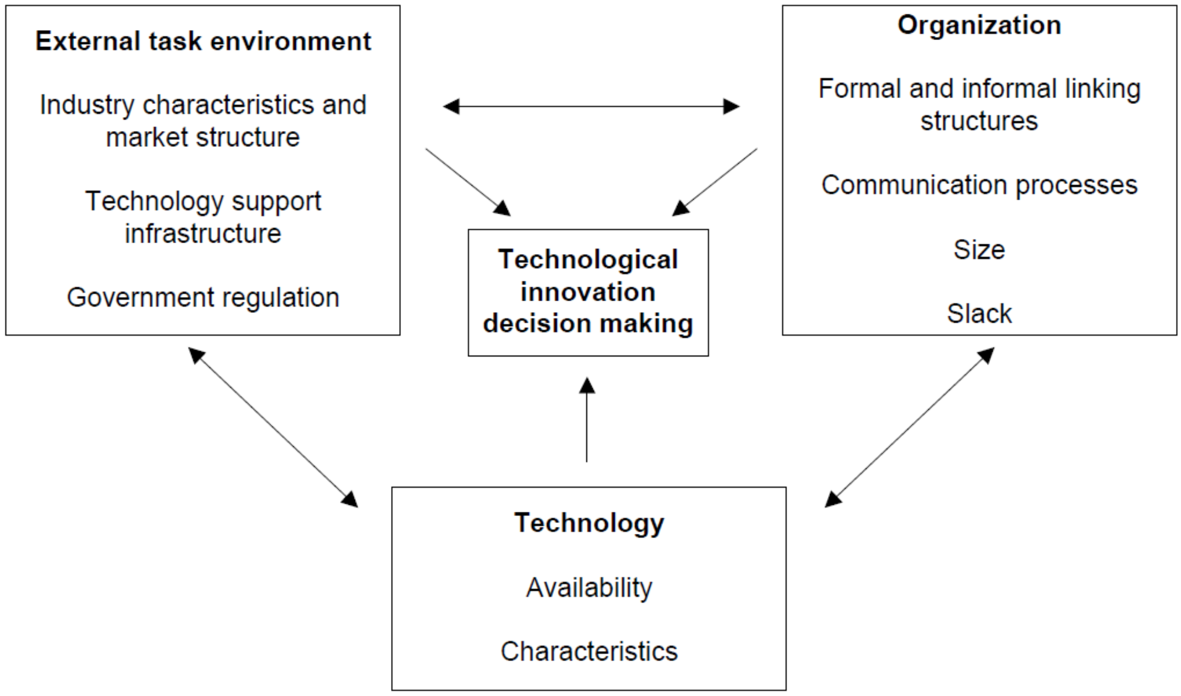

Figure 3: Technology, organization, environment framework (Tornatzky & Fleisher, 1990) shown in (Oliveira & Martins, 2011)

2.4.1 Technological Context

The technological context includes all technologies that are relevant to the organization - both, technologies that the organization is already using internally, but also those that are available externally in the marketplace but currently not in use (Baker, 2012). This includes current practices as well as equipment internal to the organization (Starbuck, 1976). It is important according to the TOE framework to understand the organization's current technology in order to set a limit on the scope and pace of the technological change an organization commences (Collins, Hage & Hull, 1988; Baker, 2012; Oliveira & Martins, 2011).

The same mindset can be applied to innovations in general. Innovations that exist but are not yet in use in the organization also influences the organizations innovativeness by showing what is possible as well as showing organizations how technology can enable them to evolve and adapt (Baker, 2012). Within the group of innovations that does not exist internally within the organization there are three types that create incremental, synthetic, or discontinuous changes. Incremental changes refer to new features or versions of existing technology that generally have lower risk and change to adopt for organizations. Synthetic changes represent innovations that have a moderate impact on the organizations where existing ideas or technologies are combined in an innovative manner. Finally, discontinuous change, also known as "radical innovations", causes significant changes to current operations or technology. Organizations need to carefully consider which type of organizational changes that will be needed to adopt a new innovation, some innovations will have a greater impact than others (Baker, 2012).

2.4.2 Organizational Context

According to Baker (2012), the organizational context refers to the resources and characteristics of the organization. Examples of that includes the firm size, amount of slack resources, the linking structures between employees, and communication processes within an organization (Baker, 2012).

In regard of the organizational size, a conclusive established link has not been determined (Baker, 2012). For example, Acs and Audretsch (1987) found the tendency that large firms have a relative advantage in capital intensive, concentrated and highly unionized industries. On the other hand, small firms where advantageous in innovative industries being at early stages of the life-cycle, where utilizing their labour and the innovation plays an influential role, and where large firms have a large share of the market (Acs & Audretsch, 1987). However, Kimberly (1976) argue that organizational size often is defined in too vague global terms, generating a lacking understanding of its relation to organizational structure. Hence, proposing a fuller and richer view of size when studying organizations, will generate research of more dynamic theoretical and empirical orientation (Kimberly, 1976).

Furthermore, slack resources are explained by Baker (2012) as one of the most discussed factors affecting innovation. In the context of when a problem arises, slack resources are described by Galbraith (1973) as "The organization responds by increasing the resources available rather than by utilizing existing resources more efficiently" (p.24). Nohria and Gulati (1996), clarifies slack resources as including extra inputs in terms of e.g. unused capacity, redundant employees, and unnecessary capital spending.

However, Nohria and Gulati (1996) presents a scattered research field of whether or not slack resources is of positive or negative effect on innovation. Still, in a highly cited study with data from 264 functional departments worldwide, Nohria and Gulati (1996) addresses this question head on. Their findings indicate that there is an inverse U-shaped curve between innovation and slack in organizations, meaning that both too little and too much may be harmful for innovation (Nohria & Gulati, 1996). Whilst slack nurture experimentation, it also reduces innovative projects discipline, creating a curvilinear relationship (Nohria & Gulati, 1996).

Furthermore, in terms of organizations having linking between internal subunits of an organization, it has been argued by Galbraith (1973); Tushman and Nadler (1986) that it promotes innovation. Additionally, Galbraith (1973) explains that organizations' responses to concern of decision quality is to create new roles within the organization. Baker (2012) explains that product champions, gatekeepers, and boundary spanners is associated with adoption because of their mere presence. In clarification, cross functional teams or employees having a connection to several departments (Galbraith, 1973), are example of such mechanisms that foster innovative adoption (Baker, 2012). Similarly, Tushman and Nadler (1986) presents three linking functions: teams, committees or task forces; project managers; and formal meetings.

In terms of critical factors for managing innovation, Tushman and Nadler (1986) explains that informal communication networks are important both within the organization, but also towards the customers, suppliers, vendors, and external professionals. In particular, the most innovative organizations are explained as having diverse set of internal communications, and that the people of the organization know who to contact (Tushman & Nadler, 1986). Furthermore, Baker (2012) suggests that the existing communication processes of an organization can inhibit or promote innovation. Top management communication processes and leadership behaviour have to describe the role of innovation in the organization's overall strategy and highlight the importance of it to the employees. Also, emphasising the innovation history of the organization as well as determining the informal and formal reward for current innovation (Baker, 2012).

Yet, although the factors above refer to the characteristics and resources in the organization, Gangwar et al. (2014) summarizes in a literature review on IT adoption using TOE-framework several other variables in organizational context of significance. These are, for example, firm structure, trust, innovation capacity, technological resources, knowledge capability, financial resources, strategic use of technology, support for innovation, quality of human capital, organizational slack, expertise, operational capability, top management support, organizational knowledge accumulation, infrastructure and organizational readiness.

2.4.3 Environmental Context

The environmental context describes the arena in which the organization operate its business (Tornatzky & Fleischer, 1990; Oliveira & Martins, 2011). Areas included are, the regulatory environment (Baker, 2012; Salwani et al., 2009), industry structure in terms of rivalry and competition (Baker, 2012; Chau & Tam, 1997), and technology service providers absence or presence (Baker, 2012).

In terms of rivalry and competition, Mansfield (1968); Mansfield, Rapoport and Romeo (1977) cited in Chau and Tam (1997); Baker (2012), found evidence that suggested that intense competition stimulates the innovation speed to become more rapid and that organization confronted with high degree of uncertainty in the market, have a higher likelihood of pursuing an aggressive technology policy. However, according to Tushman and Nadler (1986), an organization faced with an environmental threat, highly inertial organizations that continue on its current trajectory may not be aware of the threat due to organizational self-righteousness or little external perception. Instead, these organizations continue on in the same manner (Tushman & Nadler, 1986).

Moreover, in terms of industries, it has been argued by researchers that organizations in rapid growing industries, have a tendency to rapidly innovate (Baker, 2012). As Baker (2012) explains it, some organizations use the decline of an industry to innovate by expanding the business into new areas or through efficiency initiatives. Still, Baker (2012) acknowledges that studies investigating the industry life cycle and its relationship to innovation remains to be validated empirically.

Rai and Bajwa (1997) conducted a study on executive information systems (EIS), which is a type of decision support system. Evidence suggest that environmental factors do influence the implementation of EIS in organizations. In information environments that are more volatile, it will serve as a catalyst for exploration of EIS and that it also generates a spread among executives for decision support.

Still, in the literature review by Gangwar et al. (2014) on TOE-framework in IT adoption, light is shed on several significant variables. These are for example, competitive pressure, customer mandate, internal pressure, external pressure, vendor support, trading partner pressure, environmental uncertainty, commercial dependence, information intensity and network intensity.

2.5 Selected Factors

While there are several factors that have been applied in studies investigating organizational technology adoption with TOE, this study chose seven factors that are rooted in the literature and applicable to the adoption of AI in organizational decision making. The chosen factors are described and motivated below.

2.5.1 Technological Context

Perceived direct and indirect benefits, meaning an investigation of organizations' recognition of benefits prior the adoption of an AI enabled system in decision making. By direct benefits, it could simply be having the support of a computerized support system (Bonczek et al., 1979; Bonczek et al., 1980a; Bonczek et al., 1980b), in this case a highly sophisticated system, meaning that the management get a feeling of control and reliable trust (Kottemann et al., 1994; Davis & Kottemann, 1994). Also, as proposed by Kahneman et al. (2016), AI enables unbiased decisions free of noise affecting the decision maker, e.g. time of day, weather, time since last meal etc. These could be viewed as examples of indirect benefits. If an AI-enabled system was purchased by a vendor, explicitly stated benefits may have been communicated directly, while indirect benefits may have been considered by the organization.

Other studies have also used perceived benefits as a factor in the TOE-framework for IT adoption, for example, the perceived benefits of adoption of open systems were found to be insignificant (Chau & Tam, 1997). On the contrary, a study on electronic data interchange found significance for direct benefits but not for indirect benefits (Kuan & Chau, 2001). Nevertheless, these are different systems and since the technology has evolved, the perceived benefits by organizations might vary today. With the speed of collecting and analysing data with AI, combined with human's superior intuitive judgement and insight, possibilities for better decisions is created (Jarrahi, 2018). Thus, if the perceived benefits are understood, there is a significant influence on justification of costs by the organization and the effectiveness as a support tool for the process of decision making (Keen, 1981; Meador, Guyote & Keen, 1984; Money, Tromp & Wegner, 1988). Likewise, building on these early works, if the benefits of AI in decision making are understood, we see it as a potential influencing factor of the adoption.

The **amount of data** refers to an organization's ability to collect, process and understand data and information. This has been discussed earlier in the literature both in terms of decision making and AI-enabled systems. In the decision making literature, earlier research has shown that humans are limited in their capacity to consume and deal with data and information, creating the phenomenon of information overload (Zahra & George, 2002; Hilbert & López, 2011). In the AI-literature, studies have shown that in order to create high-performing AI-capabilities, the amount of data is more important than perfecting the algorithm (Yarowsky, 1995; Banko & Brill, 2001; Criminisi et al., 2004). Furthermore, Ransbotham et al. (2017) argues that an organization's ability to value and manage data is one of the primary factors which differentiates being a pioneer or a late adopter of AI-enabled systems among organizations. There is also evidence that organizations believe that they have sufficient data for an AI-enabled system to learn from which in many cases is not true (Ransbotham et al., 2017). Even though this factor has not been investigated in any earlier research regarding technology adoption, we believe that it might influence the choice of adopting AI because of the capabilities that AI possess and the nature of organizational decision making. Furthermore, the TOE framework often has contextual customizations based on the technology it investigated. Therefore, we believe that this factor might be influential in adopting AI in decision making.

2.5.2 Organizational Context

Perceived technical competence attributes to how an organization perceive their technical knowledge. While the perceived benefits of AI-enabled systems are important to understand by an organization, it is also important that the benefits can be achieved by the organization (Kuan & Chau, 2001). Earlier research has shown that technical knowledge is one of the most impactful factors in hindering IT growth in smaller organizations (Cragg & King, 1993). There is also the factor of aversion or appreciation when using AI-enabled systems in decision making in the organization (Dietvorst et al., 2015; Logg et al., 2019; Prahl & Van Swol, 2017; Davenport & Harris, 2007a). Lin and Lee (2005) shows that technical competence has a positive effect on adopting new technology among organizations. Other studies looking at technology adoption have shown that the perceived technical competence is an important factor when choosing to adopt technology innovations (Kuan & Chau, 2001; Lian, Yen & Wang, 2014). We therefore believe that the perceived technical competence could be influential as it could make the employees more willing to use AI in decision making and make the whole organization willing to adopt AI-enabled systems in general.

Decision making obstacles may exist within the organization prior to adoption. Decision making can be an ambiguous task within an uncertain setting (Cohen, March & Olsen, 1972). During the organizational decision phases, barriers may arise, leaving the organization to iterate back and start over (Mintzberg et al., 1976; Eisenhardt & Zbaracki, 1992). Because in decision making, organizations are often confronted with uncertainty, complexity, and equivocality (Choo, 1991; Simon 1982). For example, employees with contradicting preferences from various departments may exist and there might be different stakeholders to consider, leaving the organization to do trade-offs (Saaty, 2008). This can be because of equivocality, leaving the organization with conflicting interpretations about the organizational situation (Daft & Macintosh, 1981). Additionally, there are nonprogrammed and unstructured decisions that may create obstacles for organizations since the problems have not been encountered before (Mintzberg et al., 1976). Such complex situations are characterized by abundance of elements or variables (Jarrahi, 2018). Therefore, this requires the decision maker to process a waste amount of information at a high speed which can be troublesome for the decision maker. Thus, as figure 1 shows, AI have the capabilities to support humans in decision making with complex, equivocal, and uncertain situations. Consequently, decision making obstacles prior the acquirement is considered as a probable influential factor in the adoption of AI-enabled systems within decision making.

Top management support refers to managers within an organization being able to establish an environment where innovative thinking is encouraged and provided resources to innovate (Borgman et al., 2013). Top management support is critical for providing a supportive climate and adequate resources for the adoption of technologies (Lin & Lee, 2005; Wang et al., 2010; Low, Chen & Wu, 2011). The adoption of AI-enabled systems may require changes of decision making processes and integration of resources. Thus, it is vital that the top management provides a vision, communication and commitment to the innovation (Lee & Kim, 2007; Pyke, 2009). Top management support is also required in smaller changes within an organization which AI-enabled systems could be according to Brynjolfsson and Mcafee (2017). It might be regarded as less important from the rest of the organization because of the size of the project. Other studies concerning technology adoption have shown a positive relationship between top management support and the adoption of new technologies (Pan & Jang, 2008; Zhu et al., 2004; Rai & Bajwa, 1997; Low et al., 2011). This tells us that top management support is important when organizations adopt new technology in terms of getting all the employees on the same page and supporting the technology as a whole. Thus, we have chosen this factor because we believe it might be influential.

2.5.3 Environmental Context

Competitive pressure refers to the degree an organization perceives its competition within the industry it is conducting business in (Oliveira & Martins, 2011; Zhu & Kraemer, 2005). It has long been recognized as a driver for innovation in the innovation adoption literature (Grover, 1993; Iacovou, Benbasat & Dexter, 1995; Crook & Kumar, 1998; Zhu & Kraemer, 2005). Organizational adoption of technological innovations can become a strategic necessity for organizations to compete and sustain a competitive advantage in the industry they are conducting business in (Oliveira & Martins, 2011; Dwivedi et al., 2009). Ransbotham et al. (2017) argues that by implementing AI-enabled systems, organization might gain a competitive advantage. Furthermore, Kahneman et al. (2016) provides evidence that in many decision making contexts, algorithms outperform humans, thus another incentive for organizations to adopt AI-enabled systems to gain competitive advantage. Therefore, the factor of competitive pressure could be an important factor influencing the decision to adopt AI-enabled systems in decision making.

Environmental uncertainty refers to the environment that the organization operates in. It has been a studied factor within the information systems field, sometimes referred to as market uncertainty. Research has, for example, been performed on adoption of open systems where it was found to be insignificant (Chau & Tam, 1997), whereas in adoption of RFID it was found to be significant (Lee & Shim, 2007). However, whether or not there is a dynamic environment in decision making, it significantly influences the perceived uncertainty (Duncan, 1972). When organizations face problems with high uncertainty, the information process within the organization increases (Daft & Macintosh, 1981). Therefore, facilitating the collection, gathering, and processing of information becomes crucial (Tushman & Nadler, 1978). This may create a need for AI tools because of the proven benefits in speed of collecting and analysing data with AI.

In addition, studies by Mansfield (1968) and Mansfield et al. (1977) cited in Chau and Tam (1997) found that organizations confronted with a high degree of uncertainty in the market, have a higher likelihood of pursuing an aggressive technology policy. An uncertain market is a force in the environmental context that presumably generate nonprogrammed or unstructured decisions that an organization must face without a clear set of planned responses, leaving the organization with uncertain alternatives that are unsure to solve the problem (Soelberg, 1966; Mintzberg et al., 1976). Although environmental factors cannot be dictated by the organizational management, it may significantly affect how the business is done.

Therefore, environmental uncertainty becomes an interesting factor to investigate in the adoption of AI-enabled systems for decision making.

2.6 Thematic Overview

Finally, below is Table 1 which presents an overview of the themes, concepts and literature of this thesis which provides a basis for the interview guide presented in the upcoming method chapter. The table's aim is to summarize and thematize literature used in this chapter to get the reader an overview of the whole literature (Kvale & Brinkmann, 2009).

Table 1: Thematic overview

Theme	Concepts	Literature
Organizational decision making	• Equivocality of organizational decision making • Uncertainty of organizational decision making • Complexity of organizational decision making • Computational support in organizational decision making	Vroom and Yetton, 1973; Saaty, 2008; Cyert et al., 1956; Dane et al., 2012; Hayashi, 2001; Dane and Pratt, 2007; Jarrahi, 2018; Alter et al., 2007; Soelberg, 1966; Mintzberg et al., 1976; Newell and Simon, 1972; Eisenhardt and Zbaracki, 1992; Daft and Lengel, 1986; Saaty, 2008; Daft et al., 2017; Daft and Macintosh, 1981; Tushman and Nadler, 1978; Duncan, 1972; Tung, 1979; Wood and Bandura, 1989; Stewart, 1988; Simon, 1960; Daft and Lengel, 1986; March and Simon, 1958
Artificial intelligence	• Quantity of data • Natural language processing • Machine learning • AI in decision making	Rzepka and Berger, 2018; Russell and Norvig, 2018; McCarthy et al., 1995; Russell and Norvig, 2010; McCulloch and Pitts, 1943; Picinini, 2004; Brynjolfsson and McAfee, 2017; Burgess, 2018; Duan et al., 2019; Russom, 2011; Davenport et al., 2012; Yarowsky, 1995; Banko and Brill, 2001; Criminisi et al., 2004; Searle, 1990; Scheiber, 1994; Young et al., 2018; Fernandes de Mello and Ponti, 2018; Jarrahi, 2018; Simon, 1965; King and Grudin, 2016; Goul et al., 1992; Simon, 1972; Choo, 1991; Tshilidzi, 2015; Wang et al. 2016
Technological context	• Perceived direct and indirect benefits • Amount of data	Baker, 2012; Starbuck, 1976; Collins et al., 1988; Oliveira and Martins, 2011; Bonczek et al., 1979; Bonczek et al., 1980a; Bonczek et al., 1980b; Kottemann et al., 1994; Davis and Kottemann, 1994; Kahneman et al., 2016; Jarrahi, 2018; Chau and Tam, 1997; Kuan

		and Chau, 2001; Guimaraes et al., 1992; Keen, 1981; Meador et al., 1984; Money et al., 1988; Zahra and George, 2002; Hilbert and López, 2011; Yarowsky, 1995; Banko and Brill, 2001; Criminisi et al., 2004; Ransbotham et al., 2017
Organizational context	• Perceived technical competence • Decision making obstacles • Top management support	Baker, 2012; Acs and Audretsch, 1987; Kimberly, 1976; Galbraith, 1973; Nohri & Gulati, 1996; Tushman and Nadler, 1986; Gangwar et al., 2014; Kuan and Chau, 2001; Cragg and King, 1993; Davenport and Harris, 2007a; Dietvorst et al., 2015; Logg et al., 2019; Prahl and Van Swol, 2017; Lian et al., 2014; Cohen et al., 1972; Mintzberg et al., 1976; Eisenhardt and Zbaracki, 1992; Choo, 1991; Simon, 1982; Saaty, 2008; Daft and Macintosh, 1981; Borgman et al., 2013; Lin and Lee, 2005; Wang et al., 2010; Low et al., 2011; Lee and Kim, 2007; Pyke, 2009; Brynjolfsson and McAfee, 2017; Pan and Jang, 2008; Zhu et al., 2004; Rai and Bajwa, 1997
Environmental context	• Competitive pressure • Environmental uncertainty	Tornatzky and Fleischer, 1990; Oliveira and Martins, 2010; Baker, 2012; Salwani et al., 2009; Tushman and Nadler, 1986; Rai and Bajwa, 1997; Gangwar et al., 2014; Zhu and Kramer, 2005; Grover, 1993; Iacovou et al., 1995; Crook and Kumar, 1998; Zhu and Kramer, 2005; Dwivedi et al., 2009; Ramdani et al., 2009; Kahneman et al., 2016; Chau and Tam, 1997; Lee and Shim, 2007; Mansfield, 1968; Mansfield et al., 1977; Chau and Tam 1997; Soelberg, 1966; Mintzberg et al., 1976; Duncan, 1972; Daft & Macintosh, 1981

3 Research Strategy

The aim of the study is to answer the question of "What factors were perceived to influence organizational adoption of AI-enabled systems in organizational decision making from a qualitative perspective?". Thus, this thesis sought to present a description of the respondents' perceptions of their organizational adoption of AI-enabled systems in organizational decision making. Therefore, we consider the study to consist of descriptive characteristics (Recker, 2013). Additionally, Bhattacherjee (2012) argues that descriptive research usually aims to answer research questions such as "what". We therefore formulated our research question in line with Bhattacherjee (2012) arguments. Moreover, Recker (2013) claims that exploratory research is suitable for building new theories, which is not our attempt nor purpose.

We have used a qualitative descriptive method in order to understand the human's and organization's own subjective opinion of a certain phenomenon - the organizational adoption of AI-enabled systems in organizational decision making (Kvale, 1996; Brinkmann & Kvale, 2005; Recker, 2013). We also wanted to differentiate ourselves with studies who have examined similar phenomena such as Leyer and Schneider (2019a) who use a quantitative method. In addition, the TOE framework by Tornatzky and Fleischer (1990) is often used with a quantitative method in other studies (Oliveira & Martins, 2011; Gangwar et al., 2014; Liu et al., 2008). By using a different method, the phenomena will be examined more completely (Niederman & March, 2015; Goodhue, Klein & March, 2000). Furthermore, there is little research available when combining AI-enabled systems, decision making and technology adoption, thus there is little knowledge. Qualitative methods are according to Recker (2013); Creswell and Creswell (2017) the best fit for this type of study where limited knowledge exists. Moreover, the qualitative method enables deeper description of the underlying factors which can pave the way for any future causal quantitative research also using the TOE framework (Alshamaila et al., 2013; Mallat, 2007).

Finally, we chose a deductive approach where we test the Technology-Organization-Environment framework by Tornatzky and Fleischer (1990) in a new context. According to Bhattacherjee (2012) deductive research is theory-testing research. Since there are quite a few theories and frameworks that have been used over the years to examine technology adoption (see subchapter 2.3) among firms and individuals, we believe that a deductive approach is the most productive one in this context in terms of knowledge contribution. This is aligned with Bhattacherjee (2012) who believes that a deductive approach is the most productive choice when there are many competing theories. Following in the next subchapter, an explanation with argumentation is made of how we found our literature and theories.

3.1 Progression of the Literature Review

We started our thesis by reading literature within subject areas that interested us. A Leyer and Schneider (2019b) paper about delegating decisions to algorithms got us interested in the subject of AI-enabled systems and decision making within organizations. We then started to read literature extensively within the subject. To have an idea on what to look for, we took Bhattacherjee's (2012) three-folded purposes of literature review into consideration. These purposes are: 1) investigating what knowledge that already exists within our selected research area, 2) identifying key authors, actors and articles within our research area, and 3) performing gap-spotting to understand what focus areas that needs to be further investigated due to lack of understanding and knowledge in the field (Bhattacherjee, 2012). It was important for us to find literature that offered an alternative interpretation from the first papers we read, since we wanted to gain a multifaceted view (Randolph, 2009). Finding alternative literature was also vital in understanding where there was a knowledge gap and whether it is important to understand that certain phenomena or not (Randolph, 2009).

Once we started to develop an understanding for the subject and what knowledge gap we wanted to proceed, we started to limit ourselves in what kind of literature that was of significance to us. We considered Randolph (2009) thoughts about increasing the transparency of our study and increasing the possibility to replicate the study as good as possible. Therefore, we saved our most used search queries (keywords) to increase the reliability of the thesis (Randolph, 2009). We used the keywords to search for literature on search engines such as LUBSearch, maintained by Lund University, Google Scholar and Google. The search terms are listed below:

- (“AI” OR “Artificial Intelligence”) AND (“Organizational decision making”)
- (“TOE framework” OR “Technology-Environment-Organization framework”) AND (“Technology Adoption” OR “IT adoption”)
- (“DSS” OR “Decision support system” OR “Expert system” OR “Knowledge-based system”) AND (“AI” OR “AI-enabled system”)
- (“Weak AI” OR “Narrow AI”) AND (“General AI” or “Strong AI”)
- (“Decision Making” OR “Organizational Decision Making”)

The search terms being used developed over time as we got a better understanding for the phenomena. For example, terms such as “weak AI” and “narrow AI” have similar meanings but obviously are different words and to avoid missing important literature, we made sure to check the paper's references to see if we could further develop our understanding. However, we do acknowledge that we might have missed acronyms in our thesis that could be of use. Still, we believe that our keywords have given us papers and books with good quality since our search terms originated from other peer-reviewed articles. While trying to find new literature we made sure that the ones we selected were peer-reviewed and hopefully had quite some citations to see how other scholars interpret the certain phenomenon being examined in the papers.

As mentioned before, we used references in the articles we read to find new material to our literature review. This is in line with Randolph (2009) who argues that 90% of the source's researchers have been found in other papers. We made sure that we located the primary source instead of relying on secondary sources. For example, there is quite some literature about the paper that is now recognized as the first work in the field of artificial intelligence from 1943. Instead of relying on how others interpret the papers, we made sure to read it ourselves with the help of other scholars' interpretations in mind. This increased the validity and quality of the paper since we do not assume the information from other authors is correct and unbiased (Randolph, 2009). We ended our literature review once we felt saturation was reached, and no articles we came across added more knowledge of significance to our study (Randolph, 2009).

3.2 Data Collection Techniques

The purpose of interviewing is to enter the interviewee's perspective based on our assumption of that it is meaningful, knowledgeable and can made explicit (Patton, 2015). Therefore, the selection of respondent becomes important. Although, this understanding was of subjective nature from the respondents, when exploiting multiple individuals' perspectives of this phenomenon we enabled for a comprehensive and multi-faced description (Recker, 2013). From this, an interpretive understanding could be generated.

However, when choosing between structured, unstructured, and semi-structured interviews, the latter was chosen because of its appropriateness for the studied phenomenon. Conducting structured interviews with strict scripts to follow could prevent the necessary exploration, and unstructured could result in a too broad scope of conversations harming the identification of factors. Therefore, semi structured interviews were selected as the appropriate technique, balancing the structure needed, while having room to improvise and generate additional insights (Bhattacherjee, 2012; Oates, 2006). However, Ryen and Torhell (2004) acknowledges that the flexible structure can result in respondents' deviation from the subject, something we had in mind during the interviews. Still, according to Recker (2013) semi-structured interviews have several benefits over other interview approaches. They are less intrusive, encouraging a two-way communication, with the possibility of justification of interviewees answers and the rationale behind them. Likewise, the interviewee has the possibility to gain the same clarity about the questions asked.

3.2.1 Conducting Interviews

Although, the most prominent form of interviews has been argued to be face-to-face interviews (Bhattacherjee, 2012; Recker, 2013), the current situation of pandemic covid-19 prevents face-to-face interviews as a suitable and reliable option. Therefore, video interviews were selected as a safe form to conduct the interviews. This also enabled a geographical spread of respondents, resulting in participants from various parts of Sweden and Europe. In addition, conducting video interviews was an efficient approach since travel needs were diminished. Thus, the research context was done over video-calls. Because of Covid-19, several organizations have ordered their employees to work from home, thus some of our respondents were in their home environment. Interestingly, a qualitative longitudinal study by Weller (2017) investigating internet video calls for qualitative interviewing, found that the pressure of presence with remoteness and physical separations created a greater sense of ease. Because of the physical absence of equipment and the researcher, risk of exposure or embarrassment was reducing (Weller, 2017).

Nevertheless, as Patton (2015) points out "the quality of the information obtained during an interview is largely dependent on the interviewer." (p.630). Indeed, conducting rich and well-crafted interviews is a skill. However, from our previous work (Entzenberg & Söderqvist, 2019), valuable experiences were made, that we have had in mind during this process. Additionally, inspiration from Patton (2015) ten interview principles and skills have been reviewed to cultivate the quality.

1. Ask open-ended questions, inviting the interviewee for in-depth responses.
2. Be clear, asking questions that are answerable, understandable, and focused.

3. Listen, letting the respondent know that they have been heard, then follow up with an appropriate response.
4. Probe as appropriate, when answers are incomplete ask for clarification. This will make the interviewee understand the sought level of degree and detail.
5. Observe, to guide this interactive process. Each interview is an observation as well.
6. Be both empathic and neutral, offer non-judgemental encouragement and interest.
7. Make transitions, guide the interview process and help the respondents through it.
8. Distinguish types of questions. Separate interpretive questions, from descriptive, behaviour, knowledge, feeling and attitude questions.
9. Be prepared for the unexpected, being flexible and responsive.
10. Be present throughout. The interviewees see when interest is lost, distractions appears, or the interviewer does not care about the answers.

Furthermore, being two researchers enabled one being the head interviewer, leading the conversation, while the other took notes and formulated new, follow-up questions based on what was said. As Patton (2015) points out, being too focused on notes can lead to that the interviewee gets secondary attention. Therefore, although formulation of new questions could be done by both, the main interviewer was more focused on giving concentrated attention to the interviewee.

3.2.2 Interview Guide

Research that primarily collects data from interviews can use open-ended questions to explore participants experiences about the phenomenon, followed by questions about predetermined categories (Hsieh & Shannon, 2005). Hence, the interview strategy was selected as a mixed approach building on the three basic types of qualitative interview being: the informal conversational interview, the interview guide, and the standardized open-ended interview (Patton, 2015).

First, each interview started with the explanation of the study, the confidentiality of it, and asked consent to record the interview to transcribe it. Second, in the beginning of each interview, a conversational interview approach was taken, to explore the background of each respondent in terms of pervious roles. However, following the conversation about the respondents' background, pre-determined topics follows through part 1,2,3, and 4. These are derived from the literature presented in the thematic overview (see subchapter 2.6).

In part 1 of the interview guide, the two themes of decision making and AI focused, enabling an exploration of these two crucial themes that could be further built upon later in the interview. Further, parts 2, 3, and 4 in the interview guide concerned the factors of the applied theoretical framework, TOE. In the beginning of each part, we explained how this thesis perceives the different context and factors. Then, a standardized open-ended interview approach was taken, striving to use the exact wording and sequence of themes for every interviewee (Patton, 2015). This enabled an increased comparability of responses, and reduced interviewer effects and biases (Patton, 2015). However, as acknowledged under 3.2 "Data Collection Techniques", our approach was semi-structured. Thus, even if the sequence and wording of these themes remained the same for each interview, various follow up questions were asked to gain e.g. clarification, flexibility, and depth regarding some themes depending on the respondent's answer. Lastly, the respondents were asked to reflect on the factor in the adoption.

In part 5 of the interview guide, broader open-ended questions were asked regarding insights that were derived after the adoption of AI in decision making. Here, the interviewees were given the chance to speak freely regarding things that had not previously been asked about.

3.3 The Target Sample

In the selection of the target sample, inspiration was derived from the Bhattacherjee (2012) sampling process, following population, sampling frame, and sample. The population of this study are organizations. Considering that AI enabled tools are used for chatbots by customer service, making production more efficient or optimize operations, there are many organizations that applies AI to enhance the business potential. However, since we investigate the adoption of AI in decision making context, our sample frame focused. Specifically, our sample frame consisted of organizations that had adopted or had the decision to adopt AI in the organizational decision making. As Baker (2012) explains, a conclusive established link between organizational size and pursuit of innovation has not been determined. Similarly, Acs and Audretsch (1987) study suggested that small and large firms have different innovative advantages. Therefore, we have not considered the size of the selected organizations.

Still, in the organizational context there were several potential respondents. However, when contemplating that this study seeks the factors for AI-enabled systems in decision making, the scope of potential respondents narrowed. In addition, the respondent needed to have a clear understanding of the adoption process of such a tool, otherwise the knowledge and insight desired to derive factors would have been difficult. Furthermore, they also needed to use the technology themselves as a tool in their organizational decision making. Therefore, as described above, we have tried to follow an expert sample but considering the timeframe and difficulty of finding the ideal respondent, it is a mix of expert/convenience sampling.

3.4 Respondent Selection

In the respondent selection, most of the initial contact was taken over LinkedIn and email, while others were called directly over phone. Although our strive were to solely interview managers, simply choosing respondents because of their title appeared to be unwise and only something that narrowed the selection without safeguarding the depth of knowledge. Thus, to ensure that the respondents had enough insight of the adoption and the organisation, pre-interviews were held with some of the interviewees. Others were sent the interview guide and asked to review it before accepting to participate.

Table 2 summarizes the participants. Most of our selected respondents were managers, but others were well qualified with similar insight into the organizational operations and the adoption. Overall, we gained the perspective of decision makers with a deep organizational knowledge, enhancing the understandings of this phenomenon.

Table 2: Interview respondents

Respondent	Role	Industry	Meeting Type	Time
R1	Project Manager	Real estate	Microsoft Teams	35min
R2	Project Manager	Retail	Zoom	31min
R3	Account Manager	Computer software	Zoom	38min
R4	Partner IT R&D	Pharmaceuticals	Cisco WebEx	47min
R5	Chief Data Scientist	Financial services	Google Hangouts	30min
R6	Co-founder, head of customers	Computer software	Google Hangouts	41min

3.5 Data Analysis Techniques

3.5.1 Transcription

Patton (2015) describes the raw data of interviews as the price sought by the qualitative inquirer, and that nothing can substitute these data. Therefore, every interview was recorded on both phone and computer for security reasons. However, to get the most out of the transcription, they were conducted in close connection to the interview. Furthermore, the interviews conducted in English were transcribed with the help of the software tool Trint. To enable for a simple identification of specifics used in the empirical results and discussion, an index was applied to each row in the transcripts. One of the authors conducted the transcription, and that is stated on the transcripts, while the other one proofread while listening to the recorded interviews. This enabled the transcripts to be developed as accurate as possible. The same procedure was applied when Trint was used as well. The interview transcripts can be found in appendix B-G.

3.5.2 Coding

To reduce the qualitative data to meaningful information (Recker, 2013), coding was carried out. Often, coding is applied to gain structure of the data around concepts, themes, or key ideas that was identified in the data. A directed approach was selected that aligns with the intention of this thesis "The goal of a directed approach to content analysis is to validate or extend conceptually a theoretical framework or theory." (Hsieh & Shannon, 2005, p.1281).

The analysis of data starts with relevant research findings or a theory to serve as guidance for initial codes (Hsieh & Shannon, 2005). Thus, providing predictions about interesting factors. Since investigation of influential factors is the centre of this study, each factor will serve as a coding label. The coding analysis were carried out in two phases, inspired by one of Hsieh and Shannon (2005) presented strategies on directed content analysis. First, the predetermined codes were added to the transcripts. Second, the data that was not directly identified as suitable for the selected codes were analysed in a second round of coding. An overview of the applied codes can be viewed in table 3.

However, we wanted to leverage the fact that we are two researchers. Therefore, when identifying and applying the codes to the transcripts, the first phase was carried out independently then we reviewed the results of the coded transcripts to fully leverage two interpretations. Hence, if disagreements arose, a discussion about the interpretation made was clarified and explained. Then we carried out the second phase, adding subcategories to the data that was not identified in the first round. This was followed by a review of the other persons codes.

Table 3: Transcription codes

Codes	Description of codes	Sub-codes	Description of sub-codes
ODM	Organizational decision making	ODM-CS	Computational support
AI	Artificial intelligence	AI-C	AI Capabilities
TC	Technological context	TC-PDI	Perceived direct and indirect benefits
		TC-AD	Amount of data
OC	Organizational context	OC-PTC	Perceived technical competence
		OC-DMO	Decision making obstacles (equivocality, uncertainty, complexity)
		OC-TMS	Top management support
EC	Environmental context	EC-CP	Competitive pressure
		EC-EU	Environmental uncertainty

3.6 Research Quality and Ethics

3.6.1 Literature Review

As explained in the subchapter 3.1 “Progression of the Literature Review”, we started our thesis by gathering broad knowledge within the subject, both the historical context and the current research. We considered Klein and Myers (1999) argumentation about the importance of understanding the historical background of the research setting.

Moreover, we presented the historical context of each concept first in our literature review to make the reader also understand the historical context and where certain concepts and definitions derive from before going into detail about the current state of research. We also emphasized that certain terms were consistently used throughout the thesis which enables valid conclusion drawings (Miles, Saldaña & Huberman, 2014).

When selecting literature to use from in our literature review, we made sure that the articles were peer-reviewed and that their argumentation is based upon findings, references, or citations. Some of the papers that we found were literature reviews over certain subjects and phenomena, thus most of the content was secondary sources. However, we made sure to check the primary sources when applicable and made sure that there was no bias or incorrect information, which we based our argumentation upon. This is in line with Randolph (2009) who argues that rather than assuming the information is correct, the researcher should investigate the primary source and to increase the validity of the thesis.

3.6.2 Data Collection

In the selection of respondents, each were given an information sheet with brief introduction to the subject, as well as procedures and methods used during the study. Additionally, clarification was given to the fact that the participation of this study was voluntary, meaning that respondents were free to decide whether or not to participate, without any consequences (Recker, 2013; Bhattacherjee, 2012). Since all respondents received identical sheets, the same information was provided to all. Moreover, the respondents were offered disclosure, which is the offer to the potential respondents with information regarding the study and giving them the possibility of withdrawing their participation based on our thesis objectives and general themes of the questionnaire before the data is collected. This was done as explained in subchapter 3.4, by conducting a small pre-interview over phone or email which was not recorded or transcribed. Bhattacherjee (2012) argues that it is important to make the respondents aware of who the researchers are and make the respondents aware of the objectives of the study. Furthermore, prior to the interview, the respondents received a short interview guide containing some of the broader questions to get the respondent a better understanding of our objective with the study.

If any questions would arise before the interview, respondents were informed to ask us, enabling for clarification before the interview began. Moreover, prior to the interview the respondents were informed that they were going to be anonymized which is in line with Bhattacherjee (2012) arguments about anonymizing all respondents.

The interviews were mostly held in Swedish except for interview 4 and 6 (appendix E and G) which were conducted in English. Since there is no available software tool, to the best of our knowledge to transcribe Swedish interviews, we did it manually. To ensure that the transcriptions were correct, one of the authors of this thesis did the transcription and the other one checked for any potential mistakes. This is in line with Kvale and Brinkmann (2009) who state that researchers should perform two transcriptions for each interview to enhance the reliability of the transcript. Furthermore, the English interviews were transcribed by the help of a software tool called Trint. To ensure that the software tool had not made any mistakes, we also checked these transcriptions and made changes where it had made mistakes or misinterpreted the recording. Finally, we cleaned up all verbatim language such as mumbling, laughter and break words to provide a fair picture of the respondents and provide transcripts with more fluent written style which we believe makes it easier to read. We experienced from our previous work (Entzenberg & Söderqvist, 2019), that respondents were not satisfied with the verbatim language in our transcriptions when we sent our transcriptions for feedback because it made them, in their opinion, be perceived as incompetent about the topic. Thus, we kept this in mind during this thesis, which is also aligned with Kvale and Brinkmann (2009) who think that transcriptions with verbatim style could appear to be unclear and scattered.

However, when the transcription was done, the respondents got the chance to read through, give comments and validate the interview (Seale, 1999; Ritchie et al., 2013). This was done to minimize the risk of us as interviewers mishearing or misinterpreting something important, which is a concern during a qualitative study (Maxwell, 1992). Still, by giving the information regarding confidentiality before the interview, our hopes were that this might generate respondents to speak more freely. But also to reduce the possibility for damage of reputation, self-esteem, and career prospects for the respondents (Booth et al., 2003). While their identities remain know by us because of our process for selecting respondents as well as the form video-interviews, confidentiality of the data has been followed. This means that the participants cannot be identified through any form of research disclosure (Recker, 2013).

Finally, to avoid poor quality of audio recording, we recorded our interviews on two separate phones. We considered the risk of poor audio quality as high since all our interviews were conducted through digital services on our computers. Hence, when we recorded the interviews on two different phones, we increased the possibility of having good quality throughout the entire interview which leads to enhanced reliability of the transcriptions (Kvale, 2008).

3.6.3 Analysis

This thesis has used a theoretical framework containing factors that might affect the adoption of AI-enabled systems in decision making. These factors do not only derive from other studies and papers using the theoretical framework in similar contexts but also by making conclusions from earlier literature. Thus, it was important for us to maintain an openness and scepticism when we analysed the data even though it could result in all of our factors being non influential. Miles et al. (2014) stress the importance of the researcher to keep an open mind and scepticism of phenomena it studies throughout the whole research process.

Furthermore, we present some possible interpretations from our collected data which is then argued for and against to provide a high scientific quality and to enhance the credibility of the research (Gummesson, 2003). In conclusion, we have been aware that our semi-structured interviews from a mix of professional and individual standpoints could answers our questions. Still, there is a risk of not representing the organization at large. We have therefore put attention to finding connotations to ensure to the best of our ability, as much objectivity as possible as Recker (2013) recommends.

4 Empirical Result

As an introduction to the empirical results, the organizations and respondents are presented briefly. Following, the organizational decision making is portrayed in terms of what kind of decisions they make. Then, the computational support is presented, followed by how AI-capabilities are used in organizational decision making. After that, the factors are presented. The specific row of the interview transcript from where the empirical result is taken is presented next to the respondent.

4.1 Organizational Decision Making

The first organisation was a real estate company and our respondent worked in the department for real estate valuation (R1:2). This was a department for which R1 was the director for nearly 20 years. In valuating real estate, R1 explained that they use a database for calculations of cash flows to determine the real estate's value (R1:4).

The second organization was a retail company. Our respondent worked at the department for product development and supply chain, within the advanced analytics group as a project manager (R2:4). In the supply and range department, complex decisions are made about e.g. what products to sell and in which countries (R2:40). R2 worked with developing decision support tools for the business operations (R2:6), therefore the decisions were mostly project based. However, since the organization has a long history, the knowledge and experience gained from that time was used with the data presented in the decision tools (R2:22).

The third organization was a computer software company. R3 was an account executive, working with sales across the Nordic region. The platform that they sell help organizations to gather, process and work with data (R3:4). Therefore, R3 foremost took decisions on which organization to target, but also regarding which resources that is needed to drive a project (R3:6). Overall, a major part of the culture was explained to be that the organization should make decisions based on data rather than opinions or feeling (R3:8,24).

The fourth participating organization was a pharmaceutical company. R4 was a partner for the IT and research development department (R4:2). That means that demands are received from various areas of the organization or potentially a drug discovery process. Then, R4 formalized the demands, understood the operations, and then translated it into IT components (R4:2). Thus, resulting in transformational technology that R4 created a business case around to pitch to the executive level and later conduct change management (R4:4,6,50).

The fifth participating organization was a bank where R5 was the Chief Data Scientist (R5:2). Overall, R5's work description was to inspire the bank to become more data driven (R5:2), including strategic decision and providing recommendations regarding their data (R5:5). Further, uncertain decision making situations in this organization where the is a potential high market effect, decisions were made by committees. If it is low, one could take these decisions themselves by receiving risk mandate (R5:68).

Lastly, the sixth organization was a computer software company, helping other organizations with sales prospecting, customer relationship management, and marketing automation (R6:2). The participating respondent was the co-founder and head of customer sales. However, being one of the co-founders there was organizational strategic decisions to be made as well as client specific (R6:4). Overall, the organization was very data driven (R6:16).

4.1.1 Computational Support in Organizational Decision Making

Here a description of the organizations computational support in organizational decision making will be presented. Specific usage of AI in decision making will follow under the next section. In this section, focus is more on the general idea of having the computational support, and what it brings to the decision making body of the organization.

Overall, for the organizations it was common to use a computational supportive tool in the decision making (R1:4; R2:8; R3:8; R4:2; R5:6; R6:8). Because R2 worked with advanced analytics and creating supportive tools to the business operations (R2:4,6), a positive view of computational support was emphasised in several parts of our conversation. Similarly, since R4 decided which systems to support the business needs (R4:2), the positive potential to accelerate their operations was accentuated. Likewise, R2 emphasized top management's openness to use computational support (R2:52). Correspondingly, R3 had IT tools for almost everything (R3:8), and an organizational openness to innovative solutions (R3:42). In the financial industry, there was little that was allowed to be solely human intuition; therefore, IT system was used as support (R5:6). For R6, the decision making tools are mostly used in marketing and sales (R6:8), but an overall positive attitude towards supportive systems was expressed.

For several organizations, these decision support systems were developed inhouse (R1:16; R2:14; R6:26,36,42), others purchased off the shelf (R4:34), while some had a mix (R3:14). R4 described a paradigm shift from being system centric, which created silos in the organization, to data centric with an understanding of that the produced data can be reused (R4:4,6). R5's role as Chief data scientist was to inspire the organization to become more data driven, using the highly qualified teams of PhD's in computational science (R5:2).

Similarly, other organizations were expressed as data driven (R3:8; R6:16). From R3's perspective, the sales system was the core, but then there were also additional tools for customer analysis and planning. Similarly, R6 systems were used to identity which customers to target and why (R6:8). For R2, business intelligence tools such as Qlik was use, where the employees had the possibility to retrieve useful data to use in the decision making (R2:8). This enabled for e.g. sales, product, and costs to be visualized and considered (R2:8), which was expressed as enough for several areas of business decisions (R2:72).

Furthermore, some information was emphasized as difficult to place in a computational supportive tool, for example the relationship with customer's decision makers (R3:26). Therefore, these supportive computational solutions were viewed as a one piece of the decision making, thus the employees should not solely make data driven decisions (R2:40). On the contrary, R3 still stressed in letting the data decide (R3:8), with the consideration for that the system was missing certain human like inputs (R3:26). Likewise, R6 stressed the need of humans for complicated organizational decisions, while repetitive work can be increasingly done by computers (R6:74). R5 agreed that some information might be missing in the computational system, thus it was important that the humans are responsible in the end for their decisions (R5:84).

Still, the computational support was explained to bring confidence and efficiency to the decisions. R1 explained that one often had an idea of what a decision should be, but that the computational support gave confidence in that you would make the right decision, which created the ability to make fast decisions (R1:80). Similarly, R3 highlighted the confidence from the system support when confronted with different decisions, but also the improved time efficiency (R3:71).

4.2 Applications of AI in Organizational Decision Making

Here the different organizations' AI capabilities will be described and how AI is specifically used in the organization.

The organizations in this study used AI differently but had similar capabilities. R1 organization used AI in organizational decision making to make judgements of what is currently happening in the market and purpose ideas (R1:12). The purpose of the AI-system is to manage larger volumes of data in a short period of time (R1:10). While its system is not good at handling unstructured data, the system is according to R1, excellent in following and analysing structured data quickly (R1:78).

R2's organization has adopted machine learning to help optimize the internal processes and which products customers usually buy together to suggest customers other similar products (R2:12). AI also helps the organization to make decisions on which products should be sold in which countries and optimize the supply chain (R2:12). AI is also adopted in more parts of the organization such as logistics and warehousing (R2:84). R2 is currently looking into AI-systems that are capable of dealing with text, pictures and voice recognition (R2:12).

R3's organization has adopted machine learning and other AI-models which supports companies to collect and analyse information (R3:4). An example of where machine learning is applied, is the forecasting software which helps the employees of the company to make a decision of where they should put their attention in terms of sales (R3:10).

R4's organization has adopted an off the shelf solution called Sinequa (R4:8). Sinequa is an AI-enabled system which helps employees and organizations to deal with a large number of documents (R4:8). The system is like a search engine where the user puts in keywords to find relevant information(R4:8). It is using a natural language processing capability when searching for the right documents (R4:10). By using a capability like natural language processing, the organization can find information quicker and make decisions faster (R4:10). The organization is currently looking into a system that could classify documents automatically as well (R4:12).

R5's organization has adopted several AI-capabilities. The organization is using digital assistants to automate what R5 refers to "every-day" tasks (R5:8). An example of "every-day" tasks is to help customers with simple questions on their website (R5:8). The organization is however mostly using machine learning to deal with the large amounts of data that humans are not capable of processing themselves (R5:10). With the help of machine learning, employees can get a better holistic view of the problem and make more informed decisions (R5:70).

R6's organization has adopted AI to acquire data primarily for sales and marketing purposes (R6:8). Similar to R5, R6 organization deals with large quantities of data that they feel like they need AI to help make sense of the data and understand it (R6:8). The organization is primarily using machine learning and natural language processing to process all data (R6:10). Some decision making is automated with AI (R6:8).

4.3 Technological Context

4.3.1 Perceived Direct and Indirect Benefits

This factor represents the organizations' recognition of perceived direct and indirect benefits prior the adoption of AI in decision making. The results varied between the different respondents. Some organizations were not especially aware of what they could gain from AI (R1:18, R4:16), apart from efficiency advantages in operations (R1:18). One organization purchased off the shelf which enabled them to see the benefits of the AI-system before the adoption (R4:16, 18). These benefits were for example the possibility to accelerate compiling of information for research and presenting it on a dashboard (R4:18). This was very important for the pharmaceutical company because it enabled scientist to focus on science and not administrative tasks (R4: 20, 22).

Furthermore, R1 also acknowledged the speed of AI in the possibility of improving valuation tools to become faster and simpler than if done in a traditional way (R1:20). With this, they saw the possibility of expanding the business operations into new industry branches (R1:20). Similarly, R5 (16) acknowledged efficiency advantages as perceived benefits before the adoption.

Likewise, R6(14) understood that they could harness much more data with AI. Others recognized before the adoption, the importance of making sense of the data, and where AI could help and assist them (R2:16, R4:18). In addition, benefits were seen in the autonomous data flows, enabling for more advance analytics with more variables, creating a broader context for the analysis (R2:16). Still, these benefits were known by the analytics team, but perhaps not by the whole organization and top management (R2:50). Instead, top management wants to see results before making decisions based on the AI tool (R2:58).

Moreover, another perceived benefits prior the adoption was the advantaged that AI brings in decision making. Also, the human intuition can be wrong sometimes (R5:16), hence there is a risk of relying on human intuition which can result in a focus on the wrong things (R3:18). However, with AI they would be able to not miss opportunities and focus on the right things (R3:18), thus getting additional support (R5:16).

Regarding the influential effect on the adoption of AI in decision making, respondents were asked to reflect on how it influenced the adoption. Results show that it was not perceived to be influential for R1(18), unsure but hopefully influential for R2(20), and perceived as influential by R3(18,22); R4 (20, 22); R5(18); R6(18).

4.3.2 Amount of Data

The factor of amount of data refers to an organization's ability to collect, process and understand data and information in this thesis. In its essence it is about how organizations value and manage data.

All organizations that participated in this study claimed that they were dealing with large amounts of data, from their perspective, which affected their decision making to some extent (R1:10; R2:16; R3:24; R4:6; R5:10; R6;14). Some organizations had an outspoken policy or vision where the whole organization was "data-driven" which means that all decisions have to be made on the basis of data (R3:8; R6;16). While the other organizations were also data-driven to some extent, it was not as outspoken as organization R3 and R6. This means that all the organizations valued data as an important resource. For example, R5 had a policy that says all types of information are a valuable asset and therefore has a high priority within the organization (20). Nevertheless, while R2 acknowledged data as an important resource, the organization also emphasized other values such as experience of the decision-maker (R2:22).

The respondent's organizations collected data differently. Several of the organizations were doing business in different industries within this study which resulted in different data needs. In organization R6 for example, the data was largely provided by different governments which made it easy to automate the transaction (R6:2). In addition, R2 collected a lot of data from their internal processes such as sales data which was also to some extent automated (R2:24). However, R1 was collecting data from external sources which was collected manually by the employees (R1:26).

The management of data is quite similar for all organizations. R4 collects documents in their AI-system which is then analysed by the AI. It is collected into a system which R4 describes as similar to Google's search engine (R4:16). The employees search for keywords into the system and are then provided with documents that contain information which could help them with the decision (R4:16). Thus, the employees do not need to analyse themselves all the documents to find the correct information. Nevertheless, R1 has some help from AI to analyse the data but is also analysing the data manually themselves (R1:26). The other organizations are analysing the data similar to R1 with some automation and some work done manually (R2:26; R3:28; R5:29).

Moreover, some organizations perceived they gained new insights with the help of AI-enabled systems, while other organizations did not believe they gained new insights yet. R1 and R4 had not yet discovered new insights with the help of AI-enabled systems, however both believed they will in the future when they further develop and integrate AI into their organization and decision making (R1:28; R4:30). R5 had like the other remaining organizations gained new insights with AI which both could be surprising and obvious such as the number of Swish transactions are higher during Friday evenings when people tend to eat at restaurants (R5:26).

To make AI-enabled systems worthwhile, all organizations believed the amount of data was key (R1:32; R2:34; R3:73; R4:66; R5:29; R6:26). R1 believed it is nearly impossible to implement AI without having access to a large amount of data (R1:32). Moreover, R6 stressed that the AI-system can use more complex models and be more accurate the more data they have (R6:22).

Finally, R1, R4, R5 and R6 believed the amount of data was influential in their choice to adopt AI-enabled systems into their organizational decision making (R1:30; R4:74; R5:29; R6:26). R4 and R5 believed that it was one of the most influential factors when deciding to adopt AI out of the ones that are presented in this thesis (R4:78; R5:78). The remaining organizations did not believe that it was influential in their choice of adopting AI. This is because they did not believe the organization had full insight into what kind of data they were in possession (R2:34). One respondent also stressed the culture of the organization was to always explore new technologies rather than considering the data (R3:34).

4.4 Organizational Context

4.4.1 Perceived Technical Competence

The perceived technical competence refers to how an organization perceives their technical competence. The study has focused on the general level of employees, the IT-staff and the managers of the company.

R1 believed the technical competence of the organization was varied (R1:34). Some were more knowledgeable and aware than others (R1:34). R2 and R5 had a similar view of its organization and says it depends on the nature of the different roles in the company. Some had more technical roles while others had less which affected the technical knowledge and awareness (R2:36; R5:33). R4 said the organization was currently shifting into better technical knowledge but the technical knowledge was currently low (R4:38). R3 and R6 believed the general level of technical knowledge was high within the organization (R3:36; R6:28). R6 acknowledged that it could and should be improved upon, but in general had a high level (R6:28).

The IT-department had a high level of technical competence in most of the organizations. All organizations except R4 had developed their own AI-solution, some with a bit of help, which makes them believe their IT-department has a high level of technical skill (R1:16; R2:14; R3:14; R5:14; R6:12). R4 had bought their AI-system off the shelf (R4:18).

Moreover, most organizations believed that the technical competence within the executive board or managers were varied as well. R1 believed the organization had low technical competence among the managers, and believes it was still low after the adoption (R1:40). R2 stressed that the managers reflect the employees overall by having varied technical competence depending on backgrounds and interests which was also aligned with R6 managers (R2:38; R6:30). R6 emphasized that they want to disrupt the current industry and therefore needs the whole management on board which means both technical knowledge and awareness (R6:32). Nevertheless, R3 believed that the technical competence was very high among the managers and executives (R3:38). All members of the board had a PhD within technical areas and many of them were still keeping close contact with top universities in the world (R3:38). R5 also believed that the technical competence was high within the board (R5:37). The chairman of the company had a huge interest in AI which reflected the technical competence (R5:37).

Concludingly, R1 and R4 stressed that the lower technical competence of the managers affected the decision to implement AI in decision making. The organization had been trying to implement more AI-functionalities to assist their decision making which the managers resisted. R1 perceived that the technical knowledge was not the main issue, but instead the technical awareness and what consequences the system would have for the organization (R1:44). R4 also believed that the employees would not use the AI-system if they did not understand how to use it (R4:40). R2 did not believe that lower technical knowledge within the organization affected the adoption AI, but instead as R1 said, the technical awareness and interests played a larger role (R2:42). Furthermore, R3 believed that the high technical knowledge of the organization had a positive effect on the adoption of their AI-system because it was in the company's nature to try new tools (R3:40). R5 had a similar view but says it depended more on the technical awareness of the managers (R5:39). R5 had adopted AI a few years before its competitors and think it was because of the technical knowledge of the managers (R5:39). Finally, R2 and R3 saw the technical competence as one of the most important factors when deciding to adopt AI in organizational decision making (R2:82; R3:79).

4.4.2 Decision Making Obstacles

This factor represents the obstacles in decision making, for example uncertain, complex, and equivocal situations, but also nonprogrammed and unstructured decisions that perhaps are new and ambiguous.

In uncertain decision situations, R1 explained that depending on the decision, it will be approved in different parts of the organizational decision making structure (R1:74). These processes were described as time consuming in an organizational environment where decisions must be made fast. Thus, this time pressure resulted in another decision process of whether to take the new mission (R1: 74). Furthermore, in the real estate evaluation, object specific information was not always available (R1:12). Although acknowledging that there were no obstacles in the decision making process prior the adoption (R1:46), humans were explained to be different as "some do have a positive outlook, and some do have a negative outlook." (R1:50). Similarly, R3 explained a decision processes of high uncertainty being conducted manually with human gut feeling of what was best for the individual, rather than the organization or the customer (R3: 62). Further, R1's organization strived to improve the decision consistency and that the individual competences should not be connected to conduct qualified balanced analysis and decision (R1:41). Likewise, in general for the financial industry, it was expressed that very little was allowed to only be human gut feeling (R5:6).

Uncertainty was also something that appeared for R5 in the situation where they shifted to the contact with customers being over digital channels, therefore they needed to maintain the contact and humanness of it (R5:16). Thus, they had to compile the generated data. Also, in situations whether it was the stock market or how many times you should call your customer, created decision situations of various complexity (R5:29). Similarly, the decision making situation for the retail organization was also acknowledged as complex, determining what product to develop and in which countries to sell them (R2:40). Thus, both soft and hard factors were needed to determine what to decide (R2:40). In the product development, conflict of interest emerged when dealing between functionalities, cost-effective production, and visual appeal. R2(45) explained that as a reason why they had different roles in a team, to leverage the competences of the organization.

Similarly, in larger strategic decisions, R6 organization’s normal data driven approach was not applied, instead it was done by discussion among the founders and stakeholders, taking in to account the employee’s voices (R6:56). Thus, potentially posing organizational equivocality in the decision making. Nevertheless, R6 explained that they were data driven when it comes to targeting customer segments and that this leaves little room for innovation and leaps of faith (R6:56).

Still, solely considering the data and the decision making obstacles that it may bring, R2(45) expressed a belief that it existed in several organizations. Similarly, the data for the financial services organization had more of a silo approach before the adoption, possibly having redundant customer and market information (R5:22). Likewise, the pharmaceutical company, had existing obstacles before the adoption: “We do things not in a harmonized way. It is difficult to find information and it's difficult to take decision. Sometimes we redo things which were already done elsewhere, by not knowing what was done.” (R4:8). In addition, considering that there are millions or billions of records that are available for the scientist of the pharmaceutical organization to compile prior the adoption, it created a difficult situation for them (R4:18).

Furthermore, R4(24) explained that they have several systems that were not connected and that there was not a database in place to compile all those data points. This was because of software being tailored to a person in one phase of for example a drug discovery process (R4:24). Thus, creating a crucial situation based on human assumption about the quality, if any error were made in the beginning, it would be repeated each phase resulting in failure (R4:24). Therefore, it was expressed as essential to create a central platform for the truth (R4:28). Likewise, it was described by R2 that individuals have different data as ground for their point of view, possibly because of different data sources, thus resulting in different reality views (R2:45). This were described as dangerous for this organization, because of uncertainty in knowing which view to rely on (R2:45).

Regarding if obstacles in decision making was influential in the adoption, it was expressed as not influential by many (R1:41; R3:44; R5:43; R6:56). Although it was stated that AI would bring a more uniformed image, the decision making obstacles were not perceived as influential in the adoption by R2 (47). Moreover, even though R1 and R4 did not acknowledge any decision making obstacles prior the adoption, the examples provided above (R1:12, 41, 46, 50; R4:8, 18, 24, 28) creates a compelling argument that it may have been influential. Similarly, R5 shows the existence of decision obstacles by providing examples (R5:16, 22, 29), but not as compelling as R4’s. Although, the adoption of AI capabilities was explicitly expressed as the solution to the digital channel transition problem, as described above (R5:16).

4.4.3 Top Management Support

Top management support refers to managers within an organization being able to establish an environment where innovative thinking is encouraged and resources is provided to innovate.

In the process of adopting AI into organizational decision making, R1, R3, R5 and R6 perceived the top management either governed the whole project or supported the decision and implementation of AI (R1:51; R3:46; R5:45; R6:40). The top managers showed commitment by adding resources to where it was necessary within the organization. In R1, the employees themselves pushed for the implementation of AI in decision making but received necessary funds from the top managers to execute the idea (R1:56). In contrast, the adoption of AI in R5 was driven by the top management themselves who created new job positions to facilitate the adoption and created a vision of what the AI would achieve in organizational decision making (R5:49; R5:47). R3 was also driven by the top management by creating a culture where technologically innovative thinking is encouraged and rewarded (R3:48). Some AI-solutions in R3's organization had been created by the employees themselves who had received support from their managers by allocating time (R3:50). R6 top managers had a similar approach to R3 where a lot of freedom was given to the employees and innovative thinking is encouraged (R6:42).

Nevertheless, in R2 and R4 organization, the management also showed interest and support in the adoption of AI but did not have an idea of what the results would be (R2:50; R4:50). In R2's organization they created a team who was responsible for AI in general. The team investigated AI and created a vision for AI themselves (R2:50). In R4's organization the top management worked as a controller of innovation. The top management of R4 worked as a sponsor of the projects if the employee can manage to create a solid proof of concept, similar to how a start-up would make its business case for investors (R4:50). If the proof of concept was valid, the top managers would allocate resources to the employee with the idea (R4:54).

The results varied in terms of how important the factor of top management support was perceived for the organizations in this study. All organizations in this study but R1 believed that top management was an influential factor when adopting AI into decision making. R2 and R3 believed the resources the top management provided was vital into adopting AI (R2:58; R3:50). R2, R3, R5 and R6 also believed that the top management support plays an important role in implementing the AI-enabled system in decision making (R2:82; R3:81; R5:78; R6:44). R4 stressed that if the project of implementing AI had no support from the top management, it would go nowhere and emphasized change management as something important (R4:56). However, R1 did not think top management support was influential in adopting AI in organizational decision making because it was the employees themselves who drove the project forward (R1:62).

4.5 Environmental Context

4.5.1 Competitive Pressure

Competitive pressure refers to the degree an organization perceived its competition within the industry it was conducting business in.

Some organizations in this study were aware of competitors using AI-enabled systems in organizational decision making prior to adopting (R3:52; R4:58; R5:55). R3's organization had off the shelf solutions which was most likely used by competitors, while R4 and R5 were inspired by its competitors to adopt AI (R4:58; R5:57). While the R2 organization was not confident that its competitors were using AI, they were presuming that some of them ere (R2:60). R1 was confident that none of its competitors were using AI in organizational decision making before them which R1 believed is because they were the only organization that is using big data in the industry (R1:20; R1:64).

All organizations believed that AI in organizational decision making give them a competitive advantage. R1 stressed that by showing that the organization is using AI to the public could generate market share (R1:66). R1 also believed that while the competition is getting tougher, organizations need to defend its positions which AI could help with (R1:68). R2 expressed that many industries were moving towards AI was considered a buzzword (R2:20). R2 saw the online businesses as a potential major competitor and to be able to sustain its market share, the organization needed to use the data in a better way which AI could help with (R2:68). While R3 believed it was a competitive advantage with the usage of AI in organizational decision making, R3 did not believe organizations should care too much about its competitors and focus more on its own internal processes (R3:54). Moreover, R6's organization was trying to disrupt the industry by challenging the status quo with the usage of AI (R6:46). R6 could see how bigger players are gradually moving towards the direction where they already are (R6:48).

While R6 was trying to disrupt the industry, they did not see competitive pressure as something that influenced their choice of adopting AI into organizational decision making (R6:48). R5 and R3 stressed some parts of AI in organizational decision making were influenced by competitive pressure while others were not (R5:61; R3:58). R2 also believed they were influenced by the competitive pressure, but more on an internal level to become more efficient (R2:68). R4 believed competitive pressure influenced them a lot when deciding to adopt AI because of the niche market they were conducting business in (R4:62,78). R1 also believed that competitive pressure was an important factor when adopting AI which has to do with being perceived as an innovative company that leverages high quality (R1:86).

4.5.2 Environmental Uncertainty

Environmental uncertainty refers to the environment that the organization operated in and its dynamical effect on the organizational adoption.

R1's organization operated in the real estate industry and had to keep track of interest rates and movements in the market (R1:12). They had noticed a successive downfall in profits in Europe, and to solve this problematic situation, they looked at new smarter and more efficient ways to work (R1:70, 78). On the other hand, the retail organization acknowledged the stability of their business and history that hopefully contributed to calmness if movements in e.g. customer behaviour appeared. Still, because of the organizational size they partly establish the market trends (R2:70).

Because of the R3's product could be sold to various industries and branches they had created a protected product to the environmental dynamics, therefore it was not apparent (R3:60). Similarly, the pharmaceutical company operated on a niche market, and did not perceive the environment as uncertain (R4:64). Likewise, as companies always will need company data, which is a fundamental aspect of marketing, sales, and the company's life, R6's organization felt protected to environmental dynamics (R6:54). However, the legislative aspect of the environmental uncertainty was as acknowledged as apparent R6:56), because of the very core of their business being collecting open data and data mining (R6:2,60).

On the contrary, in the financial services industry, there was a dynamic environment with several smaller companies trying to gain market shares, therefore the organization tried to find the best and partnering with them (R5:66). During the interview, R5 also talked about the high-level expert group in the European union that developed guidelines for ethical AI (R5:10), which may be viewed as a dynamic force for all organizations. On a similar note, R4 expressed that new buzzwords appeared each year e.g. Cloud, SaaS, and AI, that the business had to cope with. Thus, it was said to be difficult for the business because of “too many things happening”, but also motivating as they had to try new things and new ways of working (R4:72).

The environmental uncertainty was reflected as not influential by several of the participating organizations (R1:76; R2:74; R3:66; R4:68,70; R6:60). However, R5 explained it as highly influential, mostly because of the areas where one cannot compile enough information to gain an overview and total image of the situation. Therefore, machine learning was needed (R5:70).

5 Discussion

In this discussion the themes of organizational decision making, computational support, and applicability of AI in decision making were incorporated into discussion on the different factors where it was relevant. Overall, the empirical findings are discussed together with the presented literature. Lastly, the limitations of this study are discussed.

5.1 Technological Context

5.1.1 Perceived Direct and Indirect Benefits

Early on, Bonczek et al. (1979) argued that computers were seen as supportive tools regardless of the decision makers application. Similarly, these perceived benefits of AI that is recognized by the respondents, enlightens that these can be found regardless of the organization's industry. Overall, the respondents understood that the support of a computerized system (Bonczek et al., 1979; Bonczek et al., 1980b; Bonczek et al., 1980a), in this case AI-enabled system, could improve their operational efficiency as well as the compiling of information in the decision making process (R1:20; R2:16; R4:18; R5:16; R6:14). Possibly, because of the common experience of using computational supportive tools in the decision making (R1:4; R2:8; R3:8; R4:2; R5:6; R6:8).

Furthermore, R1(41, 50), R3(18) and R5(16) explained the benefits of using AI in decision making where solely trusting the human intuition can result in wrong doings. As Kottemann et al. (1994); Davis and Kottemann (1994) described, the computational support can create a feeling of control and reliable trust. This was recognized by R5 and R3 as they would not be missing opportunities, instead getting additional support from AI. That is in line with Jarrahi (2018) proposition on how to create better possibilities for better decisions and Kahneman et al. (2016); Tshilidzi (2015) explanations of that in many decision making contexts, algorithms outperform humans. Still, although others also acknowledged these types of benefits, it was not expressed as something that was realized before the adoption, thus not applicable to consider as influential in the adoption.

Moreover, as Keen (1981); Meador et al. (1984); Money et al. (1988) suggested, if the perceived benefits are understood, there is a significant influence on justification of costs by the organization and the effectiveness as a support tool for the process of decision making. With similarities to Mintzberg et al. (1976) incremental decision making model, this was seen in how R4 prepared the business case from formalization of demands to IT-components. R4 argued for its beneficial effect to the executive board, where R4 could explain that this would enable for scientist to solely focus on science and not administrative tasks (R4: 20, 22). However, while R2 explained that top management expressed an openness for AI computational support, results still wanted to be seen before making decision on the AI tool on a broader scale (R2:50, 52), consequently illustrating the benefits was important.

As past IS research has shown, the perceived benefits were presented to be both insignificant (Chau & Tam, 1997) and significant in the adoption (Kuan & Chau, 2001). Although both R1; R4 were not aware of what to gain from AI in decision making. R4 had the possibility of trying the system before, thus we argue benefits were known before the adoption for R4, while R1 had to learn throughout the development of the AI tool. Nevertheless, in this study those who recognized the benefits of AI-enabled systems in decision making prior the adoption deemed it as an important influential factor (R3:18,22; R4:20,22; R5:18; R6:18).

5.1.2 Amount of Data

The amount of data has shown to be important in earlier literature when considering humans processing and dealing with the data and information (Zahra & George, 2002; Hilbert & López, 2011). Moreover, there is also evidence that the amount of data is more important than perfecting the algorithm for AI-enabled systems (Yarowsky, 1995; Banko & Brill, 2001; Criminisi et al., 2004). Ransbotham et al. (2017) also showcases an organization's ability to value and manage data is a primary factor for adopting AI as a pioneer rather than a late adopter.

All respondents perceived that their organization was dealing with a huge amount of data (R1:10; R2:16; R3:24; R4:6; R5:10; R6;14). This can be an indicator that the organizations are valuing data highly because of its amount. However, it is unclear how the respondents perceived a huge amount of data. As Ransbotham et al. (2017) acknowledged, organizations can believe they have sufficient data for AI-enabled systems, which might not be true. Some organizations did not have full insight into what kind of data they were in possession of (R2:34; R3:34). Nevertheless, R3, R5 and R6 were all part of data-driven organizations which should indicate that the organizations were valuing data highly and put it as a valuable resource. R1's organization collected data from external sources which were done manually by the employees which might indicate that they were not dealing with sufficient amounts of data which also reflects on the insights derived from AI (R1:26). R1 believed they had not yet discovered any new insights which could be the case that the AI-algorithm did not yet have sufficient data (Yarowsky, 1995; Banko & Brill, 2001; Criminisi et al., 2004).

When asked about what new insights had been gained through the help of AI-enabled systems, R2, R3, R5 and R6 said that they had gained new insights which could showcase that the organizations are dealing with sufficient data for the AI-algorithm to learn (Yarowsky, 1995). Moreover, Ransbotham et al. (2017) thoughts about organizations' overestimating the amount of data they possess when adopting AI was not supported by a majority of the respondents in our findings. However, the insights generated from AI-enabled systems did not necessarily had to reflect on the sufficiency of data but should be an indicator whether the system is performing and assisting the human in its decision making.

Moreover, the organization's managed data similarly by having some parts of the process done automatically and some part of it done manually (R1:26; R2:26; R3:28; R5:29). This could demonstrate that the organizations were dealing with the issue of information overload which led them to the choice of automating some parts of the management (Zahra & George, 2002; Hilbert & López, 2011). However, when faced with questions regarding decision making obstacles, no organization mentioned information overload as an example, but instead referred to becoming more efficient. This could mean that the organizations were not aware of information overload or did not see it as an issue. Nevertheless, some insights derived from the data were seen as obvious but not yet discovered by R5(26) which could mean that the organization was dealing with information overload.

Finally, when asked about how the amount of data influenced their choice of adopting AI-enabled systems in organizational decision making, all respondents but R2 and R3 believed it influenced their choice (R1:30; R4:74; R5:29; R6:26). According to Ransbotham et al. (2017) the organization’s ability to value and manage data is one of the primary factors differentiating early and late adopters. Interestingly, R3 said its organization was data-driven, thus valuing data as an important resource, and did not acknowledge the amount of data as an influential factor. This could mean that valuing data is not as important as Ransbotham et al. (2017) argue. However, R4, R5 and R6 believed it was influential while valuing data highly.

5.2 Organizational Context

5.2.1 Perceived Technical Competence

R1, R2, R4 and R5 believed that the technical competence within the organization was varied (R1:34; R2:36; R4:38; R5:33). This was not in line with earlier research that has shown that high perceived technical competence is important when adopting technology (Cragg & King, 1993; Kuan & Chau, 2001; Lian et al., 2014). The executive board and managers among the organizations reflected the organization as a whole in most cases. However, R5 believed that the technical competence was high within the board which reflected on the huge interest in AI (R5:37). This could indicate that the higher technical competence within the executives or managers might enable appreciation for AI-enabled systems in decision making, rather than aversion (Dietvorst et al., 2015; Logg et al., 2019).

Nevertheless, R3 and R6 perceived that there was a high level of technical competence within the organization (R3:36; R6:28). Both companies were in the computer software industry which could affect the level of technical competence. One could also argue that the baseline for what is high technical competence could be higher within the computer software industry in comparison to more traditional ones in our study. This is however in line with Lin and Lee (2005) who showed that technical competence was influential when adopting new technology among organizations.

When asked about the perceived technical competence within the IT-department, all respondents claimed to have a high level of technical competence. However, R4’s organization bought their AI-system off the shelf (R4:18), R1 organization had help from the outside to develop their AI-enabled system (R1:16), and R3 organization had bought some AI-solutions from other companies (R3:14). While the development of AI-systems was not the only factor influencing the level of technical competence, it could however be an indicator that certain technical competence was missing when deciding to adopt AI.

R1 and R4 believed that the lower technical competence was an influential factor which was shown when trying to implement new AI-solutions in the organizational decision making was often met with resistance (R1:44; R4:40). The varied technical competence in R1 and R4 organizations could indicate some AI-aversion (Dietvorst et al., 2015; Logg et al., 2019). Nevertheless, R2, R3 and R5 believed the technical competence within their organizations were influential (R2:42; R3:40; R5:39). Both R3 and R5 believed to have a high level of technical competence within the executives and managers which could influence. However, R2 believed it was varied in its organization. Thus, the perceived technical competence could be equally important among the employees, IT-staff and executives.

5.2.2 Decision Making Obstacles

As Cohen et al. (1972) explained, decision making can be an ambiguous task within an uncertain setting. Further, organizations are confronted with uncertainty, complexity, and equivocality (Simon, 1972; Choo, 1991), which our evidence supported. Since uncertain (R1:74; R5:16; R6:56), complex (R2: 40; R5:29), and equivocal (R2:40) decision situations were described in the interviews. It also showed that computational support may not erase these situations, as all information does not exist in a system.

Moreover, R2 explained that conflict of interests from different departments existed in the decision making, leaving the organization to do trade-offs (R2:45). Thus, supporting situation described by Saaty (2008); Eisenhardt and Zbaracki (1992); Jarrahi (2018). Although there were conflicting interpretations as explained by Daft and Macintosh (1981), R2's described example was about the product development not about the organizational situation. Still, supporting Galbraith (1973) explanation that organizations uses cross functional teams to enhance the decision quality, and foster innovation (Baker, 2012), R2 explains it as the reason to leverage the competencies in the organization (R2:45). Thus, possibly trying to improve the outcome from the decision.

To deal with complex environments, managers try to find decision rules, information sources and structural designs that provide an understanding to cope with complex and uncertain environments (Daft & Lengel, 1986). However, for R1 it was the very organizational decision structure and process that created a time-consuming obstacle (R1:74).

Furthermore, organizational theory suggest that organizations process information to reduce uncertainty and equivocality (Daft & Lengel, 1986), which was one of the expressed reasons for adopting AI in decision making. Several organizations had troubles in the processing and storage of information prior the adoption. There were some that described an existing information silo approach prior the adoption (R2:45; R4:24; R5:22), harming the information flow (R4:8,18,24), and resulting in different reality views (R2:45). Thus, showing signs of existing equivocality as explained by Daft and Macintosh (1981).

Furthermore, R1 wanted to improve the existing decision consistency (R1;41, 50). It was expressed that the reason was that the individual competences should not be connected to conduct qualified balanced analysis and decision (R1:41). Possibly, this meant that this could have been an obstacle before the adoption, and that the individual had to use the best of their intuition and analysis. Furthermore, Saaty (2008) explained that to develop good judgment in decision making, information is gathered about the occurrence. In the information processing, Dane et al. (2012) pointed out that both intuitive and analytical practices are used. However, R1 acknowledged an obstacle with that humans are different and that all the information is not always available when making a decision (R1:12, 50), therefore the consistency may vary, which was one reason to adopt AI in decision making.

Interestingly, Eisenhardt and Zbaracki (1992) explained that research shows that decision makers satisfice instead of optimizing, because of bounded rationality and limited information. On the contrary, R1's examples above enlighten that a good enough solution is not accepted and that the initiative with AI can be considered as an attempt to optimize the decision making, creating the most out of the available information. Similarly, R4 explains that they relied on human assumption of information quality before the adoption (R4:24), which was described as a risk. To simply trust the human gut feeling was expressed as used before the adoption (R3:62). However, in R5's organization there were few decisions that were allowed to be solely trusted by human intuition (R5:6). These examples may indicate that the common experience of using computational supportive tools in the decision making was not enough to cope with these obstacles prior the adoption, and simply left the decision maker to satisfice instead of optimizing. Nonetheless, as Jarrahi (2018); Kahneman et al. (2016); Tshilidzi (2015) explained, AI may create possibilities for better decisions outcomes. On the other hand, R6 explained that their data driven approach generated little room for innovation and leaps of faith (R6:56), which may indicate the importance of balancing data and human decision making.

Moreover, Mintzberg et al. (1976) expressed that nonprogrammed and unstructured decisions may create decision obstacles for organizations, characterized by abundance of elements or variables (Jarrahi, 2018). This was seen in an example where R5 explained that humans have limited capacity to compile information and create an overview of uncertain environments (R5:70). Hence, supporting Daft and Lengel (1986) explanation that humans cannot interpret and process all the available information, which also were said to contribute to an uncertain environment.

Although the decision making obstacles were said to be non-existent and not influential (R1:41; R3:44; R5:43; R6:56), the obstacles stated above did indeed create a demand for processing of a lot of information or data preferably at high speed to gain a competitive advantage as Jarrahi (2018) claimed, but also to overcome these decision obstacles as the examples show.

5.2.3 Top Management Support

The decision to adopt AI in organizational decision making was driven by the top management in R5's organization, who created new job positions and facilitated the adoption overall by creating a vision for example (R5:49;47). This is in line with Borgman et al. (2013) who stressed that the provided resources to innovations are important. It was even more important for an organization like R5's who had several AI use-cases in organizational decision making (R5:8) which could risk some parts of the AI-projects being regarded as not as important (Brynjolfsson & Mcafee, 2017). Moreover, R4 emphasized change management from the top management to deal with the required changes in processes and to convince the employees to use the system (R4:56). This was both in line with Borgman et al. (2013); Brynjolfsson and Mcafee (2017) arguments about the role of the top management in adoption of technology and our thoughts of getting employees on the same page.

When asked how the top management support influenced the adoption of AI-enabled systems in organizational decision making, the result varied. R2 and R3 perceived top management support as crucial, which was in line with Pan and Jang (2008); Zhu et al. (2004); Rai and Bajwa (1997); Low et al. (2011) findings in other studies of technology adoption. R5 and R6 also expressed the importance of top management support (R5:78; R6:44). However, R1 did not perceive that the top management support influenced the choice of adopting AI in organizational decision making because the employees themselves drove the project forward (R1:62). While the top managers in R1 organization did not seem to provide the resources necessary, they seem to have established an innovative environment because of the ideas coming from the employees (Borgman et al., 2013). Moreover, R1 did believed that their top management supported the decision of implementing AI in organizational decision making, even though the employees faced resistance (R1:51).

5.3 Environmental Context

5.3.1 Competitive Pressure

Some organizations were confident in that competitors were using AI-enabled systems in organizational decision making (R3:52; R4:58; R5:55), and some presumed it as a possibility (R2:60). The adoption may have been viewed as a strategic necessity. As Dwivedi et al. (2009); Oliveira and Martins (2011) explained, organizational adoption of technological innovations can become a strategic necessity for organizations to compete and sustain a competitive advantage in the industry they are conducting business in. Additionally, as Ransbotham et al. (2017) argued, organization might gain a competitive advantage by implementing AI-enabled systems. Indeed, all organizations believed that AI in organizational decision making gave them a competitive advantage. However, while R6 also recognized it as a competitive advantage which was influential in the adoption, the competitive pressure on the market was not (R6:46,48). This was because of their attempt of disrupting the market by challenging the status quo, thus becoming the competitive pressure for others to consider.

Nevertheless, competitive pressure has long been recognized as a driver for innovation in the innovation adoption literature (Grover, 1993; Iacovou et al., 1995; Crook & Kumar, 1998; Zhu & Kraemer, 2005). Correspondingly, apart from R6(48), the rest of the respondents in this study recognized it as influential (R1:86; R2:68; R3:58; R4:62,78; R5:61). However, where it was perceived as influential differs, seeing how R5(61); R3(58); R2(68) deemed it as influential on some parts or levels in the organization, and R4(62,78); R1(86) considered it as highly influential overall.

5.3.2 Environmental Uncertainty

This factor appeared dependent on the type of product or service that the organization sold. Some argued that the product was protected against environmental dynamics because of steady demand (R3:60; R6:54) or being at a niche market R4(64). However, for the organization in the financial services industry, there was a perceived uncertainty in the environment (R5:66). As Daft and Macintosh (1981) acknowledged, information processing in the organization increases. Creating a cruciality in facilitating the gathering and processing of information (Tushman & Nadler, 1978), which R5's organization claimed to be enabled by machine learning to gain a total overview of the situation (R5:70). Thus, supporting the claim by Duncan (1972), that whether or not there is a dynamic environment in decision making, influences the perceived uncertainty.

Furthermore, R5 explains the emergence of smaller companies trying to get market shares, which they cope with by partnering with the best of those businesses. Thus, in combination with the acknowledged uncertain environment, glimpse of pursuing an aggressive technology policy can be seen, which was in line with Mansfield (1968); Mansfield et al. (1977) cited in Chau and Tam (1997). Similarly, the pressure of investing in a technology policy is something that R4 described. R4 acknowledged the appearance of new buzzwords each year affected them and that the business must cope with these (R4:72). It may be plausible that others had similar experiences although it was not recognized in other interviews.

Previous IS research has found environmental uncertainty as significance (Lee & Shim, 2007) and insignificant in technology adoption (Chau & Tam, 1997). Our evidence showed that although an uncertain environment was described in some cases, it was viewed as not influential by most of the respondents (R1:76; R2:74; R3:66; R4:68,70; R6:60). Apart from R5 who explained how it influenced them (R5:66,70), R4 also presented examples what shows that it was a considered factor (R4:72).

5.4 Limitations of This Study

Like any empirical research, this study has limitations. One of them is that data was collected from organizations of various industries and countries, therefore one cannot generalize a specific industry nor country. Additionally, there was also the limitation of small sample size which may make it difficult for external validity. Given the current Covid-19 pandemic and its repercussions on society, some potential respondents that expressed an interest in participation got unfortunately laid off before we had a chance to interview them and therefore did not want to participate.

Furthermore, another reflection of this study was that there should have been additionally open-ended questions to gain further description of this phenomenon. While the interview approach created a structure for systematic description of each factor and the phenomena as a whole, some respondents prosperity may have been harmed by that approach. Also, some questions that were phrased like “To what degree it influenced” may be of quantitative nature, but we interpreted them like an open question that the respondents could reflect upon. In some cases where we perceived it was necessary, we asked the follow up question of how it influenced. In reflection, it would have been better to directly ask how, although that was found in other answers of the respondents that not explicitly were asked that question.

6 Conclusion

The purpose of this study was to investigate possibly influential factors in organizational adoption of AI-enabled systems in organizational decision making as perceived by decision makers. Therefore, we aimed to reach a conclusion, by trying to answer the following research question: *What factors were perceived to influence organizational adoption of AI-enabled systems in organizational decision making from a qualitative perspective?*

In this study, seven factors were investigated through the lens of TOE framework. The result show that some factors were perceived as influential, some not influential, and some were inconclusive because of a scattered view among the respondents. From the empirical findings and discussion of factors in the technological context, *Perceived Direct and Indirect Benefits* were recognized as influential for those who acknowledged the benefits of AI-enabled systems in organizational decision making prior the adoption. Two respondents had little awareness of what to gain from AI in organizational decision making, but here one had the advantages of trying the system before adoption, while the other one developed it in-house. Thus, this enlightens the advantage of acquiring a system for organizations who are not aware of the benefits early in the adoption process. Also, the acknowledgement and understanding of the benefits enabled for justification of the investment. Furthermore, *Amount of Data* was also perceived as influential by a majority of respondents. All respondents believed data was important for their organization, however some had not full insight into what kind of data they were in possession of. Moreover, while information overload was not seen as an issue for the organizations, one respondent gained some new insights with the help of AI which was perceived as rather obvious which highlights the need of AI or other computerized system to help make sense of a large quantity of data.

In the organizational context, *Perceived Technical Competence* was deemed as influential by many of the respondents, although from different perspectives. Those who perceived the organizational technical competence as low, considered it as an obstacle posing resistance in the adoption. While those who perceived the organizational technical competence as high, deemed it as positively influencing for adoption. Based on our findings, it was of importance to not solely rely on the technical competence of the IT-department, as the adoption process appears to be driven by various parts of the organization. Furthermore, *Decision Making Obstacles* were said to be non-existent and not influential in the adoption. However, the examples expressed during the interview shows existence of uncertainty, equivocality, and complexity in decision making. Additionally, many expressed the limitations and risks of solely relying on human decision making, where AI was somewhat expressed as an attempt to overcome these decision obstacles and optimize instead of satisfice the decision making. Therefore, the decision making obstacles factor are deemed as inconclusive. Moreover, *Top Management Support* was deemed as influential in the adoption by most of the respondents. The support was however shown differently. One organization had the top management leading the adoption while others was more focused on creating an innovative environment and adding resources to what they perceived as good ideas.

In the environmental context, *Competitive Pressure* was recognized as influential by many respondents. While expressing an awareness of competitor's usage of AI in organizational decision making, it was not considered as a threat. In fact, all organizations perceived that AI in organizational decision making gives them a competitive advantage against their competition. Thus, the participating organizations perceived the opportunities of the technology rather than the pressure from their competition. Furthermore, *Environmental Uncertainty* was perceived as not influential by most of our respondents. While some respondents acknowledged uncertain environments for their organization, it appeared to have no influence in the decision to adopt AI in organizational decision making. Interestingly, it appeared that this factor was perceived as dependent on the type of product or service that the organization sold.

Conclusively, out of seven factors explored, the respondents perceived *Amount of Data*, *Perceived Direct and Indirect Benefit*s, *Perceived Technical Competence*, *Top Management Support* and *Competitive Pressure* to be influential when adopting AI-enabled systems in organizational decision making.

6.1 Further research

We believe that AI, while being present for several years, still is an emerging phenomenon with knowledge gaps. Therefore, more research in general regarding AI in decision making is needed, especially the socio-technical aspect of it. Looking at the technology adoption of AI, this thesis explored seven factors that could influence the adoption of AI in organizational decision making. Many factors are still unexplored and could be further explored by scholars. We also believe that there is a need for a causal quantitative research to examine the effects and interrelationships between the factors we investigated. This is something that Mallat (2007) acknowledged as a beneficial for studies on adoption of new technologies. Furthermore, we identified two new factors that possibly could influence which was the *Amount of Data* and *Decision Making Obstacles.* Our findings reveal that it was perceived to be influential when adopting AI in organizational decision making, therefore we think this factor needs to be further examined with a quantitative methodology to be able to generalize the result. Moreover, this study had six respondents, although insights could be gathered, a larger number of respondents would be beneficial for generalizability of the results. Finally, the respondents were from different parts of Europe which generated a European perspective; hence we argue that a broader sample size from different parts in the world would most likely generate different insights.

Appendix

Appendix A – Interview guide

Codes	Themes
Part 1: *Introduction*	
Background, organizational decision making, Artificial Intelligence	*Background* • Can we record this interview? • Please tell us about your current and previous roles in the company. *Decision making* • In your role, what types of decisions does you make? • What is the impact of those decisions? • How established is using a supportive tool in decision making? • When did your organization decide to adopt AI in organizational decision making? • - Please describe that process. *Artificial intelligence* • What kind of AI-enabled system are you using in decision making? • In short, describe the current AI capabilities of that system.
Part 2: *Technology Context*	
Perceived direct and indirect benefits, Amount of Data	*Perceived direct and indirect benefits* • Prior the adoption, what was the perceived direct and indirect benefits of AI in the organizational decision making context? • To what extent did that influence the adoption? *Amount of Data* • How do you value and manage data? • Prior the adoption, how did you make sense of that data? • Have you discovered new insights with AI?

	• To what degree did the amount and management of data influence the adoption?
Part 3: *Organizational Context*	
Perceived technical competence, decision making obstacles, top management support	*Perceived Technical Competence* • Prior the adoption, how did you perceive the technical competence within the organization? • -For the IT-staff • -For management • If high, to what extent did it influence the adoption? • If low, was this considered to be a barrier of the adoption? • How did you perceive the technical competence influencing the adoption? *Decision Making Obstacles* • Prior the adoption, what decision obstacles existed? • To what extent did these obstacles influence the adoption of AI in the decision making? *Top management Support* • Prior the adoption, how involved was top management in this process? • How was that shown? (e.g. supportive conversations, restructuring, facilitation of resources, established vision) • To what degree did that influence the adoption?
Part 4: *Environmental Context*	
Competitive pressure, environmental uncertainty	*Competitive pressure* • Prior the adoption, to your awareness did any of your competitors use AI in decision making? • If yes, were you affected by that? • If no, did you see the adoption as a competitive advantage? • To what degree did the competitive pressure influence the adoption? *Environmental uncertainty* • Prior the adoption, did you consider your organization to be in an uncertain environment?

	• In decisions where the problem is new and ambiguous, what did that decision process look like? • To what degree do you consider the environmental uncertainty as influential in the adoption of AI in decision making?
Part 5: *Wrap up*	
Artificial intelligence, organizational decision making	• After the adoption, what has changes with after this implementation? • Does the organization manage more data today than prior to the adoption? • When, if not already, do you think the adoption of AI will be considered “normal” within the organization and not innovative? • Are there any of these selected factors that you consider as more influential than others? • In what specific decision-making situations do you consider AI to be a suitable complement? • Do you have anything else regarding adoption of AI in decision making that you would like to bring forward?

Appendix B – Interview 1

ES=Erik Söderqvist (head interviewer)

LE=Ludwig Entzenberg (transcriber)

R1= Respondent

Section	Person	Text	Code
1.	ES	Den här intervjun sker helt anonymt, ingen information om dig kommer att presenteras i transkriptet, varken du eller din organisation kommer att bli identifierbara i det vi presenterar i vår uppsats, utan syftet är mer att få en förståelse för vilka faktorer som influerar i valet av en sån här teknik vid beslutsfattning. Så vi kan börja lite att du berättar om din nuvarande roll och dina föregående roller på den här organisationen och gärna lite kort vad ni gör på den här organisationen?	
2.	R1	Ja, jag var chef för värderingsverksamheten under 20 års tid inom organisationen tidigare, sen ett år tillbaka har jag lämnat över chefsrollen till en kollega som nu får sköta om dom bitarna. Det vi pysslar med på den avdelningen som jag då är verksam med är, huvudsakligen fastighetsvärderingar och vi genomför värderingar av fastigheter av flera olika skäl. Dels en stor andel har att göra med att fastighetsbolag som är noterade eller ägda av stat och kommun måste redovisa sina faktiska värden löpande i enlighet med revisionsreglerna. I och med att kompetensen inte finns “in-house” hos dom här företagen så anlitar dom konsulter som oss. I annat syfte är ju i samband med kreditgivning att bankerna måste ha något form av underlag för sin kreditprövning, man ställer till exempel fastigheter som pant för lån. Sen finns det ju andra syften också i och för sig men det är väl dom två som är dom dominerande skulle jag vill säga.	ODM
3.	ES	I beslutsfattningen i organisationen nu, hur etablerat är det att använda någon typ av IT-system som stöd?	

4.	R1	Ja, vi använder alltid IT-system för att i det traditionella värderingsarbetet så använder vi oss av en databas-modell som vi då använder för att kalkylera olika kassa-flöden och utifrån det då gör en bedömning av fastighet-ernas värden.	ODM-CS ODM
5.	ES	När beslutade ni att införa AI som ett ytterligare stöd i beslutsfattningen?	
6.	R1	Ja det är inte så länge sen, det kanske är två, två och ett halvt år sen.	AI ODM-CS
7.	ES	Så runt 2018 där nånstans?	
8.	R1	Ja det kan nog stämma	
9.	ES	Vad är det för typ av AI-funktionaliteter som ni använ-der som stöd idag?	
10.	R1	Syftet med den är att kunna hantera större volymer data på kort tid. Inte att marknadsvärdera fastigheter styckvis utan värderas då på ett bolag.	TC-AD AI-C
11.	LE	Menar du då att den hämtar in data åt er eller kan du ut-veckla lite vad du menar? Vad menar du med att hantera data?	

12.	R1	Ja det är ju, när man använder sig av en AI-produkt så har ju den möjligheten att göra bedömningar över vad som händer i marknaden, utvecklingar på räntor och allt sånt där. Däremot har den väldigt svårt att ta in dom här objektspecifika sakerna så att i vissa fall kan det vara som så att det är en fastighet som blir helt tom och då måste man nog träna den här roboten betydligt mycket mer för att kunna ta in den typen av bedömningar. Däremot är det ju så att den här objektspecifika informationen är inte alltid tillgänglig, utan däremot tittar man på ett större fastighetsbolag så tar ju dom här eventuella objektsspecifika sakerna ut vartannat. Så att när vi gjort tester på dom här AI, så landar den ganska mitt i prick på helheten. Däremot tittar man på dom enskilda objekten så finns det alltid ett antal "outliers".	ODM-CS AI-C EC-EU OC-DMO
13.	ES	Bara för att tydliggöra, dom enskilda objekten är olika typer av fastigheter då?	
14.	R1	Japp stämmer!	
15.	ES	Visst är det så, vi talades ju vid tidigare. Är det här ett system som ni utvecklat själva eller något som ni köpt in från en leverantör?	
16.	R1	Nej vi har utvecklat det själva	OC-PTC
17.	ES	Nu går vi in lite mer på det ramverk som vi använt oss av i studien som består av olika typer av faktorer och hur dessa då påverkar organisationen i att förvärva innovation och ny teknik. Då har vi då teknologiska, en organisationskontext och en den miljö som då organisationen verkar i kontext då. Så om vi börjar på den teknologiska kontexten. Vilka typer av direkta och indirekta fördelar med AI var ni varse om innan implementeringen av tekniken?	

18.	R1	Vi var inte varse om speciellt mycket egentligen. Utan vi såg det här med ett steg för att öka effektiviteten i verksamheten. Så att när vi började på så visste vi egentligen inte vart det skulle ta vägen.	TC-PDI
19.	ES	Och då kanske det är svårt, men till vilken grad att dessa fördelar och då var det främst effektivisera verksamheten. Till vilken grad influerade det valet att gå vidare med den här implementeringen så att säga?	
20.	R1	Nej men i och med att vi lever i en väldig hård konkurrensutsatt värld så är vi ju tvingade på olika sätt att genomföra effektiviseringar och vissa typer av värderingsprodukter kan man då genomföra på ett betydligt snabbare och enklare sätt med AI än om man skulle göra det mer traditionellt. Det är där som vi såg möjligheten att expandera verksamheten till nya delar av branschen.	TC-PDI EC-CP
21.	ES	Sen har vi en faktor som är mängden av data. Så om vi börjar med, hur värderas och hanteras data hos er?	
22.	R1	Vi har ju samlat på oss värderingsdata sen 2000 och nu vet jag inte exakt hur mycket som finns i den här databasen men det är ju åtskilliga hundra tusen fastigheter och en exponentiellt andel ytterligare hyreskontrakt.	TC-AD
23.	ES	Så hur hanteras den? Ni hämtar ner så sparar ni ner och kanske strukturerar den. Hur ser den processen ut i hanteringen av data?	
24.	R1	Den hämtas hem då.	TC-AD
25.	LE	Men analyserar ni datan själva eller har ni något slags system som gör det åt er?	

26.	R1	Nej det har vi gjort själva. AI gör vissa typer av analyser också så liksom när vi hämtat hem data så väljer den ut vissa typer som ska va med i körningen.	TC-AD AI-C
27.	ES	Skulle du säga att AI har genererat nya insikter?	
28.	R1	Nej det skulle jag inte säga. Utan det kommer säkerligen att göra det beroende på att vi sitter på all den här informationen idag så kommer vi säkerligen utefter vi jobbar med det få en större insikt men vi är inte riktigt där än.	AI TC-AD
29.	LE	Hur viktig skulle du säga att datan är för eran verksamhet?	
30.	R1	Den är oerhört viktig. Den är liksom grundbulten med allting eftersom vi kan föra allt med bevis i och med att vi sitter på all den här datan.	TC-AD
31.	ES	Och till vilken grad influerade då den här mängden som ni har samlat på er under dom här åren, alltså mängden data, hur pass mycket influerade det valet att implementera AI i beslutsfattningen?	
32.	R1	Det var ganska viktigt egentligen, för att det hade varit nästintill omöjligt att implementera AI om man inte hade haft tillgång till den här mängden data.	TC-AD
33.	ES	Då var vi klara med den tekniska delen, eller den tekniska kontexten ska jag säga. Så vi går vidare till den organisatoriska kontexten. Den börjar i och för sig med en teknisk twist kan man säga, gällande teknisk kompetens. Innan implementeringen, hur uppfattade du att den tekniska kompetensen var inom organisationen?	

34.	R1	Den är väldig varierad skulle jag säga. Allt ifrån att vi har vissa som är väldigt datamogna och har hög teknisk kompetens till dom som är noviser. Så att spreaden där är väldigt stor.	OC-PTC
35.	ES	Om vi ser på IT-avdelningen till exempel, hur skulle du säga att före implementeringen av det här AI-systemet hur såg det ut då med teknisk kompetens där?	
36.	R1	På IT-avdelningen? Ja det är lite udda så till vida att i bolaget så har vi ju en central IT funktion som ligger nånstans utspritt i världen. Och sen har vi ju bara en person på plats. Däremot när vi har tagit fram den här AI-lösningen så har vi gjort det tillsammans med ett IT-bolag i Stockholm.	OC-PTC AI
37.	ES	Är det ett externt bolag?	
38.	R1	Ja, själva hanteringen att bygga AI gjorde vi internt med stöd av en kille som hyrdes in under ett år.	OC-PTC
39.	ES	Hur skulle du säga att den tekniska kompetensen är för ledningen är managers, innan då implementeringen?	
40.	R1	Ja den, ganska begränsad skulle jag säga. Det tycker jag den är fortsatt också.	OC-PTC
41.	ES	Men om den anses vara låg, sågs det som ett hinder för den här implementeringen? Eller var det inget som påverkade?	
42.	R1	Ja det skulle jag vilja säga. Vi som var med och utvecklade det här liksom vi har ju velat implementera det mer och mer, men där finns det liksom ett motstånd får man säga.	OC-PTC

43.	LE	Om den tekniska kompetensen eller förståelsen skulle vara högre hos ledningen tror du att ni kanske hade implementerat AI tidigare än vad ni gjort nu?	
44.	R1	Ja det tror jag för att det är just den tekniska kompetensen där som är problemet. Inte så mycket att de inte vill, utan man förstår sig inte riktigt på vad det är och vilka konsekvenser det skulle medföra.	OC-PTC
45.	ES	Då ska vi gå vidare till och kolla lite på hinder i beslutsfattningen. Hinder kan vara till exempel brist på information, eller osäkerhet med informationen man har eller att information är otydlig till exempel. Så innan implementeringen, uppfattade ni att det fanns såna här typer av begränsningar eller hinder i beslutsprocessen?	
46.	R1	Nej det tycker jag inte att det fanns i själva beslutsprocessen. Det fanns en öppenhet i organisationen att titta på dom här lösningarna.	OC-DMO
47.	LE	Du har pratat lite om att organisationen har blivit effektivare i och med AI i beslutsfattningar och dylikt. Är det något annat när det kommer till beslut som du tycker har förbättrats i och med AI? Till exempel att det tas bättre beslut idag med högre träffsäkerhet?	
48.	R1	Nej det skulle jag inte säga. Det man eftersträvar det är ju en större jämnhet i organisationen att det liksom blir inte specifikt kopplat till specifika individers kompetenser utan att alla ska kunna göra väl avvägda analyser och beslut.	OC-DMO ODM-CS
49.	ES	Så jämnhet i att en individ då ska kunna ta beslut på ett liknande underlag och att det inte man som individ påverkas av yttre faktorer och liknande också?	

50.	R1	Ja, människor är ju olika. Vissa har ju en positiv grundsyn och vissa har ju en negativ grundsyn.	OC-DMO
51.	ES	Om vi ser till den högsta ledningens involverande, hur pass involverade var dom vid införskaffandet av AI till just belutsfattande?	
52.	R1	Den högsta ledningen var djupt involverade i det där och såg möjligheterna.	OC-TMS
53.	ES	Hur visades det engagemanget i organisationen?	
54.	R1	Nej men det fanns ett engagemang. Sen är det ju som så att den dagliga verksamheten överskuggar ju vissa saker ibland. Just att driva in nya verktyg och processer kan ju då bli liksom lagt åt sidan stundtals på grund av dom sakerna. Men viljan fanns där, man var engagerad.	OC-TMS
55.	LE	Satte högsta ledningen någon slags vision över vad AI skulle åstadkomma för något inom organisationen?	
56.	R1	Nej det tycker jag inte. Det var vi några andra personer då som drev den här frågan, som försökte att påvisa möjligheterna. Det var inget visions-tänk från ledningen i det.	OC-TMS TC-PDI
57.	ES	Om man konkret slår fast. Du sa att du och några andra drev den här processen. Vilka andra typer av roller drev den här processen?	

58.	R1	Ja nej men i och med att den högsta ledningen är ju ansvarig för flera olika verksamhetsområden och just den här verksamheten är ju väldigt specifik för vår verksamhet i företaget, vilket gjorde att vi i den här verksamhetsgrenen då var ju dom som drev på. Sen så hände det ju alltid saker i ett företag i ett antal företagsområden som gör att från tid till annan, man släpper fokus då på dom här sakerna och måste då jobba med dom andra grenarna.	OC-TMS ODM
59.	ES	Är det högsta ledningen i Sverige vi tänker eller är det globalt?	
60.	R1	Nej det är i Sverige. Globalt har vi inte fått någon respons egentligen på det hela.	OC-TMS
61.	ES	Om vi ser på den Svenska ledningens involvering i den här processen, hur mycket påverkade det implementeringen av AI i beslutsfattningen?	
62.	R1	Dom var ju villiga att avsätta medel för att vi skulle kunna genomdriva det här. Men det var ju upp till oss att se till att vi själva kunde liksom hitta personer och företag som då kunde hjälpa oss med att utveckla det här.	OC-TMS OC-PTC
63.	ES	Då ska vi gå in på miljö kontexten. Det är då den externa miljön som påverkar företaget men som ni kanske inte har så mycket att säga till om. Det kan till exempel va ekonomiska svängningar eller en pandemi så yttre faktorer som påverkar kan man säga. Så vi var inne på det lite tidigare gällande eran konkurrenskraft, men var ni medvetna om era konkurrenters användande av AI i deras beslutsfattande?	

64.	R1	Nej våra konkurrenter har inget liknande. Vi var först där och vi är det enda bolaget som har tillgång till big data och det har därför varit svårt för andra att bygga eller göra något liknande. Jag vet att man tittar på lösningar hos några av våra konkurrenter men man har fortfarande en lite uppförsbacke.	EC-CP
65.	ES	Jag förstår. Ser då du AI, vi pratade om det tidigare vilka konkurrensfördelar i form av effektivare då. Ser du några fler konkurrensfördelar som AI kan ge er kontra era konkurrenter?	
66.	R1	Det är väl lite rent marknadsföringsmässigt också. Att man påvisar att man ligger i framkant och man liksom inte håller på och traggla gamla excel dokument.	EC-CP
67.	ES	Så till vilken grad skulle du säga att ni påverkas av konkurrensen på marknaden att införa AI?	
68.	R1	Nja, det är klart att det var en ganska betydande del av beslutet beroende på att man ser konkurrenssituationen bli tuffare och tuffare. Det nagar i vinstmarginalen så någonstans måste man göra nånting för att försvara sin position.	EC-CP
69.	ES	Och om vi ser innan implementeringen, hur ansåg ni som organisation att ni befann er i en osäker miljö och då tänker jag specifikt kring osäkerhet på marknaden, eller ekonomiska svängningar att den typen av tryck påverkade er som organisation?	
70.	R1	Ja nej det man såg, och det fanns framförallt ute i Europa var att man såg lönsamheten successivt gick ner då, och att om man ska ha ett berättigande framöver måste man se till att lösa den problematiken och att bli effektivare och det finns ju olika vägar att gå där i och för sig men vi tyckte då att det mest intressanta var ju att hitta sätt att jobba smartare och snabbare.	EC-EU

71.	ES	Och, vi beslutssituationer där det uppstod hög osäkerhet kring själva beslutet, alltså ostrukturerade beslut som ni kanske inte tagit tidigare lite ovissa för organisationen kan man säga. Hur såg den beslutsprocessen ut innan implementeringen av AI?	
72.	R1	Ja, det kommer jag knappt ihåg.	ODM
73.	ES	Jag förstår. Har ni några typer av kriterier som ni ställer mot beslutet?	
74.	R1	Ja det finns ju alltid som så att vissa beslut måste ju liksom förankras inom organisation och då finns det ju olika råd vart man ska fråga nånstans för att få beslutet godkänt. Dom processerna kunde bli ganska tidskrävande och vi jobbar under väldigt hård tidspress så att uppdrag som kommer in ska vara klara väldigt snabbt. Då har en beslutsprocess innan om man ska ta uppdraget eller inte gör ju att man helt plötsligt inte kan vara med på den typen av uppdrag.	ODM OC-DMO
75.	ES	Och om man ser till stort, till vilken grad var osäkerheten i den miljön ni opererar inom en faktor vid implementeringen av AI i beslutsfattningen?	
76.	R1	Nej det skulle jag inte säga. Den miljön är ganska statisk över tid egentligen. Sen har vi ju marknadssvängningar som just nu där vi befinner oss i en situation där vi inte riktigt vet var vi står nånstans. Där har vi inte egentligen någon hjälp av AI. Vi testkörde ju hårt för att se effekterna av finanskrisen, hur AI hanterade det. Den är väldig svår att få AI att förstå egentligen.	EC-EU AI
77.	ES	Så det är svårt för AI att förstå den typen av marknadssvängningar? Eftersom de inte är rationella?	

78.	R1	Ja, däremot svängningarna som beror på räntehöjningar, förändringar i bnp tillväxt och allt sånt där. Det fattar AI väldigt snabbt. Men såna här irrationella händelser som man inte kan förutse, då kan inte heller AI förutse.	AI-C
79.	ES	Ja nu har vi lite övriga frågor. Vi har nu gått igenom vårt ramverk. Så vi ska egentligen bara samla upp lite och om du har några frågor till oss och sådär. Men vi tänkte börja med en liten större fråga som är, efter införandet av AI, vad skulle du säga har förändrat organisationen om vi då ser specifikt då på AI i beslutsfattning?	
80.	R1	Ja men det är lite det vi var inne på tidigare, det är ju att man får en större konfidens i att man tar de rätta besluten. Båda sin egen bild av hur det borde va men sen har man hjälpmedel vid sidan av som förhoppningsvis kommer fram till liknande resultat. Då blir man mer konfident då och kan ta snabba beslut.	ODM-CS
81.	ES	Skulle du säga att ni som organisation hanterar mer data idag än vad ni gjorde innan implementeringen?	
82.	R1	Nej, mängden data den har ju egentligen inte så mycket att göra med den implementeringen utan den har mer att göra med den dagliga verksamheten som förhoppningsvis har vuxit lite ytterligare. Mängden data har inte AI bidragit med.	TC-AD AI
83.	ES	Och när om inte nu, skulle du säga att AI vid beslutsfattande skulle ses som normalt i organisationen och inte som något innovativt system eller teknologi?	
84.	R1	Ja det kommer nog ta ytterligare något år innan man kommer se på det här som något normalt inom verksamheten. Fortfarande är det så att det är under experimentstadie så att säga.	AI ODM-CS

85.	ES	Skulle du säga att det finns några andra faktorer som vi berört här som skulle va mer inflytelserika vid implementeringen av AI?	
86.	R1	Det är nog, det som var viktigast och fortfarande är det är konkurrenssituationen att vi kan liksom uppfattas som ett innovativt företag och vi ska kunna leverera med hög god kvalité och ändå vara prismässigt okej.	EC-CP
87.	ES	Så både konkurrensen då och hur ni ses hos konsumenten?	
88.	R1	Ja för den har blivit viktigare och viktigare i och med att många företag som förutsätter att man ska som konsultföretag va långt fram i teknikutvecklingen.	EC-CP TC-PDI
89.	ES	Ja då har vi gått igenom alla de frågor vi har haft. Har du något du vill ta upp?	
90.	R1	Nej inte vad jag kommer på.	
91.	ES	Då får vi tacka för att du ställt upp på den här intervjun. Det har varit väldigt givande.	
92.	LE	Vi är supernöjda. Vi har fått några nya insikter.	
93.	R1	Ja vi får se vad det blir för något resultat av det här.	
94.	ES	Vi delar självklart med oss uppsatsen då när den är klar någon gång i slutet av maj, början på juni. Då tar vi och skickar över den.	

95.	R1	Mm låter spännande!	
96.	ES	Men återigen, tack för hjälpen! Du får ha en fortsatt trevlig dag, på återseende.	

Appendix C – Interview 2

LE = Ludwig Entzenberg (head interviewer)

ES = Erik Söderqvist (transcriber)

R2 = Respondent

Section	Person	Text	Coding
1.	LE	Är det okej att vi spelar in intervjun med syftet att använda den vid transkriberingen?	
2.	R2	Ja det går självklart bra!	
3.	LE	Härligt! Då tänkte jag börja med att be dig din nuvarande roll och vad du har haft för tidigare roller, samt vad det är som ni gör på organisationen?	
4.	R2	Jag jobbar på produktutveckling och supply på organisationen. Det är en rätt så komplex organisation, jag vet inte hur mycket ni vet om det? Jag har jobba på organisationen i tre och ett halvt, fyra år, och jag vet fortfarande inte hur det fungerar. Så att jag svarar ju på det som jag vet för vår del av organisationen, vi jobbar med utveckling av produkter och supply flödet. Jag jobbar nu som project manager inom vår advanced analytics grupp som skapades för kanske två år sen, med syftet att kika in på hur man kan använda AI då. Det är ju ett ganska brett koncept. För att förbättra verksamheten. Innan dess så var jag mer med uppföljning av projekt, PMO, project management office, men också en del projektledningsutbildningar och sånt. Jag har ju varit konsult tidigare och så att jag har ju drivit mycket projekt sen tidigare.	ODM AI
5.	LE	Ja jag förstår! Men i din nuvarande roll, vilka typer av beslut fattar du?	

6.	R2	Beslut och beslut, det handlar mer om projekten och sen är det mer i projekten som vi fattar beslut. För vi utvecklar ju då verktyg som då ska stötta businessen, där de själva då ska kunna ta fram olika beslutsunderlag och beslutsstöd. Så vi utvecklar ju dom typen av verktygen då, typ qlik sense, qlikview sånna saker. Så vi bygger ju då verktyg som med hjälp av AI ska kunna vara ett beslutsstöd för verksamheten.	ODM ODM-CS
7.	LE	Jag förstår. Så vid era beslutsfattningar då inom organisationen. Hur etablerat är det att använda sig av något typ av IT-system som stöd?	
8.	R2	IT-system är väl väldigt etablerat. Sen får man väl tänka om man räknar med rena business intelligence lösningar och sånt. Blir lite enklare då som visualiserar våra produkttyper och sälj, men även kostnader och använda det som ett stöd i besluten. Det är väldigt etablerat skulle jag säga.	ODM-CS ODM
9.	LE	Aha super. Då går vi in lite på AI då. När beslutade ni som organisation att införa AI som ett ytterligare stöd då vid beslutsfattningen?	
10.	R2	Ja som sagt organisationen är så himla stort att det är svårt att svara för hela organisationen. Men vår grupp som syfte att göra AI lösningar för organisationen, det var väl ungefär två år sedan i runda slängar. Och då kollade vi in på i vilka områden kan man använda AI och vad finns det för olika typer av exempel i branschen och hela industrin. Och sen har vi utvecklat under tiden då så att säga. Så det kom lite från fall till fall om det finns värde i att använda AI då.	AI-C
11.	LE	Ja för vi tänkte komma in på det där lite grann. AI kan ju ses som diffust vad det faktiskt är för någonting. Men vad för typ av AI funktionaliteter använder ni som hjälp till beslutstöd idag?	

12.	R2	Ja det vi har jobbat med handlar ju en hel del om liksom machine learning, där vi då kollar på vilka produkter som köps tillsammans, vi kollar också en del på rena optimeringar av saker och ting också. Vissa av de kan räknas till AI också. Optimera sortiment i ett land till exempel. Det är väl sådana typer av AI vi arbetar med för närvarande. Men det är klar vi kollar mycket annat också med text, bild, ljud och röst och allting sånt.	AI-C
13.	LE	Mm intressant. Är det här något ni har utvecklat själva på organisationen eller har ni köpt in det från leverantörer?	
14.	R2	Vi utvecklar våra lösningar själva kan man säga, ofta tillsammans med en extern partner. Men vi köper ju inte in färdiga beslutsstöd eller lösningar, utan vi utvecklar det mest själva. Det finns ju liksom själva algoritmerna är ju ofta bransch standardiserade så det passar vår kontext, men vi utvecklar ju lösningarna själva.	ODM-CS AI-C
15.	LE	Ja det är intressant. Men då kommer vi in på den första kontexten som är den teknologiska kontexten i vårt ramverk. Och då tänkte jag börja med att fråga om direkta och indirekta fördelar. Så innan implementeringen av AI, vad för direkta och indirekta fördelar ser ni i beslutsfattningen som ni skulle kunna ha nytta av?	
16.	R2	Det är väl egentligen viktigt att kunna make sense of the data. Vi samlar ju på oss enorma mängder data såklart. Sen får man inte samla in all data med nya GDPR reglerna. Men det är klart att vi vill kunna processa det lite mer automatiskt men också att kunna make sense. Så att man tar några steg framåt och att man inte behöver analysera grundläggande dataflöden, utan att man får beslutsstöd. Lägga mer tid på avancerad analys och sätta det i kontext tillsammans med många andra variabler. Det är väl liksom, att flytta analysen till en bredare kontext, istället för att sitta själv och göra den analysen.	TC-PDI TC-AD

17.	LE	Skulle du säga att ni har blivit effektivare, att ni kan ta snabbare beslut?	
18.	R2	Kanske inte än så länge att vi har blivit så mycket effektivare i och med att det är nya saker som implementeras så tror jag att det först tror jag att man ser ett värde, men du måste fortfarande lära dig lite nya sätt att visualisera, vad är det som visualiserats, och vad är det som behövs i beslutsstödet. Effektivare som i efficient i engelska, kanske inte än så länge förrän det har kommit in i organisationen. Mer kanske effective, att vi gör rätt saker. Det är lite enklare på engelska att skilja på efficiency och effectiveness.	ODM-CS AI ODM
19.	LE	Aa exakt. Jag tänker de här direkta och indirekta fördelarna vi pratat om då, till vilken grad skulle du säga att de påverkade ert beslut att implementera AI?	
20.	R2	Ja förhoppningsvis var det ju med fördelarna som vi som organisation valde att implementera AI. Sen är det ju alltid sådär med buzzwords att man vill testa det så man inte hamnar efter, så det kan säkert vara anledningar också. Jag var inte den som tog beslutet. Men man ser ju att det är dit omvärlden går och att vi också måste gå i den riktningen.	TC-PDI EC-CP
21.	LE	Jag förstår. Då kommer vi in på andra faktorn, som handlar om mängden data. Men hur värderas och hanteras data hos er? Alltså, skulle du säga att ni är en datadriven organisation så att säga.	
22.	R2	Ja det är en bra fråga. Organisationen har ju funnits länge och det finns ju liksom en in-ärvd kunskap. Man använder absolut data, men man tar inte beslut helt på dom datamässiga grunder på sätt så att man bara baserar på den datan man ser framför sig. Utan man använder sig mycket av den erfarenhet man som kan vara baserad på data, men som liksom har ärvts in i organisationen och individen. Så det är nog någonstans mittemellan kanske.	TC-AD ODM-CS

23.	LE	Okej, och hur hanteras den här datan hos er, analys, processer. Vem står för den liksom?	
24.	R2	Mycket av inhämtade data liksom är ju strukturerat bara genom att det bara blir köptransaktioner och sådana saker. Och produkterna har ju sin produktdata som man gör produktutvecklingen. I och med att vi har hela kedjan så har vi ganska bra koll från leverantören till vi vet mycket om produkten eftersom vi äger och utvecklar dom. Så att mycket av det finns redan i våra system så att säga.	TC-AD
25.	LE	Aa jag förstår. Innan ni implementerade AI då, har det skiljt sig något i hur ni hanterar data, ser det annorlunda ut idag?	
26.	R2	Ja alltså jag kan inte så mycket av det tekniska men jag tror det skiljer sig ganska mycket mer. Jag tror man börjar mycket mer använda avancerade analyser, så man ser värdet i att strukturera bättre, insamlad bättre, liksom uppdaterad oftare, ha koll på sina data strukturer. För det är ofta det som våra projekt mycket handlar om, att få struktur på datan, vet hur man använder rätt data. Så absolut så har nog det påverkan på insamlandet av data.	TC-AD
27.	LE	Ja jag förstår. Har ni fått några nya insikter, som har genererats med AI?	
28.	R2	Ja det har vi fått jättemånga, det märker man när man väl börjar jobba med det att det finns mycket att hämta där, mycket intressant.	TC-AD
29.	LE	Skulle du kunna ge ett exempel på en ny insikt du kommer på såhär på rak arm?	

30.	R2	Ja men det kan nog handla mycket om, hur prisförändringar påverkar kunders köpbeteenden, sådana saker. Det kan handla om vilka produkter som ofta köps tillsammans och vilka produkter som är väldigt viktiga att ha i vårt sortiment, det ger en bredare kontext liksom.	TC-AD
31.	LE	Mm intressant. Till vilken grad skulle du då säga att den här mängden data som ni har och hanteringen av den, var till grund för att implementera AI?	
32.	R2	Du menar att vi har mycket data och så?	
33.	LE	Ja exakt, var det en faktor som påverkade er när ni valde att implementera AI?	
34.	R2	Jag tror inte att beslutsfattarna hade full koll på exakt vilken data vi hade när vi skulle börja kolla på AI. Hade vi haft mindre data hade vi nog kunnat samla in den data, men nu låg vi kanske lite bättre i och med att vi redan hade datan. Men just beslutet, tveksamt. Däremot fick vi ju lite snabbare resultat i och med att vi hade mycket data, vilket kan, då kan man ta beslutet att fortsätta med sådana här typer av projekt.	TC-AD
35.	LE	Aha intressant. Då tänker jag att vi går vidare till organisatoriska kontexten istället. Innan implementeringen av AI, hur uppfattade du att den tekniska kompetensen var inom organisationen?	
36.	R2	Ja den var blandad. Det finns olika typer av personer som jobbar inom organisationen, det är ju allt från designers och folk som jobbar med sådana saker, till tekniker, till sådana som är vana att jobba med analys och sådant. Väldigt blandad skulle jag säga.	OC-PTC

37.	LE	Har du någon uppfattning om hur den tekniska kompetensen är bland era chefer och ledningen och managers så att säga?	
38.	R2	Den är nog också, det skiljer sig nog också ganska mycket, det beror ju på vilken bakgrund man har och tagit sig fram, det vill säga vad man gjort tidigare. Det är en så pass stor organisation att det finns allt från relativt låg kompetens till att man är superduktig i dom här områdena.	OC-PTC
39.	LE	Om vi skulle leka med tanken att den var låg hos några hos några i ledning som tar beslut om det här.	
40.	R2	Ja det är väl klart att man kan ibland känna att vara allt för datadriven och låta det fatta besluten istället för att man går på erfarenhet och kunskap så att säga. Och där brukar vi alltid trycka på att detta är en pusselbit. Man är rätt så långt ifrån att liksom automatisera alla beslut som är så pass komplexa, som vilka produkter ska vi utveckla och i vilka länder ska den finnas. Det är både mjuka och hårda faktorer där. Så det kan nog absolut liksom vara, så vet man inte vad man kan leverera för lösningar så är det nog svårt att släppa på kontrollen där.	OC-PTC OC-DMO ODM-CS
41.	LE	Om vi tittat lite generellt. Skulle du säga att det är de som har en hög teknisk kompetens, är det dom som ofta är mer drivande i dom här nya IT projekten som ni har framför er?	
42.	R2	Ja och de är nog ofta mer intresserade, så är det ju liksom, man är ju ofta intresserad om det man är kompetent inom. Så det handlar nog mycket om personligt intresse och testa nytt och sådana saker.	OC-PTC

43.	LE	Då går vi vidare till nästa faktor som handlar om hinder i beslutsfattningen. Innan implementeringen, uppfattade du att det fanns några begränsningar eller hinder i beslutsfattningen med eran beslutsprocess? Typ brist på information, osäkerheten kring informationen eller otydligheten i information	
44.	ES	Låt mig bara flika in. Det kan också vara att det ska medlas mellan olika medarbetare, att det är olika intressen i en organisation till exempel. Att det ses som ett hinder också.	
45.	R2	Jo men absolut. Det är väl hela, det är ju mycket av det vi gör i produktutvecklingen, i att man måste liksom ha kostnadseffektiv produktion, bra funktioner, och att produkterna ska var snygga, men det ska vara rätt billiga i produktionen. Så det är klart, att medla där är ju, det är ju därför man har olika roller i ett team på ett sätt. För då ser man till att man har olika kompetenser helt enkelt, men rent datamässigt, så absolut. Ibland kan det ju va att man har olika, har man inte samma data som grund så blir det ju att man kolla på lite olika datakällor och kanske har olika syn på verklighet, det är ju absolut inte bra. Och det tror jag ganska generellt, inte bara för vår organisation, det ser man i väldigt många företag, det är alltid lite farligt när man inte riktigt vet vilken bild av verkligheten man ska utgå ifrån i organisationen.	ODM OC-DMO
46.	LE	Intressant. Till vilken grad skulle du säga att det här påverkade organisationen att införa AI?	
47.	R2	Inte så mycket om jag ska vara ärlig. Jag tror inte att man införde AI för att få en mer enhetlig bild, utan snarare för att ta nästa steg, se nya vilka analyser, kan vi spara kostnader, tjäna mer pengar, utifrån att man gör saker man inte gjort förut. Mer än att man gör det man redan har lite bättre.	OC-DMO
48.	ES	Aha absolut, jag förstår.	

49.	LE	Då går vi vidare till den sista på organisation, som handlar om top management support. Vi var inne på det här lite tidigare, men hur involverade var högsta ledningen i införskaffandet av AI i beslutsfattningen?	
50.	R2	Jo men dom var nog ganska intresserade så att säga, men hade nog väldigt svårt att veta vad det skulle mynna ut it. Så att det fanns nog absolut en vilja att testa, och det kommer ju därifrån, att vi skulle starta den gruppen jag jobbar i att man skulle starta ett AI projekt. Så det fanns nog ett intresse, men sen så i takt med att man resulterar faktiska resultat, då blir också förståelsen större och då så växer intresset ytterligare. Och då förhoppningsvis även kompetenser så att säga.	OC-TMS TC-PDI OC-PTC
51.	LE	Hur visade sig det här i organisationen då? Satte de upp en vision för att det här är det vi ska uppnå, eller hur såg det ut?	
52.	R2	Nej det tror jag inte. Utan det var nog mer att man skapade ett team som själva fick arbeta fram visionen, det blir lite mer trial and error. Man tillsätter ett team som själva liksom får sätta sig in i området.	OC-TMS OC-PTC
53.	LE	Så man kan säga att de allokerade resurser?	
54.	R2	Ja snarare det skulle jag tänka mig, än att man själva visste vart man skulle liksom.	OC-TMS
55.	LE	Nej jag förstår. Så till vilken grad skulle du säga att den högsta ledningens involveringen, påverkade er att införskaffande i AI?	
56.	R2	Om ni menar införskaffande av AI i att vi skapade vår grupp som jag arbetar med, så är det klart att det är ju	OC-TMS

		dom beslutat om resurserna, så hade de inte varit intresse-rade hade det inte blivit någonting.	
57.	LE	Så du skulle säga att det var ganska viktigt?	
58.	R2	Sen är det ju bara en sak. Sen är det ju att trycka in det i organisationen och få det att användas. Där är man fortfarande ganska öppen och vill se resultaten innan man går all in på att det är det här vi ska använda och vi ska ta beslut baserat på de här verktygen så att säga. Men det var en stor öppenhet för att testa så att säga.	OC-TMS ODM-CS TC-PDI
59.	LE	Jag förstår. Då kommer vi in på den sista kontexten, och då tänkte vi kolla på konkurrenssituationen inom er industri. Innan er implementering, var ni medvetna om några konkurrenter till er som använde av AI i beslutsfattning?	
60.	R2	Jag har svårt att svara på den frågan. Jag var medveten om det personligen men om man tänker från ledningens håll så dom har säkert hört om det. Man läser ju om detta, ja men ni vet, AI liksom kommer genom alla branscher, även oss då. Sen är vi ju verksamma inom så många olika branscher med olika typer av produkter, så att det är olika. Men generellt så kan jag tänka mig att de nya konkurrenterna ligger ju, man är ju mer stressad mer av dom. Amazon säljer ju våra produkter och sånt, och dom är ju kanske längre fram inom dessa områden.	EC-CP AI
61.	LE	Skulle du säga att de påverkade ert beslut, att era konkurrenter hade införskaffat det? Att ni kände er tvungna att skaffa det också.	
62.	R2	Ja jo just införskaffandet, men att de jobbat med mycket sådana här saker, det hade nog absolut en påverkan.	EC-CP
63.	LE	Ser du AI generellt som en konkurrensfördel?	

64.	R2	Generellt inom branschen så absolut.	EC-CP AI
65.	LE	Intressant. Till vilken grad tror du att ni påverkades av konkurrensen på marknaden att införa AI?	
66.	R2	Det blir ju liksom kvalificerade gissningar eftersom det inte var jag som fattade beslutet.	
67.	LE	Nej jag förstår, men utifrån ditt perspektiv?	
68.	R2	Jag skulle väl tro att det är klart att den här nya konkurrensen från mer online baserade konkurrenter som jobbar mer med AI, det hade nog en stor påverkan på att vi ville vara med och använda vår data på ett bättre sätt.	EC-CP AI TC-AD
69.	LE	Aha jag förstår. Då går vi vidare till osäkerhet i omgivning eller industrin. Så innan implementeringen, ansåg ni att ni som organisation befann er i en osäker miljö till exempel att det var ekonomiska svängningar, förändrade kundbeteenden på korta perioder, snabba förändringar så att säga.	
70.	R2	Ja bra fråga. Båda ja och nej. Eftersom vi har funnits ganska länge och har ganska stabil business så tror jag inte folk är så stressade av så skiftningar från månad till månad i kundbeteenden så, Där hoppas jag inte att vi blir allt för påverkade. Sen måste man ju följa med i trenderna. Inte att man blir stressad av korta skiftningar och så. Vi är ju och med och sätter trenderna i och med att vi är så pass stora.	EC-EU
71.	LE	Aa intressant. När du tar beslut, när du är i beslutssituationer där det uppstår en hög osäkerhet? Hur såg den	

		beslutsprocessen ut innan ni hade implementerat AI? Hur gick du tillväga så att säga?	
72.	R2	Ja i mitt förra jobb på organisationen tänker du då? För just på det området så har det nog inte hänt så mycket AI. Så där använder man ju mer basic data som man försöker visualisera på ett tydligt sätt. På vissa områden så är ju det fullt tillräckligt och bara göra data tillgängligt och visualisera den på ett tydligt och bra sätt liksom. Det är ju verkligen inte så att alla områden har påverkats av AI än så länge.	ODM-CS AI
73.	LE	Nej jag förstår. Så till vilken grad skulle du säg att osäkerheten runt omkring var en faktor som påverkade införandet av AI?	
74.	R2	Kanske osäkert på lång sikt med konkurrens och så, där var det nog en hög grad. Men inte osäkerhet så här att, korta svängningar i marknaden. Så är det ju allmänt att man måste hänga med konkurrensen och känna att man är up to date.	EC-EU
75.	LE	Mm jag förstår, intressant. Då har vi gått igenom hela ramverket som vi hade. Så vi tänkte köra lite wrap-up, så lite vad som hänt efter implementering så att säga. Så efter införandet av AI, vad har förändrats inom er organisation?	
76.	R2	Ja vi har ju infört AI lösningar inom vissa ganska specifika områden och det är ändå ganska nytt. Implementering har skett senaste halvåret, kanske nio månaderna, och då tar det tid för folk att lära sig det. Man kanske uppdaterar lösningarna och så tar det tid att göra de användarvänliga. Vissa beslut har ju säkert kunna förbättras, att man har blivit lite effektivare, samtidigt som det är ett nytt arbetssätt och det tar tid för det kan kännas lite jobbigt för vissa.	AI-C OC-DMO

77.	LE	Skulle du säga att ni hantera mer data, eller att ni klarar av att hantera mer data än vad ni gjorde innan implementeringen?	
78.	R2	Ja det skulle jag nog säga, absolut. Vi plockar ju mer data, det kan ju vara data vi kanske redan haft men som vi inte vet vad vi kan göra med eller som vi inte visualiserat på ett bra sätt. Så AI är ju en del av det, en annan är ju att det ska vara schysst för användarna så att säga.	TC-AD
79.	LE	Ja juste, intressant. När om inte redan nu tror du att AI kommer att upplevas som en normalitet istället för något innovativt och nytt?	
80.	R2	Ja det kan det nog göra inom ett eller två år, givet att vi fortsätter att utveckla de här saker. Sen tror inte jag att användarna tänker på att det vi gör har en del machine learning algoritmer i bakgrunden. Jag tror inte dom tänker att det här är en AI lösning och det här är inte en AI lösning. I och med att vi kanske visualiserar det genom en qlik lösning eller power bi, det finns ju andra program. De tänker inte på vad som är i bakgrunden och vad som är AI och inte så att säga. Det vill ju vi, det ska ju vara så enkelt som möjligt. Det ska ju inte va så att oj det här var en AI lösning, den var svår sådär.	AI-C
81.	LE	Intressant. Av de här faktorerna som vi talat om tidigare, skulle du säga att någon faktor är mer inflytelserik än någon annan? Jag kan läsa upp dessa för dig om du vill. Då hade vi teknisk kompetens inom organisationen, vi hade hinder i beslutsfattningen, vi hade top management support, vi hade konkurrensen på marknaden, vi hade osäkerheten på marknaden, och så hade vi direkta och indirekta fördelar och slutligen mängden data. Skulle du säga att nån var mer inflytelserik än dom andra?	

82.	R2	Jag tror att top management support är ju väldigt viktigt för oss nu tror jag, för att kunna implementera det på ett bra sätt liksom. Teknisk kompetens också till viss del, men där behöver man ju också bli bättre på att rulla ut saker som är väldigt enkla vilka roller man än har liksom. Där tycker inte jag man behöver skylla på att användaren inte har teknisk kompetens. Ja menar det behöver du ju inte för att använda Google liksom, även fast det sker smarta grejer i bakom det. Så att visst teknisk kompetens för de som utvecklar grejerna men sen måste man göra något som är bra för alla slutanvändare. Ja menar de är över två tusen pers som bara jobbar på vårt kontor, då kan man ju inte förvänta sig att alla dom ska ha en jättehög teknisk kompetens.	OC-TMS OC-PTC
83.	LE	Nej det förstås. I vilka beslutssituationer använder ni AI idag?	
84.	R2	Jo men det vi har drivit är ju till viss del sortimentbeslut, vilket sortiment man ska ha i vilka delar av världen, prissättning, det finns ju också en del i supply som jag har dålig koll på men som optimerar en del i logistik och lagerföring. Det är väl några exempel iallafall. Men jag kan tänka mig, nu arbetar inte vi med e-commerce lösningar i vår del av organisationen, men där finns det ju en del i kombinationsmotorer som läser ganska mycket, men det är inte vårt område som sagt.	AI-C
85.	LE	Nej jag förstår, intressant. Då tänkte jag om det är något annat du vill ta upp som vi inte frågat dig om?	

86.	R2	Nej men jag tror att för den stora massan så kommer man kanske inte liksom. När man börjar jobba med AI så blir det bara ytterligare verktyg, om man nu liksom ser AI som ett antal tekniker som voice recognition, image recognition, machine learning, ni vet lite olika sådana där, deep learning eller vad det nu kan va. I framtiden kommer det säkert vara något man har in bakgrunden, men det kommer nog inte vara så att nu använder vi AI, nu använder vi inte AI. Det är nästan för brett uttryck för att säga så, så det blir nästan för svårt i en organisation till att göra till en kutymen. Det skulle jag nog säga från vår erfarenhet liksom, vi jobbar med advanced analytics men sen gör man ju det som behövs för verksamheten och vissa grejer kanske är mer advanced medan andra är jätte basic. Man gör ju det som kan förbättra verksamheten.	AI-C
87.	LE	Ah intressant. Då hade inte vi några fler frågor så då får vi tacka dig så hemskt mycket för intervjun! Vi har verkligen fått några insikter att jobba vidare med här. Resultatet blir färdigt i början på juni så då får du självklart ta del av den. Så tack så mycket, du får ha en fortsatt trevlig dag!	
88.	R2	Det var trevligt att prata med er, tack detsamma!	

Appendix D – Interview 3

LE=Ludwig Entzenberg (head interviewer, transcriber)

ES=Erik Söderqvist

R3=Respondent

Section	Person	Text	Code
1.	LE	Okej, men du får gärna börja med att berätta om din nuvarande roll och dina föregående roller om du har haft det inom organisationen?	
2.	R3	Ok, rollen specifikt eller vill du veta mer om bolagen?	
3.	LE	Du kan väl börja med att berätta lite kort om vad ni gör på bolaget och sen lite också om din roll?	
4.	R3	Yes, jag jobbar som accounting executive. Det innebär att jag säljer våra lösningar. Det är egentligen en tjänst som är en plattform som hjälper bolag att underlätta arbetet med att samla in information och jobba med den. Det kan till exempel vara machine learning eller andra AI-modeller. Så det är en plattform som bygger på en open-source lösning. Jag kan berätta mer om ni vill. Jag jobbar i alla fall som accounting executive så det innebär att jag säljtjänst där jag täcker Norden och tar kontakt med företag som har visat intresse eller som vi tror kan ha värde av den här tjänsten. Det är en ganska teknisk roll så vi jobbar med ingenjörer på vår sida för att identifiera om det finns behov och isåfall hur man implementerar såna här lösningar hos kund.	ODM AI-C
5.	LE	Intressant. I din nuvarande roll, vilka typer av beslut fattar du?	

6.	R3	Det är framförallt beslut om vilka företag vi vill bearbeta, det finns ju en uppsjö av bolag i Norden. Som ni säkert vet är ju AI och machine learning något som alla bolag snackar om. Så jag tror att de flesta bolag i någon mening försöker utveckla. Sen är det ju så att vissa bolag är ju mer mogna än andra så då handlar det ju om att identifiera vilka som är de lågt hängande frukterna så att säga. Sen handlar det också om att sälja internt. Jag kan fatta beslut om vilka resurser jag behöver internt för att driva ett visst projekt, men det gör jag kanske inte helt på egen hand utan då kräver det att man liksom säljer inte potentialen i det här internt. När det kommer till förhandling och den faktiska transaktionen så är det ju något som säljare äger också.	ODM
7.	LE	Mm. Vid den här beslutsfattningen då inom organisationen, hur etablerat är det att använda sig utav något IT-stöd?	
8.	R3	Väldigt! Vi är ett ganska ungt och modernt bolag som sådant. Vi har ju kanske för mycket IT-stöd, men vi har ju liksom verktyg för allt. Vi har ju vårt säljsystem som kanske är kärnan som säljare. Sen har vi en massa verktyg kopplade till det för att göra allt som planering och analysera kunden osv. Så vi har ju en massa verktyg och en av våra värderingar, vi har liksom 4 olika värderingar. En av dom är just att låta data bestämma. Så det är en stor del av vår kultur att alla beslut i vår organisation ska fatta på en datamässig grund snarare att det är någonting som är en känsla eller som någon tycker. Det kan handla om när man jobbar med befintliga kunder som man vill analysera en kunds användning för att föreslå en uppförsäljning eller någonting annat. Det kan också vara att man vill presentera alternativ eller fatta beslut på deras faktiska konsumtion.	ODM-CS TC-AD
9.	LE	När beslutade ni som organisation att införa AI som ett ytterligare stöd i er beslutsfattning?	

10.	R3	Oj, det vet jag nog inte exakt, men jag skulle nog säga att det har funnits med från start. Sen när det gäller att använda AI själva är det ju lite av en definitionsfråga. Det finns ju en konkret applikation av det där och det är ju dels, det vi säljer är en plattform som konsumeras och konsumtionen mäts i en viss enhet. Den konsumtionen kan man ju då forecasta eller försöka förutse för identifiera vilka kunder man ska lägga mest tid på. Dels kan man ju se hur deras konsumtion är nu och hur den är historiskt. Sen kan man ju då baserat på vad du vet om kunden och deras bransch och en massa andra faktorer försöka se hur konsumtionen ser ut om ett år från nu. Med hjälp av det då försöka identifiera vilka konton du ska fokusera på. Just den produkten är relativt ny, jag tror den är kanske ett halvår gammalt. Sen använder vi ju andra verktyg som har inbyggt nån slags intelligens. Det kan handla om att "scora" prospekts då genom att se hur dom beter sig, liknar dom befintliga kunder, hur dom beter sig på vår hemsida, hur dom interagerar med oss och historiken liksom. Vi kan då ranka återigen vilka konton man ska fokusera på då. Det har vi gjort sen ett tidigt skede.	AI-C
11.	LE	Du var inne på det lite här, men vilka typer av AI-funktionaliteter använder ni?	
12.	R3	Vi använder en forecasting modell då som kanske är det tydligaste exemplet. Det är någonting vi jobbar aktivt med. Sen återigen jobbar vi med andra produkter som är mer kopplade till tidiga sälj faser som liksom skickar signaler till oss att nu har det skett ett antal aktiviteter kopplade till att den här kunden har en viss profil, kopplat med andra faktorer som gör att vi bör interagera med dom.	AI-C
13.	LE	Är det här någonting ni utvecklar själva eller är det något ni köpt in från en leverantör?	
14.	R3	Så den här forecasting produkten har vi utvecklat själva men de andra har vi köpt. Det är produkter vi använder från en leverantör.	AI-C

15.	ES	Bara innan vi går vidare. Vilket år grundades bolaget?	
16.	R3	Början på 2010-talet. Så vi är ganska unga. Vi har växt ganska snabbt.	
17.	LE	Men då kommer vi in i det här ramverket då och våra faktorer och då tänkte jag börja med den teknologiska kontexten och tänkte jag kolla lite med vår första faktor som är direkta och indirekta fördelar som ni ser då med AI. Så innan implementeringen av AI, vad för direkta och indirekta fördelar uppfattade ni inom beslutsprocessen som organisation?	
18.	R3	Det är en bra fråga. Här är jag inte helt säker, men jag tror återigen, du kan koppla ihop det med vår filosofi att vi vill förlita oss på datan när vi fattar beslut och det är ju ganska intuitivt att annars blir det ju mycket magkänsla och det i sin tur gör att man riskerar fokusera på fel saker. Så fördelen är ju det att man inte missar möjligheter och att man fokuserar sin tid på rätt saker. Alla organisationer vill ju vara effektiva men för oss är det extra viktigt eftersom vi växer snabbt och vi har höga mål och ganska många investerare som vill ha avkastning och man har gjort vissa kalkyler att vi ska nå en viss tillväxt. Så allt som gör att vi kan fokusera på rätt saker är såklart kritiskt.	TC-PDI OC-DMO
19.	LE	Till vilken grad skulle du säga att dessa uppfattade fördelar påverkade ert beslut att implementera AI i beslutsfattningen? Alltså hur pass viktigt skulle du säga att det är?	
20.	R3	Vill du att jag ska svara på en skala?	
21.	LE	Nej du får gärna resonera hur pass viktigt du tror att det var för organisationen.	

22.	R3	Nej men jag skulle säga att det var väldigt viktigt och avgörande liksom.	TC-PDI
23.	LE	Då går vi vidare till mängden data som vi också har pratat om lite tidigare. Vi kan börja med, hur hanteras och värderas data hos er?	
24.	R3	Återigen, det värderas väldigt högt och jag tror fördelen med det är ju att oavsett vilken roll eller titel man har så tror jag syftet med den här värderingen vi har är ju att du ska som organisation komma fram till det bästa beslutet baserat på data och det gör ju liksom att man får en kultur där man inte har en chef som tycker något på känsla utan motiveras med data. Det skulle liksom strida mot vår värdering. Återigen, det är en mekanism för att säkerhetsställa att vi fattar rätt beslut. Om vi skulle fatta fel beslut kan vi ju titta på datan som ledde fram till det och korrigera och anpassa oss. För mig är det lite en självklarhet så det kan vara lite svårt för mig att svara på den här frågan men jag fattar också att många organisationer inte funkar så, så det är en intressant fråga.	TC-AD ODM ODM-CS
25.	LE	Men den här hanteringen av data, görs den automatiskt eller gör ni den som anställda? Typ excel.	
26.	R3	Så att den, också en bra fråga. Den görs inte helt automatiskt, den levereras ju till oss anställda automatiskt. Det är ingenting jag sitter och knackar in i excel för att få ut dom här graferna utan det levereras till oss. Sen nånstans ska man ju titta på den och värdera den och sen måste man ju också förstå att den bilden vi får, vi har haft en del intressanta diskussioner om det här, den bilden man får är ju baserat på en viss input och det kan ju finnas en del input som inte tas med i beaktande. Ett exempel kan ju va att man har vissa relationer med beslutsfattare inom vissa konton som gör att man har information som är svåra att få in i den här modellen. Det är definitivt inte helt automatiserat. Den sista biten där är kanske svår att helt automatisera eftersom det är svårt att korrigera all den här kunskapen så att det finns alltid utrymme för debatt i slutändan men den bygger ju på nån slags data.	AI-C ODM-CS

27.	LE	Så innan implementering av AI, hur hanterade ni datan? Var det bara ni som hanterade den eller hade ni hjälp av något? Typ BI-system.	
28.	R3	Nej men innan, om vi pratar om den här forecasting modellen som man fick göra själv. Man kunde titta återigen då på historisk konsumtion och kan försöka hitta någon trend i det, går det upp eller går det ner så att då blir det ju nånting man får göra själv och nackdelen med det är ju att dom som inte gör det för att de inte fattar vikten av det, dom går ju miste om någonting. Men jag förstår också att det finns en tröskel liksom. Men viss automatisering har ju liksom gjort att informationen blir enklare.	TC-AD ODM-CS
29.	ES	Visst var det ändå så att en viss grad av den här AI eller machine learning köptes in från början till exempel?	
30.	R3	Ja men då pratar vi om vissa andra komponenter. Andra lösningar egentligen. Men det stämmer.	AI-C
31.	LE	Skulle du säga att ni har fått nya insikter med hjälp av AI?	
32.	R3	Absolut, utan tvekan. Framförallt underlättar det för oss att ha diskussioner med kund exempelvis. Vi kan säga att när vi diskuterar till exempel en förlängning av kontrakt och sen ska man då diskutera hur stort ett visst avtal ska bli och då försöker man ha ett resonemang kring vad som är kundens framtida konsumtion och om man sen då kan visa att vi har en AI-modell som funkar på det här sättet och den förutspår att ni kommer ligga på en konsumtion på den här graden. Så det ger ju oss insikter men också kraft i att göra vårt jobb och hjälpa våra kunder.	TC-AD AI-C
33.	LE	Till vilken grad skulle du säga att den här mängden data och hanteringen av den influerade er att implementera AI i beslutsfattningen?	

34.	R3	Jag tror att för oss ligger det i vår natur att utveckla den här typen av stöd. Jag tror det som influerar är att vi vill ha alla verktyg vi kan ha för att underlätta vårt arbete sen har jag svårt att svara på i detalj vad det som triggar det som gjorde det när det kommer just till data, det kanske kan ha gjorts tidigare.	TC-AD ODM-CS
35.	LE	Då går vi vidare till den organisatoriska kontexten och börjar lite med den tekniska kompetensen inom organisationen. Innan implementeringen hur uppfattade du den tekniska kompetensen inom organisationen?	
36.	R3	Väldigt hög. Extremt hög. Jag tror att det är på en väldig hög nivå.	OC-PTC
37.	LE	Gäller det här även för eran ledning och era managers?	
38.	R3	Absolut. Det finns olika avdelningar, men vi är väldig tech-driven organisation. Alla i ledningen är högutbildade inom tekniska utbildningar, typ PhD på de flesta. Några av dom föreläser fortfarande på högt rankade universitet i världen. Så det är ett väldigt tech-drivet bolag. De här grundarna, dom uppfann den här teknologin som är en open-source teknologi så vem som helst kan använda den och vi har kommersialiserat den. Andra organisationer kan antingen använda koden eller använda våran produkt för att enklare implementera teknologin. Stora techbolag använder vår produkt. Den är populär bland machine learning och big data så man kan säkert säga att vår ledning har en hög teknisk kompetens. Sen är vi ju en säljorganisation så jag måste ha med mig en tekniskt kunnig person för att sälja det här men jag tror att den bakgrunden våra grundare har gör att det generellt sett är en ganska hög teknisk nivå.	OC-PTC AI-C
39.	LE	Skulle du säga att den höga tekniska kompetensen eller förståelsen påverkade att ni implementerade AI som beslutsstöd?	

40.	R3	Definitivt! Utan tvekan. Det är lite därför jag menar att det ligger i vår natur att utveckla och implementera såna här produkter. Vi förstår värdet av det och vad det kan ge.	OC-PTC
41.	LE	Då kommer vi in lite på hinder i beslutsfattningen då, och istället för innan implementeringen då eftersom ni haft AI sedan starten. Innan ni implementerar nya AI-lösningar inom beslutsfattningen, uppfattar ni att det fanns några begränsningar eller hinder i er beslutsprocess?	
42.	R3	Definitivt inte. Jag kan inte alla detaljer, men det jag vet är, om vi pratar återigen om den här forecasting modellen. Den utvecklades av en “vanlig” anställd som jobbar med olika tekniska lösningar. Så han utvecklade den här komponenten på egen hand och presenterade den och den togs väl emot och sen implementerades den inom vårt säljsystem. Jag tror återigen att det ligger i vår natur att ha en ganska platt organisation och det finns många initiativ som drivs av personer. Om man sen tycker att det här skapar värde så är det väldigt enkelt och genomföra det.	OC-DMO ODM-CS
43.	ES	Jag tänker lite exempel på beslutshinder kan ju va brist på information, eller otydlig information eller kanske uppstår intressekonflikter inom organisationen. Upplever du att det finns sådana problem och att den här forecasting modellen då eller nåt annat AI-verktyg har förändrat det på något sätt?	
44.	R3	Nej det skulle jag inte säga. Från vad jag står så har jag svårt att se att den typen av hinder finns.	OC-DMO
45.	LE	Men då går vi vidare då till sista faktorn på organisatoriska kontexten som är top management support. Vi var inne lite på det tidigare, men jag tänkte bara kolla hur involverade är den högsta ledningen i att införskaffa AI i beslutsstödet?	

46.	R3	Jag skulle nog säga att de är väldigt involverade. Det är ju något som ligger i deras intresse och dom är ju väldigt tech-drivna så dom gillar ju all typ av ny teknologi och saker av den naturen. Så min uppfattning är att det finns ett stort intresse.	OC-TMS
47.	LE	Hur visas det inom organisationen? Alltså kom de med en vision till exempel? Stöttande samtal, allokering av resurser?	
48.	R3	Det är en bra fråga. Vi kan fortsätta på den här killen då som skapade AI-lösningen. Dels marknadsför sånt här internt av ledningen genom mejl till hela organisationen. Typ kolla på den här grejen som den här killen har utvecklat, jättebra initiativ och värdefullt. Det gör att alla engagerar sig. Sen fick han faktisk en annan roll sen för dom ville att han skulle fortsätta iterera på den här typen av produkter internt. Så det är ett bra exempel på att de uppmuntrar.	OC-TMS
49.	LE	Skulle du säga att utan den högsta ledningen involverade att det här inte hade skett eller?	
50.	R3	Jag tror att det här kanske hade skett ändå utan den högsta ledningens godkännande. Men ändå så måste ju den här personen redovisa vad han gör om dagarna. Men han behöver nog inte gå till VDn och fråga. Det finns dock ett annat exempel där en kille går och frågar om ett sidoprojekt. Jag kan inte detaljerna i det, men det ligger i samma linje. Det här var något som han drivs av själv och gjort utanför arbetstid och det är nog så det börjar så att man har ett intresse och ser att det finns ett behov eller ett värde och sen börjar man bygga nånting och presenterar det internt och sen lyfter man det upp. Det är klart att din närmsta chef eller näst närmsta chef måste ju ge sin välsignelse.	OC-TMS
51.	LE	Intressant. Men då går vi vidare då till miljön som ni verkar i som är den sista kontexten. Då tänkte vi börja med konkurrensen på eran marknad. Så innan ni implementerade någon AI-lösning i beslutsfattningen, var ni då medvetna om konkurrents användande av AI på ett sådant sätt?	

52.	R3	För vissa av dom produkterna vi använder som vi köpt av leverantör, är ju någonting vi vet att konkurrenter använder. Vissa dom här interna grejerna är ju så specifika för vår produkt att det kanske inte är applicerbar på just den delen. Många av de andra grejerna som vi köpt in använder våra konkurrenter också.	EC-CP
53.	LE	Skulle du säga att ni blev påverkade av konkurrensen att införskaffa AI-lösningar inom beslutsfattningen?	
54.	R3	Jag tror inte det är det som driver det. Jag tror det handlar mer om att, jag har jobbat mycket i startups och då brukar många säga att man ska va uppmärksam på sina konkurrenter och man ska inte stirra sig blind på dom utan man ska fokusera på det man själv gör. Skapa sina förutsättningar. Jag tror det är ganska genomgående här också och låter sig inte styras för mycket av konkurrenter. Det är klart att någonstans vet man ju att dina konkurrenter använder dom här verktygen också och gör det av en anledning för det ger dom en fördel. Jag tror inte det är den drivande faktorn i beslutet.	EC-CP
55.	LE	Skulle du säga att det istället har att göra med att ni kan få konkurrensfördelar?	
56.	R3	Absolut. Det gäller ju tvärs över alla, vare sig vi köper in nånting eller utvecklar själva. Det handlar framförallt om att få en edge och springa snabbare.	EC-CP
57.	LE	Så hur pass viktig skulle du säga att den här edgen är? Alltså till vilken grad skulle du säga att ni påverkas av konkurrensen för att införa AI?	

58.	R3	Det är viktigt men det är klart att vi har konkurrenter men det finns ju olika typer av konkurrenter. Det finns ingen som gör exakt det som vi gör och så är det väl för många startups för man hittar sin nisch. Sen konkurrerar man ofta om samma budget, det finns alternativet att inte göra någonting alls eller att bygga allting själv. Det handlar mer om att man man vill va bäst och ta marknadsandelar och sen finns ju alltid konkurrenter i en kontext men jag tror inte det är så centralt. Där handlar det kanske mer om hur vi väljer att utveckla produkten och hur vi väljer att ta produkten. Mycket av dom här AI-grejerna handlar ju om att förbättra våra interna processer och bli effektivare och sen med hjälp av en bra produkt tror jag att vi kommer vinna på marknaden.	EC-CP
59.	LE	Men då är vi på sista faktorn då. Det handlar om osäkerheten inom industrin. Så anser ni som organisation att ni är i en oviss miljö? Det kan till exempel vara ekonomiska svängningar, snabba förändringar inom teknologiska lösningar osv?	
60.	R3	Jag skulle nog säga att vi inte anser oss vara i en oviss miljö. En anledning är att vår produkt kan användas av ungefär vem som helst och vi säljer ju den här produkten till alla möjliga organisationer inom olika branscher. Det knyter ju an till det här som vi pratade om tidigare att alla organisationer idag pratar om data, analys och maskininlärning. Vår produkt säljs snarare som en edge för våra kunder gentemot deras konkurrenter. I och med att vi har en ganska spridd mängd kunder och de kunderna däremot kan nog känna en viss ovisshet. Till exempel säljer jag till en kund som enbart jobbar med flygbolag och de har det jobbigt just nu. Vi har ingen större panik. Vissa av våra kunder frodas i den här miljön och vissa går sämre. Vi har skyddat oss genom att vi har en produkt som säljs till olika industrier. Vi anser att vi inte är i en oviss miljö, vi ser mer att vi har framtiden för oss. Vår största utmaning är att många organisationer pratar väldigt mycket om vad de vill göra med AI men att de är väldigt omogna i sin infrastruktur för att kunna göra någonting med det. Så att där får man ha tålamod och vänta ut dom här och fokusera på dom längre fram. Vi anser dock att alla kommer komma dit tids nog. Det finns en stor potential i framtiden.	EC-EU

61.	LE	Vid en beslutssituation där det uppstod en hög osäkerhet, hur såg den beslutsprocessen ut innan implementerade AI?	
62.	R3	Den var manuell och till viss del magkänsla. Driven av vad som var bäst för den anställda i den specifika situationen snarare vad som var bäst för kunden eller organisationen.	ODM OC-DMO
63.	LE	Skulle du säga att ni kan ta snabbare och kanske mer träff-säkra beslut idag?	
64.	R3	Absolut.	AI-C
65.	LE	Så till vilken grad då skulle du säga att den här osäkerheten som vi pratade lite om en faktor som påverkade införandet av AI?	
66.	R3	Nej inte alls.	EC-EU
67.	LE	Okej, men då är vi inne på lite avslutande frågor då. Så efter införandet av AI, vad har förändrats inom organisationen?	
68.	R3	Vad tänker du på?	
69.	LE	Någon beslutsprocess som har ändrats, hur ni interagerar med varandra vid beslut? Något exempel blir bra	
70.	ES	Jag tror du har belyst mycket tidigare, till exempel pratade du om att ibland kunde beslutsfattare gå på magkänslan och liknande, men nu när ni är så pass datadrivna så kollar man istället på de hårda värdena.	

71.	R3	Nej men det är ju ett stöd som guidar. Om jag har 50 företag som jag potentiellt skulle kunna gå efter och jag får signaler från mitt system som säger att de här 5 uppvisar vissa karaktärsdrag eller beteende så gör ju det att jag fokuserar på rätt saker. Också att jag har någon slags, inte självförtroende nödvändning vis, men nånting jag kan hänga upp mitt beslut på när man tar kontakt exempelvis. Det är väl tidsparande och mer effektivt. Man känner sig också säkrare när man står inför olika beslut.	ODM-CS
72.	LE	Skulle ni säga att ni hanterar mer data idag än vad ni gjorde tidigare innan ni implementerade AI?	
73.	R3	Absolut det skulle jag säga.	TC-AD AI
74.	LE	När, om inte redan nu, tror du att AI kan uppfattas som en normalitet inom eran organisation och inte som något innovativt eller nytt?	
75.	R3	Bra fråga. Det beror lite på hur man definierar det. Utan att bli för filosofisk. AI nånstans är ju något som outsourcar en själv så är det väl då det kommer anses, alltså då är det extremt innovativt. Att komma dit tar långt tid. Innan det blir någon slags normalitet ur den aspekten kommer ta långt tid. Att jobba med data, analyser och olika modeller tror jag snarare är en normalitet hos oss som är intuitivt i organisationen.	AI
76.	LE	Tror du att era medarbetare tänker att de använder en AI-funktionalitet när de jobbar med systemen?	
77.	R3	Ja det tror jag. Det ligger lite i att vi säljer ju en produkt som hjälper bolag med AI. Vi som organisation är ju experter på att implementera AI-lösningar till bolag. Jag tror att vi ser oss själva som väldigt långt fram på området.	AI

78.	LE	Då tänkte jag om du kunde säga vilken faktor du tror är mest inflytelserik av de vi gått igenom under denna intervju?	
79.	R3	Jag skulle säga teknisk kompetens som nummer ett. Vill ni att jag ska ranka dom?	OC-PTC
80.	LE	Nej det räcker med att berätta om de du tror har spelat störst roll.	
81.	R3	Top management support skulle jag säga också har spelat en stor roll. Det var någon annan som var liknande eller hur?	OC-TMS
82.	LE	Nej det skulle jag nog inte säga.	
83.	R3	Ja okej, då rör jag nog ihop det. Men jag skulle nog ändå säga att teknisk kompetens som mest inflytelserik och top management support tätt därefter.	OC-PTC OC-TMS
84.	LE	Perfekt! Finns det någonting annat du vill ta upp som har med det vi berört under intervjun som du kanske inte fått möjlighet till att göra?	

85.	R3	En intressant frågeställning som jag tror alla som tänker på det här funderar kring. Det är avkastningen, kvantifierbart. Många av de här frågorna är liksom, vad tycker jag och vad tror man, men någonstans och det är ju för att vi tror på den här teknologin och vi är så djupt inne i den att vi anser att den är klart skapar värde. Men en stor utmaning som är en intressant fråga som vi inte har gjort. Vad är avkastningen på det här? Hur mycket tid sparar vi? Hur mycket värde genererar vi? Hur mycket hjälper det oss verkligen i beslutsstöd? Det är nånting som jag tror många organisationer brottas med, så det är ju också en intressant aspekt. Det är ju också så att, man är ju lite biased för man har spenderat mycket tid på det här och då säger man ju att det skapar ett värde, men det hade varit intressant att veta hur stort det värdet är.	ODM-CS
86.	LE	Absolut. Då är vi nöjda. Det har varit intressant att lyssna på dig och stort tack för att vi fick möjligheten.	
87.	R3	Hoppas det har varit värd er tid.	
88.	LE	Absolut, hejdå!	

Appendix E – Interview 4

ES=Erik Söderqvist (head interviewer, transcriber)

LE=Ludwig Entzenberg

R4=Respondent

Section	Person	Text	Coding
1.	ES	All right, so this will be a semi-structured interview, so we will go through the questions that I sent you but questions may arise during the conversation. We can just start with you, just telling us a little bit about your organization, what you do in your current role and what your history is at the organization.	
2.	R4	So, OK, I am *****. I started my career at the organization, you know, in 2012. But I have a background in biology, you know, molecular biology and science. And then I move to IT to be a bio informatics. So, between bio and IT. I moved to several position in or in the research area having, you know, working with sequenced DNA sequences. Then move later on to project manager, and now I'm really in the interface between IT and their research and development. That means what does it mean? I received demands from people in several areas, R&D or further look at petition money for drug discovery and sometimes they want to be supported by systems. We as a business analyst or business partner, we help them to formalize the demand, make sure we know we understand the requirements so that afterwards we implement the right system for them. It's really much more understanding the business area. And then you translate into IT components. Either we make it or largely we buy things because there's plenty of companies supporting the drug discovery process in this field. For example, what will keep things in the labs, the electronic lab notebooks. Before it was paper books. The scientists explain how you want to do this and your hypothesis. But I do in my lab and my stuff. And then they get the results and they can draw a conclusion on that. And that was all maybe 20 years ago now it's on an electronic like a word and excel. But it's more and more you know, it was unstructured data in the past and now it's becoming structured way because it was only documents. We thought any technology which is clever enough, you can do anything. You know, if you	ODM ODM-CS

		want to compile all the information, you know more than me what it means. Then to explain, we are a pharmaceutical company as this shows. And I started as business analyst in 2012, working in several areas, you know, from research and development. And so there was a clinical trials, regulatory, you it's quite a cumbersome process in the pharma from an idea to the end of a pill, it's 15 years. But there's plenty of stuff where you can really accelerate things. My role is to translate the need and execute to have a solution for the scientist. And sometimes I do the end to end process, and sometimes only the first phases to which is quite key to understand things from where you have a lot of value. Then when you select a system you know how it would be implemented. That's in essence what we do. And I have a couple of projects. And I have a portfolio of demands coming in and we prioritize them and we do budgets for next year to make sure we know where there's a couple of millions to be invested each year.	
3.	ES	And you touched a bit upon it. So in your current role, what types of decisions do you take?	
4.	R4	The decision I take is to invest in certain technology. You know, at all, I recommend, I understand the demand. I make a case. It's called business case, which, you know, the price of the technology you want to implement, you know, the plan to do it and with the resource and you present it to a board of people which are kind of senior level people, that are up to the CIO. We talk to people from around the company and you have to present it and show the benefit on the investment. And this is where I took the decision-making metric, to decide on which technology to set. It came to a default, you know, environment of the company. If you have to sort of siloed approach, that's not good. You have a border, with this platform would be maybe connected to others so that the data is going, and it's connected to all the others.	ODM ODM-CS
5.	ES	So what kind of impacts does those decisions have on the organization. Sounds like they are quite major.	
6.	R4	Yes it's, in a word, transforming transformational at the deep end. And as you said, it's technology and change management. And it's also awareness of why the data is so important today. It's really. We were, you know, in the past, looking at system, which was with silo tech. Now	TC-AD ODM

		we're really looking more at the data level saying, okay, if we want to use data correctly, it has to be borne by people in the company of people are the data owners. And then there would be system owners. And then at some point, you know, this is all paradigm shift because it was more systems centric at some point. But now it's data centric, that data is oil at the end. And we understand now to do whatever we do each time we produce data, that data can be reused. It's quite key. And I see, you know, two aspects to the unstructured world, which are the past. A bit it would still remain. But we as humans, we like narratives, you know, documents, things that make sense. But also the data points are fake. That means those two worlds are converging. And in the past, it was mainly the unstructured world. Now it is data world. It will be one big area and we will make decision on both.	ODM-CS
7.	ES	So you are kind of touching upon this as well. But how establishes using a supportive tool in decision making at your organization?	
8.	R4	And we can now move to the Sinequa. You know, it's when we started into 2016, I was asked to review a landscape, you know, a naked landscape. For most, for people who produce the medicine for the clinical trials. It's not marked that it is, you know, the powder that is put into a tube and it's used for the clinical trials. And they ask me, can you look at the landscape, can we do better? I was digging into interviews, just like you say you do today with people on each site in the world. And they told me it's a mess. We do things not in a harmonized way. It is difficult to find information and it's difficult to take decision. Sometimes we redo things which were already done elsewhere, by not knowing what was done. That means we structure a bit of the landscape. I said, okay, fine, we have to do this kind of data and or architecture. But at some point, what could be a quick win? And we thought by having a consultant with me on this, that quick win would be to have a Google internally. So that each time we have a question, we type in, so this medicine or the exact mode of action. Then you will be retrieving all the documents which were created internally. So it was for the internal information, and we said okay is there any company in the world like that for internal Google. Because Google, we use it so frequently. That was the entry point, we started that. And, you know, we started with a proof of concept. Which maked, you know, people are	ODM-CS AI-C OC-TMS OC-DMO

		very happy and they said OK, it's quite nice. And then we implement that for two hundred people, the Sinequa engine, in 2018. It was a really huge success accelerating from four hours to find something to seconds to find things. We had an acceleration of the way to find information in the company. And it was a case for the data strategy which came a bit late into 2019 saying okay, we need a data strategy for the R&D company. How can we leverage the GPI research? That the intern name to do it like R&D search. That means the platform has been scaled up, we change the platform to go 20 million documents. Now it's connected to 20 million documents in the company, a bit less, but it's scaled up to 20 a millisecond. And you know, it's very, very quick. That means you can find things with chain document measurement system and SharePoint. All the corporate memory is there. That means syndic waste is connected to what was done in the past. So now you can find a lot of things, users, facets, navigation that I need to detail you want.	
9.	ES	So when did your organization decide to adopt AI to assist the organizational decision making? So you kind of touched upon that process. Was it in 2016?	
10.	R4	You know, it was not so-called AI at some point. It was say more of natural language processing. Now we know that natural language processing is a subpart of AI. We really use that to find information and take decisions faster. Sure, that was the key, because at some point, if you take ages to find information, it's not good, that means to accelerate the decision-making process. Exactly, find the right information at the right time. That's really the thing. And it was really to make sure for whatever we have done in the past, we can find info. Now for the future, we can find other stuff because you could say, now we could structure a bit more things, and be data centric. We can use those types of system. But for the past it may remain, you know, at some point it's structured and unstructured would be just two boxes, but I have a system now for the unistructural piece.	TC-AD ODM AI-C
11.	ES	So we touched upon the functionality is being natural language processing. Is there any other A.I. functionalities that you use today?	
12.	R4	Today that, you know, classification on machine learning. No, it's not used, but it's part of the Sinequa platform. We	AI-C

		know that, you know, we try to do classification of documents based on sampling of documents we have. So that the classification could be done automatically. But that's not something we have already used. We might use it in the future. We don't know yet.	
13.	ES	So if it's possible, can you please just describe how AI, these capabilities assist you in the current organizational decision making?	
14.	R4	Today. It's the use case is quite broad. That means it could an auditor coming saying you have gotten that approbation, approval, to have these medicines on the market. There's a problem on the market. Invest in the, the submission you have created. And it would be more to find data to a specific case where you have to prove what you have done. And Sinequa is connected to all of our system. That means you ask it stays on alert on the market that was going to adverse event, on this medicine. Can this be good? And you can find information. That's one case. Another one could be a newcomer in the company. He has a new project to set up. He has to know what was done in the past, on similar projects or similar molecules. Now he could find easily all the documents on that. It could also imagine connecting the documents. One document was created, another one that was used with another one, so we have the lineage between all the documents. My final goal, you know, with Sinequa is to show visually how we have created, you know, our medicine based on the supporting documents created in the company. Look at the timeline or documents which are like in the graph. That would be a perfect view of the supporting documents. Because today we don't have any data centric view. But you could imagine extracting those data based on the information we have already in those documents, which are the one we produced to submit to the authorities and to get the approval.	TC-PDI AI-C
15.	ES	All right. So this was the first part. So now we've established a decision part and the AI part of your organization. Now we'll go into the theoretical framework that we're going to use in our thesis. And it's called TOE. So it's from the technological context, organizational context in an environmental context. So from all these context, we have developed factors that from the literature. So we will start with the first one. And that is perceived direct and	

		indirect benefits. So prior to the adoption of this system or this AI capabilities, what were the perceived direct and indirect benefits of A.I. in decision making?	
16.	R4	I think before jumping into technology, was it a black box to us. You know what was the AI, what was not? It was more or less, nobody knew how to tackle this problem. There was no competencies internally to embark into AI project. There was no skills no people to create a new field, which came very quickly. In terms of hype. There was a lot of hype, as usual people were saying, we need AI for that. But they didn't know how to make it. And then you can see that the concrete stuff about A.I. came with Sinequa, you know internally. OK. It's like Google. But again, the capability, you know, were brought by Shaniqua is really natural language processing. It is quite a huge topic behind, with no synonyms and entities. It's really a huge deal, but we started to understand, what does it mean? Can we ingest our firm dictionaries into the Sinequa engine so that it brings you know, when you do a query you get much more then what you anticipated. By having synonyms, when you create a molecule as a compound name, so that you can find everything about the topic. Again, you know, the benefits noted, the drug benefits. It was, you know, to accelerate the drug discovery process, we thought, knowing that. But, you know, as of today, it's still, I see the metric of AI in how our world either, image recognition. Or you could have also because, you know, you make some scans of, you know, x rays and when you see this patient is with this trouble and you can pinpoint with AI on to something to see this is a positive this is a negative sample. But you could imagine easily to do that for sure on images and under a microscope views for sure. It's one thing I see. And the other stuff on AI is more drug discovery. And as you see for the Covid-19 the majority of paper are, papers you know scientific papers that we distill unstructured data. And what we bring with natural language processing and AI is really extracting from those documents all the concepts. OK. This disease is connected to this gene or this disease is connected to those drugs or the symptoms. And you have in a few minutes a view of the considered data to knowledge. And that's for us at the end, the AI, what we ceased to accelerate in drug discovery. But we don't knowing how to do it now, you know, we know there's plenty of start-ups in this field. And I think it would be to select the ones which are specialized in each of the steps of our drug discovery process.	TC-PDI TC-AD OC-PTC

17.	ES	But if we look at the system that you purchased, Sinequa. Were you able to try a demo in like look at these benefits directly before you adopted?	
18.	R4	Yes. You know, I can talk about Sinequa, but also others. Each time we know we try you like, you know, Plexus or there was another one Signal Analytics. It was a people grasping all the knowledge and the world, you know, documents, scientific papers, and putting a dashboard in front of us, saying want to have the information about these diseases. That's all the graphs about this disease. You can question and get back answers very quickly. And today we are in front of millions or billions of records. We have to be quick and you have to take the right decision. And when you think that one scientist can just read the five papers per day, compiled by in his head, you know, all this information is quite a nightmare for them. To accelerate that by, you know, connecting AI to them and say, okay, I want to have those questions answered. It means that this kind of probability that this answer correct based on what you see.	TC-PDI OC-DMO
19.	ES	Yeah. So, how would you say like to what extent did those perceived benefits prior to the adoption, when you understood them, influenced the actual adoption of this system or AI in general for the organizational decision making?	
20.	R4	It was, time, time again. Because at the end, when I buy something is what does it cost and what's the benefit, I calculate you know the time spent by the scientists to find something And you know, very quickly, you know, the return on investments we saw very, very quick.	TC-PDI
21.	ES	So it was very important?	
22.	R4	You know its a, as soon as you can focus the scientists on science, you move them the burden of the admin stuff. Then you spare the time on the really added value and that's where you get it all. Always when we buy something. That's the conclusion we do.	TC-PDI
23.	ES	Yeah. We're going to move into the second factor of the technology context and that is the amount of data. So how	

		do you value and manage data at your organization?	
24.	R4	Today we have big systems supporting areas like clinical system for clinical, big system for regulatory. You started to see all the documents which create the rationale to submit to the authorities to get the approval of the drug discovery. The more you go to the early stage of the value chain, the more you have specific systems only tailored to maybe a person, you know, because it's very specific. You know, there's kind of, I want to know what is the toxicity of this molecule, so we need to have specific instruments, software. That means it's a plenty of instruments and it produce a lot of data for sure. And we don't have it pretty nicely designed database to compile all those data points, so that at each moment where they move from one phase to another. They say, we are confident, that's all the data, the quality is okay. We can pass to another state. But to date it is only systems which are not connected to each other. It's our work and we have a program which we'd probably stop soon to do that, work on early stage where we compile all the data, which are quite critical, because each time we take a decision, we make assumptions and we move to another state. If you think about the twelve years, if you do each time a small error, at the end, you replicate all the errors at the end you fail. You know, you have 10000 molecules at the beginning of the test and you just get to one molecule in the end. That's we know, we have to be very rigorous at the beginning of each of the stages.	TC-AD OC-DMO TC-AD ODM
25.	ES	So if look, prior to the adoption, how did you make sense of that data? You had one or several systems. So how did this sense making of the data look like?	
26.	R4	And when you say prior to this, prior to Sinequa?	
27.	ES	We can take, you can take both Sinequa and perhaps if you gained some new insights with Sinequa?	
28.	R4	I think Sinequa is just one small solution for a couple of cases, but if you look at the data. Well, we have to build a strategy to build the system to put all the data aggregated. Yeah, that's something. We will work on it, couple of years to build something very, very nice. Because it's mainly change or change management, handle the technology. No, I think in our field that is the change because	OC-DMO TC-AD ODM-CS

		people are not fitting ready to change. And also, to share things among each other. I know they are quite happy to be doing what they have. But if you look at all this holistically, we have to break a bit silos and make a common platform. The one central place for the truth.	
29.	ES	Would you say that you discovered new insight with A.I?	
30.	R4	As of today, I cannot tell because we only use Sinequa to get the right documents. But new insights, we could find new insights if we go beyond that. As you said, you could make the linkage between documents. You could make a classification of things. If, we really use Sinequa to the maximum. Yes, we would know much more than what we know today. But it's really, you know, we use Sinequa as the first level of the AI, as research tool. Then afterwards you can extract that information from the document to make maybe a corpus of data points, and therefore, that you could ask some question, and make some visualization. Today, no, there are several steps to go to data in or data-oriented decision making process. We are not yet there.	AI-C
31.	ES	Okay, So to what degree would you say that the amount and management of data influence the adoption of Sinequa?	
32.	R4	That's exactly, the more you have data, the more you would like to have AI to help you. Because it's a place more manageable.	TC-AD
33.	ES	All right. So that was the technology context. Now we move it forward to the organizational context. But we are still kind of technical here and we look at the technical competence. So prior to the adoption, how did you perceive the technical competence within the organization?	
34.	R4	Today, the set up in pharma at least at our organization, might not be the case for other pharma, but as we buy a lot of systems which are off the shelf, it's quite difficult to keep, you know, keep up with the technology and well, also the right skills internally. We are better at the change of the mindset, saying if we want to use AI, if you want to make the use of the data we collect, you might re-invest	OC-PTC

		into internal skills to really do the right skillset with data scientist. You know, with people can use and quit AI model, it means that we are in the shifting and having a new skill set for the future to make use of that, because today there are some, we have not yet the right skills.	
35.	ES	So how would you say that the technical competencies for management is or how prone are they like to invest in in IT and such?	
36.	R4	Now we know, as we do more and more making decision on data. The more you're good fittings, we try to do it more and more like this. Sure. We know that data is quite key, that means that data needs to be well prepared in new and then stored. Yeah, IT more and more, you know, a very, very good partner. Know even if we are not, you know. Part of the value chain in the sense of we there's not IT technology component in the appeals to me. But you know, really close to the value chain in the sense so that we provide all the technology which enables the scientists to sit down and work on science and the molecules. No, IT is quite key.	OC-PTC
37.	ES	All right, so would you say that the technically competence, is it high or low?	
38.	R4	Today internally it is low. And we really need people that are like used to dance and enjoying the market, to help adopt. And also, with the right skills. You're coding python or, you know, a lot of data science all that. It abilities to creating those data sets, sure.	OC-PTC
39.	ES	So, would you consider that it was a barrier in the adoption of such a system?	
40.	R4	Yes, sure and that means if you have same population in the company, you know, and they want to adopt something, but they don't know. It means you have to have people inside the company, that can contaminate bit the company thing. Yes, this AI is easy. And then you install things and you buy things. Sure, if you only have one guy, that is just shouting and say, hey, we have to do it better. But you understand, you know, we don't go anywhere. It's really a time to change to adopt more AI. By having a presentation by one decision to the top management. It's a	OC-PTC

		change of the culture, data awareness culture or something like that.	
41.	ES	Yeah. So now we will move forward to the next factor, which is decision making obstacles and decision-making obstacles can be that you have lack of information, that there is some uncertainty in the information. It can be equivocality so that you have somewhat a conflict of interest and yet you can interpret the data in different ways. So prior to the adoption, did you perceive that you had any decision making obstacles in your organization?	
42.	R4	When you say prior the adoption, that is AI?	
43.	ES	Yes exactly.	
44.	R4	I think of them as any new topic. It's a key to have people who understand the pharma. You know, whenever you come as an outsider, you come to a new company to make the bridge between what you know and what the company knows. And you have to make a presentation which makes people compatible and easily understand the concept. What I have made to make Sinequa come to the point of people understanding, that I worked with the guy thinking that's the pharma process. How we do things. I trained them in maybe two hours, saying that is all the steps of the pharma. Okay, and I want to do that and bringing them, you know, all the concept of terms of the pharma industry. Then we prepare back the slide deck together. Which was just a kind of market slide deck thing. Okay, we tailor it for our specific organization's executives. That's, because if the concept is too detailed, they would not understand anything. We started with something which is appealing, what you know about this and that. Then we presented to senior management. They were happy. And then there was a demo afterwards. And you start to make kind of a narrative and good storytelling. It was really about storytelling, but adapting, to the environment, adapting that, you know, the communication it was quite key, You know it's really, you tried to like your two colors, you try to make a mix so it's a nice channel between the two. It's really like this. And he's quite key. This is the translation of what you want to say and it's quirky. You have to adapt to your audience, and the audience also should be adapted. But at the end, if it comes to the kind of the guy who wants to expose something new,	OC-DMO

		you know, and you have to prepare a lot, and make sure know your message it's well tailored to your audience. As you would say, with your presentation to you as your master thesis, what your audience? What's the message I want to send? You know, the at this stage, that's the key thing.	
45.	ES	So you would say that there were some obstacles existing for you.	
46.	R4	It was the obstacle where people was doing that to make like a small, short training. What does it mean? What's the benefit for you? What's in it for me at the end?	
47.	ES	Yes. So to what extent would you say that these obstacles influence the adoption of AI in decision making?	
48.	R4	It was obstacle because it was quite new as a new thing, you know, people don't like too much new things because they are uncomfortable. You have to ease, you have to train them and make sure they understand quite quickly. As any new topic, if it's simply described, the art of simplistic simplicity is quite nice. It could be very complex. You can describe it in the simplest way so that it's kind of broadly understood. At the end it's a new topic new stuff, nobody knows, how do you ingest that to people because you think it's the future.	OC-DMO
49.	ES	All right. Now we'll move forward to the next one. That's top management support. So how involved was top management in the adoption process?	
50.	R4	There were as you start to have kind of middle management and then you want to have supported to the top. What is also good into our process? Whenever there's a new project, you have to prepare and present to this IT committee. And these are all senior V.P.s or CEOs and you have to prepare yourself a lot. So as soon as that it's endorsed. You have a very good sponsor, they are the sponsor. So then you can invest the money, but you have to bring and explain the narrative. Why do you do want to do that? What did you want to resolve? What will be the benefit to the company? I think you have to build the case as any you know, a company you want to build or make a Start-Up, you have to make a business case. It's might be	OC-TMS

		a small thing, but it's the same concept.	
51.	ES	So how was that support shown?	
52.	R4	You know, we also start some time to get support by making some proof of concept. When the proof of concept is very quick. In three months, you get the value very quickly. You bring it back to the top and see, you know, because there is small money, but there's a huge benefit. And then it gets, you know, very quickly, your sponsor there. It doesn't mean to take the two years to get something. That's where we see more and more do some proof of concept, and pilots are like this and you get the sponsorship like this.	OC-TMS
53.	ES	So it can be like allocation of resources and support conversations?	
54.	R4	Yes exactly, make a mini project. Say okay, we don't have so much money, but we think there's a huge opportunity here. You set up your small team in the event that you make something, something you do it on their servers. It's not something internal, but we bring some data which are not confidential or something and we show, each time it's to show something, you know, at the end it's to show the value.	OC-TMS
55.	ES	Yeah. So to what degree would you say that the top management support influenced the adoption?	
56.	R4	It's very, very strong, if you don't have the support it will go nowhere. So you bring the top management, and also the middle management. You know, if you can have the mandate to do that then it's quite key. Also for the change management.	OC-TMS
57.	ES	Yes. Now we're going to move into the environmental context. So this is things that happen outside of your organization and that can basically affect your organization. So first is the competitive pressure. So prior to the adoption, were you aware that any of your competitors used AI in decision making?	

58.	R4	Yes. Yes. We are not, you know, the first one you, more the laggers. We look at AstraZeneca, it is in Sweden. Those companies are really the one that are frontrunners and we are always looking at what they do. And they would like to have stuff like them, with the data scientist. This competition is quite moving us into the right direction. There's also a regulation, something we are obliged to follow. The regulation that means it does has an impact on the way we do things and we prioritize our projects. And there's a sort of competitive market, that we would like to improve things and to adopt new stuff. As usually you know, working trying new stuff, but also looking at what people do. And we do some calls to friends or sometimes we call our peers. What you do in this area? We go to forums and discuss with them.	EC-CP
59.	ES	So you were affected perhaps by the competition, but it seemed like a competitive advantage for you?	
60.	R4	Today, with AI for sure, a competitive advantage, but it's like a technology guru piece. It has to be connected to use case. I could find so many use cases today. There's nothing yet used in this space to, we tried to do something like the Covid-19. We tried to connect to all the application to find a new mechanism of action to disease. It's quite difficult to create those products which were not in the market.	EC-CP
61.	ES	So if we solely a look at the adoption of AI, would you say that the competitive pressure influence that choice.	
62.	R4	Yes, sure. You know, at our organization is not a huge pressure because it kind of a niche market. Surely with the Covid, you know what, the pressure on the cost and the non-profit this year, sure it will add up. It would take us efficiency measures, and sure efficiency means how can we automate things, and actuate thing, and use AI, sure. That has accelerated a lot, the way we do things we do a video conference a lot. We won’t travel too much. And we use AI more and more.	EC-CP
63.	ES	Yeah. So the next factor is environmental uncertainty. And what you mean by that is basically a dynamic environment, perhaps an economic movement, or that it's outside your organization that you can't really have a say about like her will be having a pandemic, but certain dynamic factors in the environment, so to say so. So prior to	

		the adoption, would you consider your organization to be in an uncertain environment? That is, the prior adoption of this specific AI.	
64.	R4	To date, no it was ok. There is not too much pressure. That is for our organization. You know, might that be the case for others? Where they are competing on cancer, you know, the topics, we are really on the niche market. But at the end, all this topic of the Covid-19, has refocused the company on specific tasks.	EC-EU
65.	ES	So in decisions where the problem is new and ambiguous, what does the decision process look like? Like if we look before you had AI, you talked before about the unstructured world and such. So that could be like a problem that you have not seen before. And that's new. That's something you don't really know how to tackle it.	
66.	R4	I think it's the amount of data which tackles the need of AI, you know, if we think about what we produce in the pharma, it's quite a big piece of data each time we produce medicines. Without AI we cannot do anything. It's also a matter of changing the mindset of people where they have to switch from paper to digital. In the actual clinician, when they compile all the data, if the data is not numerical, we cannot do anything digitalize. That's people in the ecosystem around our organization. When you work with hospitals, they have to do all to bring the data in the right format and right quality. AI will not be moving too much if we don't work on this also.	TC-AD
67.	ES	Okay. So to what degree would you consider the environmental uncertainty so the dynamic environment around your organization to be an influential factor in the adoption of AI in decision making?	
68.	R4	Difficult for me to say.	EC-EU
69.	ES	It doesn't have to be influential. You can say that it wasn't a influential factor.	
70.	R4	Today it was not too much a factor.	EC-EU

71.	ES	All right. So now we go into the last part. So kind of a wrap up, some broader questions. And you can bring things up if you feel like it and such. So after the adoption of AI in decision making, what has changed in the organization?	
72.	R4	It's I think it's the feeling that IT is more and more, you know, essential business. It should be part of the business. It's not like it's IT and it's R&D, or business. Both are partnering to do the same stuff at the end. Also, each year a new word there was Cloud or SaaS, AI, there was an LP. That means to cope with all those things, it's also difficult for the business because there's too many things happening, also for us. But it's good because it's motivating for us and new stuff new things and a new way to work. I think it's IT and business, its really more and more partner.	AI-C EC-EU
73.	ES	Yeah. Would you say that the organization managed more data, now after the adoption of AI?	
74.	R4	Yeah, probably. They need those data. That means they have to manage it.	TC-AD
75.	ES	Yeah. So when, if not already now, do you think your organization would consider AI to be normal and not something innovative and new?	
76.	R4	Okay. I think from three to five years' time, it would be normal.	
77.	ES	Yeah. So of all the factors that we've talked about here today, I'd like to hear which one do you think is the most influential? So I go through them once again. Just so you have them all. So the first one is the perceived direct and indirect benefits prior to the adoption. The amount of data, the technical competence of the organization, the decision-making obstacles, top management support, competitive pressure or the uncertain environment.	
78.	R4	Yet there's the competitive pressure. Sure. And that also includes amount of data. And also, the technical skills. And there would be more and more, I think people jumping into, the data science, is kind of nice topic. It's really maybe overhyped, but it would be becoming kind of a	EC-CP TC-AD

		standard into five years' time. And yeah. Managing having somebody or so. Right skills, competitive pressure and also too much data to cope with.	OC-PTC
79.	ES	Perfect. Yeah. So, we've touched upon this before. But if you would like to just summarize, where do you see a in decision making situation be a suitable compliment to the human decision making.	
80.	R4	From my part in drug discovery. There is an expert, you know the PHD, that need to be complemented with something else which can give us access to much more information in a summarizer way. As an expert he can say yes, this information makes sense. Because he knows by past experience and then combine it with a like a physician you know. A physician would not be replaced by AI it would be complemented by AI. All the experts will be complemented by AI.	AI ODM-CS
81.	ES	Yeah, yeah. So that was our last question. So, have you anything you want to bring forward? Otherwise we are done.	
82.	R4	No, looking forward to receiving a paper.	
83.	ES	Yes. That's perfect. Have a good day! Thank you.	
84.	R4	Bye bye.	

Appendix F – Interview 5

LE= Ludwig Entzenberg (head interviewer)

ES= Erik Söderqvist (transcriber)

R5= Respondent

Section	Person	Text	Code

1.	LE	All right, då sätter vi igång gå. Då får du gärna börja med att berätta om din nuvarande roll, dina tidigare roller inom organisationen och kanske berätta lite vad ni gör på organisationen?	
2.	R5	Yes, vi är en bank. Har funnits sedan ****, vi håller på med väldigt många olika saker. Om man ser på det globala, så är vi ganska små, vi är X antal anställda ungefär, vi har liksom från pensionsförsäkring till private banking. Så har vi finansiella institutioner, och stora bolag och små bolag. Så vi har väldigt många olika delar av banken. Om man tänker att vi började **** så kan man ju tänka att det kanske inte fanns så många datorer på den tiden. Så att vi har ju genomgått en resa lite sådär löpande. Sen 1970-talet så har bankerna jobbat med digitalisering, man skapade det första internet där bankerna kunde kommunicera med varandra. Det senaste är väl kanske liksom tio år sedan, då började man inse att okej nu börjar våra kunde kommunicera mera med oss digitalt och då måste vi fortsätta förstå hur våra kunder mår och vad dom har för behov. Och om de kanske inte vill, framförallt på retail-sidan, inte träffa oss. Så då behöver vi förstå hur dom mår via de digitala kanalerna istället. Så det är lite kort om vår organisation. Min titel är Chief Data Scientist på organisationen. Min arbetsbeskrivning är att jag ska inspirera banken att bli mer datadriven. Det är gött! Så jag har åtta stycken data scientist där alla utom en är disputerade inom någon typ av beräkningsvetenskaper, antingen computer science, matematiker, eller astrofysiker, eller olika typer av människor som hanterat stora mängder data i som forskning. Och det tror jag har varit väldigt viktigt att få in liksom en central grupp som är lite för kompetenta egentligen för där vi befinner oss idag. För det är jätteviktigt att man kan etablera en, ett gott arbetssätt när det gäller maskininlärning och AI. För det är så lätt att man, om man inte är tillräckligt kompetent så är det lätt att man gör fel.	OC-TMS ODM-CS AI-C
3.	LE	Intressant. I din nuvarande roll då, vilka typer av beslut fattar du?	
4.	R5	Väldigt strategiska beslut. Kring vilka områden vi väljer att fokusera på när det gäller implementation av AI. Och jag har i mitt team så arbetar vi mycket med liksom i ett dataperspektiv är viktigast för banken. Det är inte jag som bestämmer det men det är jag som kommer med rekommendationer.	ODM TC-AD

5.	LE	Jag förstår. Om man ser på hela organisationen då, hur etablerat skulle du säga att det är att använda sig av någon form av IT stöd när man tar beslut?	
6.	R5	Nej men jag tror att alla använder någon form av IT stöd. Det kan vara så enkelt att man tittar på ett dokument i sin dator. Det är väldigt lite som tillåts bara vara magkänsla i dagens finansiella industri.	ODM-CS OC-DMO
7.	LE	Jag förstår. Om vi går in lite mer specifikt på AI då, när beslutade ni som organisation att införa det som ett ytterligare stöd vid er beslutsfattning?	
8.	R5	Ja tror fem år sen så började man titta på digitala assistenter för att kunna automatisera mycket av sånt där tråk-arbetsgöra. Så vi har en assistent på vår hemsida som är liksom är väldigt förenklad och inte kan ta, man kan inte be den digitala assistenten att göra någonting åt en. Men vi har också en intern version som kan liksom lösa upp konton och sånt. Och den kan ju ta beslut liksom, förvisso på det som människan säger, men det är ändå en viss grad av autonomt beslutsfattande. För att funka i vårt IT landskap så fick vi skapa ett anställnings ID åt den här digitala assistenten.	AI-C OC-TMS
9.	LE	Jag förstår. Men vad är det då för AI funktionaliteter som ni använder som stöd till beslutsfattning?	
10.	R5	Aa men det är maskininlärning för mestadels. Just i sådana fall där datamängden är så stor att människan inte kan mäkta med att ta in all information, då är det väldigt tacknämligt att använda sig av maskininlärning. Sen har vi ju, jag vet inte om ni har läst den där high level expert group inom EU, som har tagit fram etiska guidelines	AI-C TC-AD EC-EU
11.	LE	Aa men den har jag kikat lite på	

12.	R5	Ja för där är typ det första dom säger att, man ska aldrig låta AI vara ensam, utan man måste se till att det är en människa där vid besluten. Så vår approach till AI är väldigt mycket att det blir ett beslutsstöd, inte något som själv får ta beslut automatiskt, automatiserat.	AI-D AI
13.	LE	Jag förstår. Är det här något som ni har utvecklat själva eller har ni köpt in det från leverantör?	
14.	R5	Den digitala assistenten har vi köpt in från en extern leverantör, och sen har vi dom maskinlärningskomponenter som vi har ute i verksamheten, dom har vi utvecklat själva till en stor grad.	OC-PTC
15.	LE	Okej. Men då kommer jag in lite här på det teoretiska ramverket som vi använder oss av, där vi kollar på specifika faktorer som kan ha influerat er att implementera AI vi beslutsfattningen. Så den första faktorn vi studerar är direkta och indirekta fördelar som ni ser med AI. Så innan implementeringen ut av AI, vad för direkta och indirekta fördelar med den här tekniken inom beslutsprocessen, uppfattade ni som organisation?	
16.	R5	Jag tror det dels är effektivitetsfördelar, att maskinen kan göra saker mycket mer effektivt i vissa fall. Och sen också, just det här med att ibland är det just att den mänskliga intuitionen kan ibland va fel, och då är det väldigt bra att kunna stödja på data. Och sen också att, i och med att vi inte, alltså tittar man tillbaka i tiden så kom ju kunden i till banken och pratade med sin rådgivare. Och rådgivaren hade kanske fyra familjer och då är det klart att det är lätt att förstå hur dom mår och man kanske till och med umgås privat. Men i dagsläget så är det inte så, utan nu har man sina digitala kanaler och då, för att vi ska kunna fortsätta hålla kontakten, och fortsätta att vara mänskliga i den kontakten så behöver vi sålla igenom den data som genereras.	TC-PDI OC-DMO
17.	LE	Skulle du säga att dom här fördelarna du nämnde här, skulle du säga att de var viktiga vid erat beslut att implementera AI? Att ni förstod dom.	

18.	R5	Ja absolut.	TC-PDI
19.	LE	Då går vi vidare till nästa faktor här som är mängden data som ni hanterar. Till och börja med, hur hanterar ni och värderar ni data hos er idag?	
20.	R5	Vi har en policy som säger att information är en tillgång, och om det är en tillgång då måste man hantera det på ett annat sätt, för då blir det ett ytterligare slags värdepapper nästan. Det låter flummigt. Men vi har liksom sen den policyn togs så har vi skapat en ny del av organisationen som ska helt enkelt fokusera på att ta hand om data. Så det finns en Chief Data Officer, och hela vägen ner till gräsrotsnivå så finns det ansvariga i banken, och det är jätteviktigt.	TC-AD
21.	LE	Så innan ni implementerade AI då, hur hanterade ni data då?	
22.	R5	Jag skulle nog säga lite mera i silos. Och inte lika, det fanns liksom lokala governance modeller och lokala ansvariga för saker, men ibland kan det ju vara så att samma marknadsdata finns på många ställen, eller att samma kund finns på många olika delar av banken. Och då må vi kunna se helheten så är det viktigt att man har den här modellen där man har en lite mera toppstyrd governance modell.	TC-AD OC-DMO
23.	LE	Skulle du säga att ni har generat nya insikter med AI?	
24.	R5	Ja det skulle jag säga, ibland är det nya insikter som är självklara, men ibland kan det vara överraskande saker.	TC-AD
25.	ES	Vill du ge något exempel på en sådan typ av insikt? Det kan vara en av de självklara eller något nytt som ni har upptäckt till exempel.	

26.	R5	En självklarhet är väl att när vi tittade på swish transaktioner, och transaktionsmängder, så var det väldigt mycket aktivitet på fredagskvällar när man tittade. Ni vet när man sitter på restaurang med sina kompisar och så swishar man efteråt. Vi kallar det för fredagsmysinsikten.	TC-AD
27.	ES	Vilken en bra insikt!	
28.	LE	En liten avslutande fråga på den här mängden data då. Till vilken grad skulle du säga att mängden data och hanteringen av den influerade införandet av AI?	
29.	R5	Ja bra fråga, det beror ju på vad det är för typ av data. När det är text så behöver man inte ha särskilt mycket för att det ska vara väldigt kraftfullt. Men när det är transaktionsdata så kan det behövas miljontals rader för att det ska bli något som överhuvudtaget går att använda. Och det är också syftet som lite bestämmer vad man kan göra med olika datamängder. Är det liksom rakt ut på aktiemarknaden då vill man ju vara väldigt säker med vad man håller på med, men är det råd att nu ska du ringa din kund så kanske det inte gör något att man ringer lite för många gånger.	TC-AD OC-DMO
30.	LE	Nej intressant. Då går vi vidare på den organisationskontexten i det här ramverket, och börjar då med teknisk kompetens. Så innan implementeringen av AI, hur uppfattade du den tekniska kompetensen inom organisationen?	
31.	R5	Just inom AI eller?	
32.	LE	Nej jag tänker mer generellt inom organisationen, hur uppfattade du den tekniska kompetensen, eller förståelsen för tekniken?	
33.	R5	Ja, varierande.	OC-PTC

34.	LE	Ja det brukar vara ett svar vi får.	
35.	R5	Ja menar det är väl just det där att vissa delar är ju fortfarande väldigt, mänsklig kontakt, och andra delar är väldigt mycket mer digital.	OC-PTC
36.	LE	Ja, hur skulle du säga att den mänskliga kompetensen är hos ledningen eller managers hos er organisation?	
37.	R5	Ja det som är ganska coolt i vår organisation, det är att vår ordförande är otroligt insatt inom AI, jättebra för då är det liksom som att man har en sponsor från toppen. Ja ska säga att i verkställande ledningen så är det väldigt många som är väldigt kompetenta, så att man kan hamna i initierade diskussioner. Och det tycker jag är en stor skillnad mellan oss och andra institutioner som jag pratar med. Att det liksom går att ta initierade beslut på strategiska inriktningar på riktigt.	OC-PTC OC-TMS
38.	LE	Skulle du säga att det var en viktig faktor att dom var så pass tekniskt kompetenta, till att ni anskaffade AI?	
39.	R5	Absolut! Men jag tror att, det känns som att vi var några år innan våra konkurrenter. Och det känns som att det är helt och hållet därför att de förstod att det behövs liksom dels en Chief Data Scientist, men också att man behövde få in en central grupp som sen, så det vi siktar på att ha det heter en federerad modell. Så vi siktar på att ha ett litet gäng del centralt, och sen har vi ute i organisationen så har vi individer som är liksom AI kunniga. Sen har vi också skapat ett Community för dom som är AI kunniga, så att de kan träffas en gång i månaden och nörda.	OC-PTC EC-CP
40.	LE	Trevligt! Då kommer vi in på nästa faktor som är hinder i beslutsprocessen. Så innan ni implementerade AI då, uppfattade ni att det fanns några begränsningar eller hinder in eran beslutsprocess? Det kan till exempel vara brist på information, osäkerhet i informationen, eller intressekonflikter mellan olika parter och dylikt.	

41.	R5	Ja men jag tror att ett generellt råd till vilken organisation som helst som vill implementera AI, det är att börja med kulturen. För dom som ska använda de här nya verktygen som man skapar, det är ju människor, och för att dom ska ändra sitt beteende så krävs det ju mycket arbete. Både uppmuntran, arbete och att man ligger på dom.	OC-TMS OC-DMO
42.	LE	Men du uppfattade inte att du hade några problem med era beslutsprocesser innan ni implementerade AI? Som gjorde att ni införskaffade det.	
43.	R5	Nej det skulle jag inte säga, men däremot blir det liksom, för att få anställda för att använda de här verktygen så är det en resa varje gång man kommer in på ett nytt område. Och det, vissa människor kommer liksom aldrig sluta använda en papperskalender. Men det kanske det inte behöver heller.	OC-DMO
44.	LE	Men då kommer vi in på den sista faktorn inom den organisatoriska kontexten som handlar om top management support, som vi har varit inne på lite innan. Så innan implementeringen då, hur pass involverande var den högsta ledningen i införskaffandet av AI?	
45.	R5	Väldigt. Det var liksom, det var väldigt mycket den verkställande ledningen som beslöt att det här är det som vi behöver investera i.	OC-TMS
46.	LE	Hur visades det inom organisationen?	
47.	R5	Genom att man skapade en ny tjänst och en ny del i organisationen. Så det var liksom inte bara gräsrotsnivå uppåt, utan också väldigt mycket uppifrån, att vi ska ha en Chief Data Scientist.	OC-TMS
48.	LE	Satte dom någon vision kanske för hela projektet?	

49.	R5	Ja det gjorde dom. Alltså, det första AI verktygen var den digitala assistenten och då hade man liksom en känsla för hur mycket tid man kunde spara med en assistent som kunde svara på frågor, istället för en anställd. Men sen när det gäller mer hantverket AI, och inte bara att köpa verktyg utifrån, det är väldigt svårt att veta hur mycket vi kan både skapa nya affärer och liksom ta bort dåliga saker. Men hittills har vi bekostat oss själva, så det är skönt.	OC-TMS
50.	LE	Till vilken grad skulle du säga att högsta ledningen influerade valet att införskaffa AI?	
51.	R5	Till hög grad, mycket hög.	OC-TMS
52.	ES	Skulle du säga att det var detsamma när det gäller AI i beslutsfattning och inte enbart i att bli mer effektiva och liknande i era processer så att säga.	
53.	R5	Ja absolut, det skulle jag säga.	OC-TMS
54.	LE	Perfekt, då kommer jag in på den sista kontexten som handlar om den miljö eller industri som ni befinner er i. Så vi tänkte börja med att kolla er konkurrenssituation. Så innan implementeringen av AI, var ni medvetna om att era konkurrenter använde sig av AI i sin beslutsfattning?	
55.	R5	Ja dom globala bankerna är kanske fem år före oss.	EC-CP
56.	LE	Skulle du säga att ni blev påverkade av det att påskynda eran process då?	
57.	R5	Kanske inspirerade skulle jag säga.	EC-CP

58.	LE	Ser du AI som något som ger er konkurrensfördelar gentemot andra konkurrenter?	
59.	R5	Ja absolut.	EC-CP
60.	LE	Hur pass viktigt skulle du säga att det var, eller till vilken grad skulle du säga att ni påverkades av konkurrensen på marknaden att införa AI?	
61.	R5	Jag tror det beror på vilken typ av AI verktyg man pratar om. Digitala assistenten var nog en kombination av internt och liksom konkurrenssituationen. Resten tror jag liksom att det är så självklart att man ska göra så. Och där tror jag kanske att vi var lite snabbare än våra nordiska konkurrenter.	EC-CP
62.	ES	I beslutsfattningen då, gällande beslutsfattningen?	
63.	R5	Ja precis.	
64.	LE	Då kommer vi in på den sista faktorn här som handlar om osäkerheten i eran omgivning eller industri. Så innan ni implementerade AI då, ansåg ni organisation att ni var i en osäker miljö? Alltså att det var mycket ekonomiska svängningar, eller snabba förändringar i er industri.	
65.	ES	Man kan säga att ni befinner er i en dynamisk miljö, alltså det behöver ju inte vara jättestora, men att det ändå är lite förändring som sker. Så nu ser vi ju till exempel en jättestor såklart, med den här pandemin, men det kan vara att det är lite svängningar sådär.	
66.	R5	Jo men absolut. Det är en intressant industri att vara i, för det finns så många små bolag som försöker ta små bitar av kakan, och göra den delen väldigt väldigt väl. Och jag tror att vi försöker hitta de bästa och partnerna med.	EC-EU

67.	LE	Jag förstår. Vid beslutssituationer där det uppstår en hög osäkerhet, hur såg det beslutsprocessen ut innan ni implementerade AI?	
68.	R5	Ja den såg nog ganska lika dan ut. Det beror nog på vad det är för typ av beslut, är det hög marknadspåverkan så finns det ju liksom kommittéer där man tar sådana typer av beslut, för det är en bank. Är det låg grad så kanske man har fått liksom på sig ett riskmandat så man kan ta dom besluten själv.	EC-EU ODM
69.	LE	Jag förstår. Liten avslutningsfråga på det här då. Till vilken grad var osäkerheten en faktor som påverkade er att införa AI?	
70.	R5	Jo men i vissa delar så var det nog en hög faktor, skulle jag säga. Jo men främst de områdena där man inte kan läsa till sig tillräckligt med information, utan man behöver använda sig av maskininlärning för att få en bättre översikt och total bild.	EC-EU ODM-CS AI-C
71.	LE	Då är vi på den sista delen med lite avslutande frågor då, som är lite mer generella. Innan ni införde AI nu, vad har förändrats inom organisationen?	
72.	R5	Nej men jag tror att det är medvetandet av vikten av data har förändrats. Det har blivit väldigt mycket högre medvetande om det. Och sen, det som krävs att man ska göra god AI, det är ju liksom data och kompetens. Vi har även skapat ganska storskaliga utbildningsmöjligheter för våra anställda, så att alla ska kunna ta ett steg framåt inom just AI.	TC-AD OC-PTC
73.	LE	Skulle du säga att ni hanterar mer data idag än vad ni gjorde innan ni implementerade AI?	
74.	R5	Ja det skulle jag säga.	TC-AD

75.	LE	När om inte redan nu tror du att AI skulle uppfattas som en normalitet inom er organisation, och inte som någonting innovativt eller?	
76.	R5	Kanske om några år. För det är fortfarande som någonting som ses som någonting fancy i vissa delar. Och det är mycket hur man strategiskt får in AI-komponenter. Ja menar en sökmotor ser man som en självklarhet, men det är ju en typ av adaptivt lärande i den också.	AI
77.	LE	Jag förstår. Då tänkte jag för att avsluta lite grann, finns det några faktorer som vi har pratat om tidigare som du anser var mer inflytelserika än andra? Jag kan läsa upp faktorerna igen här så du får höra dom. Vi har pratat om de direkta och indirekta fördelarna av AI, mängden data, teknisk kompetens, vi har pratat om hinder i beslutsfattning, top management support, konkurrens, och osäkerhet i miljön. Så vilken av de här skulle du säga är mer inflytelserik än dom andra?	
78.	R5	Jag måste välja två. Top management support och tillgång till data.	OC-TMS TC-AD
79.	LE	I vilka beslutssituationer använder ni AI som ett komplement idag?	
80.	R5	Jag vet inte vilka jag får prata om. Men internt effektivitets fördelar, till viss del i realtids applikationer, och ganska mycket i textanalyssammanhang.	AI-C
81.	LE	Men då är vi klara med dom frågorna vi hade. Finns det något som du vill ta upp angående det här, som du tycker det är viktigt att vi får med oss?	

82.	R5	Ja men jag tror. Dels så tror jag att det inte bara är teknisk kompetens som behövs för att man ska liksom få en väl integrerad AI komponent i beslutsfattande. Utan jag tror att det är datakunskap bland anställda och generell kunskap om vad AI är. För det är lätt hänt att det blir något läskigt eller något som man har övertro på. Man får liksom balansera mellan dom två.	OC-PTC AI-C
83.	ES	Jag tänkte bara på en till fråga gällande komplement, hur man använder AI i beslutsfattning till exempel, hur ser du på ett partnerskap mellan AI och människa. Hur kompletterar människan och AI varandra?	
84.	R5	Precis, det tycker jag är en helt avgörande sak. Alltså, rekommendationen från den här expertgruppen är ju att ett AI ska aldrig vara ensamt. Det måste alltid finnas en människa med. Och det är hundra procent så vi tänker. Att liksom, det exemplet med assistenten, så kan man få be om att prata med en människa istället, då får man göra det. Men säg att vi skulle ha någon slags, säg att det skulle ingå någon maskininlärningskomponent i ett kreditbeslut till exempel, då ska man alltid ha möjligheten att eskalera och be om en second opinion från en människa. Och det är helt enkelt för att liksom, visst AI kan vara intelligent, men den baserar också beslut på den informationen som den har. Ibland kan det ju finnas information som inte finns i en dator, och då är det viktigt att det finns människor som känner ansvar för dom besluten.	AI-D ODM-CS
85.	LE	Intressant! Ja men då är vi nöjda, vi får tacka så mycket för du tog dig i tid och prata med oss.	
86.	R5	Absolut, ni får gärna skicka över uppsatsen när den är klar.	
87.	LE	Självklart. Det blir nog klar någon gång i juni, och då skickar vi över den direkt. Men då får du ha en trevlig kväll!	
88.	R5	Tack detsamma!	

89.	ES	Hejdå!	

Appendix G – Interview 6

ES=Erik Söderqvist (head interviewer)

LE=Ludwig Entzenberg (transcriber)

R6=Respondent

Section	Person	Text	Code
1.	ES	Alright. We can just start with you telling us a little bit about your current role and your previous history in the company and what company does basically?	
2.	R6	Yes. So the company is *********. What we do is while we collect company data by making data partnerships with global governmental registries, such as Bolagsverket. And then we have an R&D team size of 40 people that are specialised for collecting company data from different kind of sources from the Internet. Then we package data into a product which is currently the biggest product possession we have. It is a sale prospecting tool. But we also have other other products where we integrate the company data into CRMs and marketing automation systems. We are X years old company, actually now X people. We operate our main businesses in the Nordics. So we have offices in all the other Nordic countries. In addition, we have in the Netherlands an office and business there and a very small, small office in New York. Personally, I am one of the founders. The official title is the chairman of the board, but it is lacking in any of my daily work. What I do is I'm in charge of the clients and then selling our new solutions to bigger customers like tele operators and so. I'm running that team during my everyday, everyday work as well. I've met a lot of customers as well. So that's what I do more or less.	
3.	ES	So now we will go into the two first themes of the thesis, which is decisions, and then we move into AI. So first, in your role, what types of decisions do you make?	

4.	R6	Well, a lot of different decisions I would say since we are a Start-Up company. I make decisions on very small things. From, should we send this kind of product for that kind of email to a client, to very big business decisions in terms of should we take funding more or not? or Should we take a new strategy or not? So everything in between. I tend to make a lot of decisions during the day, like constantly. But yeah, I think everything in decision making from a single client to the company strategy because I am one of the owners. So that comes with that.	ODM
5.	ES	So it sounds like some of those decisions have quite huge impact as well	
6.	R6	Yeah. Yeah. It might be that they have an even bigger impact than we originally thought they would.	
7.	ES	But if we look at using a supportive tool in the decision making of your organisation, how established would you say that is?	
8.	R6	I mean, I think where we use decision making tools is mostly in the sales and in the data acquisition and sales and marketing. In data acquisition there's a lot of AI and machine learning, automated decision making in what to understand what is relevant data and what is not that data. Amount of data is so huge that it just cannot be done by humans. They need sales and marketing and it's a lot driven by data in terms of where should we contact them and why and which kind of companies should we focus on, and then where should our employees call next. That kind of is very much driven by data. But when it comes to like structure, this is, you know, management meeting kind of things that we don't have that much structuring.	ODM-CS AI-C
9.	ES	I understand. So if we move into AI. When did your organisation decide to adopt an AI to assist in the organisational decision making?	

10.	R6	When it comes to things like today, the tech R&D, I would say they want it all along because that is what we are all about. I think with ML and AI and NLP and all these things, we are each part of the company to challenge the status quo of a typical company's data. Provided that is the data integrator and then that information provider and not a tech company as such. So we had AI from day one. Then, of course, in marketing and sales, we've had it from the very beginning as well, because we like a lot of data.	AI-C
11.	ES	So if you just ensure, we've touched upon it before, but if you just in short describe the current AI capabilities that assist you in the decision making?	
12.	R6	Yeah, well, when it comes to again, the data acquisition is I mean, there's a lot of elements where AI supporting like the decision making on whether instead of classification of the data, for example. So once we harness huge amounts of data, we index like I don't know how many millions of Websites, millions of content pieces per day but a huge amount. Then we would have like classification models that are developed by, like through our data and AI and it asks certain questions "is this, for example, an address or not?" And then if that sort of value or verification is high enough, that this company sees that that is actually an address to the company, then the AI makes the decisions for itself that, yes, this content is about address and then it collects into our database. If it's not that sure that the computer doesn't give like a 90 percent probability that it's an address. In this case, it goes to what we call human assisted AI. These like a crowdsourced crowd intelligence that are around the world, that there are people verifies if it is or not. If the address is correct then that piece of data contribute to the classification model. That's how we use AI in our everyday decision making when it comes to data acquisition. Now, when it comes to sales and marketing and AI as such. I mean, you don't need a you don't need AI-models to understand what the target group is and what is not.	AI-C ODM-CS

13.	ES	Yeah, I understand. Now we will move into the framework that we use in this thesis. It's called TOE. So we will kind of ask questions from the technological context, organisational context and the environmental context. And then we have identified certain factors that we will ask about and how these affect or influence you as an organisation to adopt AI in the decision making. So that's the overall structure of it. So the first factor is the perceived direct and indirect benefits. So prior to the adoption, what were the perceived direct and indirect benefits of AI in decision making?	
14.	R6	Well, I mean, of course, we can harness a lot of data and much more data than without. So that's that's obviously the more data we have, the more powerful we are as a business because this data business. So I guess in that sense. And then when it comes to like using data in general in business decision making. I think there I mean once you get the formula right, you know which works and which not, you have confidence on scaling. So specifically in the beginning when we saw a certain factor and in terms of which numbers, you know, correlate data on how much sales it was, it was very easy to scale it very heavily because, you know, the maths added up. So I guess that's the benefits. And I guess what's not the benefit of this case is the lack of innovation. I mean, when data is dictating what you do, then there's not enough room or that much space for, you know, making crazy decisions or innovative decisions, which in the end are the most important situations in a company, if you want to be, you know, innovative and entrepreneurial and really challenge the current situation. So that's the lack of it I would say.	TC-PDI TC-AD
15.	ES	So you follow the data. You're very data driven?	
16.	R6	Yes. We are really data-driven.	ODM-CS TC-AD

17.	ES	Yes. So to what extent would you say that those understood benefits that you had influence the adoption of AI in decision-making?	
18.	R6	I mean, of course, a lot. I mean, when you see something working at any venue, you want to scale it in the organisation. So, of course, if there's benefits, then we start working on it immediately.	TC-PDI
19.	ES	So the next factor in the technological context is the amount of data. So how do you value and manage data?	
20.	R6	Yeah. That could be a whole other topic. When it comes to managing the company data, like that IP that we have, the data set. It's a whole nother world. I cannot be very exact. Even if I would like to. I don't know that concrete like just know the basics in terms of how to manage a huge data sets. But I don't know if that's relevant for this. When it comes to running business. I think we are fairly good at understanding. So we have we've collected all the data, the relevant data into one database where you can include everything from you know, everything from company data that binder provides the internal data to marketing data. And mashing those up, it gives us a good visibility in the decision making. So I think that we are pretty good, actually.	TC-AD
21.	ES	So here we had some questions about how you did make sense of that data before the adoption. But instead, since you had AI from the beginning. How has that like, how has those capabilities evolved, have you implemented the new capabilities over time?	

22.	R6	Yeah. I mean I think the whole AI, all these things. I mean, since we have started, it's evolved drastically, of course, because during the X years, so i think looking X[1] years ago, we didn't have a clue what we are using now. Now we don't have any idea what we're going to use in two years. Mathematical models of course like, you know, you talk about, BS and all these things that the maths maths won't change in the coming years. It's something that's been invented in the 18th century if you know all the typical, typical logics behind AI. But when they get more data and more classic gadgets and such that then we use more complex models, of course, to be more accurate	AI-C TC-AD
23.	ES	So would you say that you discovered new insights with AI and the new implementation of its new capabilities and such?	
24.	R6	Yeah, I mean, of course, in the data. Obviously, you know, we have totally different technologies now than we had like three years ago. So yeah.	TC-AD
25.	ES	Alright. To what degree did the amount of and management of data influence the adoption of AI?Perhaps if we look at in your case, the new capabilities that you've implemented after the start of the organization so to say.	
26.	R6	I mean, if we are talking about the data collection and such. I mean that's the very core of it. I would say that the more we understand from the past, the more confident we can be about the future in terms of what kind of models we develop. And when it comes to collecting the company data, the positive thing about it is that so much about it. So the more varied data to be worked on, the more confident decisions you can make about the future. That's my guess. Business models from Amazon, Google and Facebook. They have so much data. They are very confident in doing the next bold moves. The company data on understanding more about that. That's I guess that's our advantage from the business side. We don't have that much.	TC-AD

27.	ES	So now we will move forward into the organisational context and we're still a bit technical here. So prior to the adoption or from the start. How would you perceive the technical competence within the company?	
28.	R6	Yeah, I would say it's high. It's very high tech specifically in the R&D and engineering team, obviously. I mean, you know, they wouldn't be here if it wasn't high. But I would say in the commercial part, I don't say it's not good, but it's not definitely high. I think it's fair to say like better in terms of like technical understanding, because I feel that that's where we all need to evolve, too. It's the whole group, whole organisational thing. And we have a commercial background. I need to understand how these things work. If I want to be successful in the future.	OC-PTC OC-TMS
29.	ES	So we only look at the management technical competence. How would you perceive it? Is it high or is it low?	
30.	R6	It's both. Because we have that engineering management, obviously very high. Then there is sales management. I mean, good compared to an average person, but not definitely high. The sales management sometimes have to use the terminal to write some code and some of them have no clue what to do.	OC-PTC
31.	ES	So how would you say that the technical competence influenced the new adoption? Is the whole management on board or is it driven by the more tech savvy parts so to say?	
32.	R6	I think everybody is on board. I mean, because that's what we want to disrupt the current industry like the old players, with our technology. So that's what we just need to do if we want to be better. Then the whole management needs to be on board.	OC-PTC OC-TMS

33.	ES	Has it at any point been a barrier that there is a lack of technical competence within management or the organisation?	
34.	R6	I mean yeah there have been a lot of discussions within us founders and they are always full of ideas and in engineering at least you might sometimes be like that you don't need people to drive the business at all. It can be self-going and make systems themselves. The whole company and then of course, and us commercial people think a lot more on other parts. Sometimes too much from the other side and vice versa. You need people from both sides, typically a discussion and then we end up in the middle.	OC-PTC ODM-CS
35.	ES	It's interesting to hear. So the next factor is decision making obstacles. And these can be basically that you have lack of information, that there's uncertainty in the information or that there is equivocality so you need to negotiate between different interests in the organisation. This is just examples of decision making obstacles. So prior to the adoption. How did you perceive? Did the decision making obstacles influence that choice, basically.	
36.	R6	I mean, not again, not much, because all these things are done in the R&D, mostly. So there is no friction in terms of what how those should be taken and what is the level of understanding on those. When it comes to like running the business as such and AI stuff, we don't have much examples off of, you know, being very AI driven. You know, we had this one test that I ran in our work. Practically an AI is telling where to call and why, make people a bit machines. It was not adopted too well. So I guess in that sense, there's been some obstacles there.	OC-DMO
37.	ES	But would you say that there are decision making obstacles that exist in the organisation?	

38.	R6	No I wouldn't say decision making obstacles rather adoption challenges. AI and tech per say is not a problem. I mean, we are such a lean organisation and we can make decisions very fast. Then the other thing is how to get people behind it. And that's that's in my opinion the bigger challenge. I think that the decision making obstacles are small.	OC-DMO
39.	ES	So the next one is the top management support and seeing how you had AI from the beginning, I guess that they were quite involved in the adoption process of AI?	
40.	R6	Yeah. Yeah. I guess if you define top management as the founders, then I would say this. It is a 100 percent thing.	OC-TMS
41.	ES	And how was that shown? I mean if we look at it from the beginning, it was only the founders. But then when you implemented new way AI capabilities, how do you show the support? How did the top management show support for the implementation?	
42.	R6	Well, I mean, if you look in a bit broader perspective in terms of how do we show support in terms of making sure that those are implemented and supported? We have again, quite a lot of freedom to R&D and tech. So today, for example, have had their own office. They have been given the opportunity to basically do what they want even with their own deadlines as well. But if you look from a commercial perspective? But then the way these models and the way they work with the products and it's not the same in sales and marketing in terms of having like calls and sales things like that.	OC-TMS OC-PTC
43.	ES	So to what degree would you say that the top management support influenced a new adoption of a new capability in AI?	

44.	R6	I think one hundred percent. I think so because of the obvious reasons. The CTO for example, he has 100 percent support for the decisions he makes. So of course support him in his decisions and that has influenced the adoption.	OC-TMS
45.	ES	So that was that was it from the organisational context. We will now move forward to the environmental context. So things happening outside the organisation basically. First one is competitive pressure. So prior to adoption or from your start basically, were you aware of any of your competitors using AI decision making?	
46.	R6	No, I mean, yes, we were aware and the answer is no, I think we are the ones that want to challenge the status quo. When there's more competition, but I like the bigger of our competitors have been around for decades and they've been very profitable and they have no pressure on changing. They just collect money practically.	EC-CP
47.	ES	So did you see it as a competitive advantage?	
48.	R6	Yeah, yeah, definitely. Now the bigger players are starting gradually to evolve the direction of where we already are. I think it's a good thing because it takes time.	EC-CP
49.	ES	So to what degree would you say that the competitive pressure influenced the adoption?	
50.	R6	I don't, I think zero.	EC-CP
51.	ES	So you were more seen as an disruptor?	
52.	R6	Yeah, I would say.	

53.	ES	And then the next factor is environmental uncertainty. And this is just basically the dynamics in the environment around you. So it can be little economical movements or any rapid technological changes or government regulation or anything like that, basically. So prior to adoption, did you consider your organisation to be in an uncertain environment?	
54.	R6	I mean, yes and no. I think in terms of looking at the customer need, I think that will never change. The company always needs company data to understand about their business. And that's a fact that I think never will change because it's such a fundamental aspect of marketing and sales. It's a very fundamental aspect of a company's life, that they need to understand their customers. But the challenge I would say is rather in the legislative side. Very much, you know collecting data is a very, there's a lot of legislation that is up in the air and hasn't you know, that has not been verified by parts. Is this way the right way or that way the right way? I think like the GDPR was the first one, it doesn't really affect us that much. But then there is this copyright about single digital market acts in the EU that left a lot of space for like judgements, which is right and which is wrong. And that, of course we follow it thoroughly so that we are a hundred percent doing things the right way. But you never know what would happen and there we try to think, so we tried to make decisions that won't affect our business in the future.	EC-EU OC-DMO ODM
55.	ES	So if we look at decisions that's quite unstructured that they are perhaps new and ambiguous to you, how do you take such a decision? How does that process look basically?	

56.	R6	Well, I mean, that's something that has nothing to do with data I would say. I mean, in some sense, some context, data we see which customer segments before which buy more and which are the happiest. Of course, that's data driven decision making where we then decide to focus on certain customer segments. But then when you look at where the world is going kind of thing, that's where the world is in five years, 10 years. That's sort of a leap of faith. You just need to take advantage of being a team to believe in it. And that had nothing to do with data, actually. And that's exactly what I've told before. When you're data driven the fact that, you know, there's less room for innovation and leaps of faith. And I guess that's crucial. You need to if you want to grow the company.	OC-DMO ODM
57.	ES	So is it if you take this leap, is it a discussion among the board members or how does that look?	
58.	R6	So it's a lot to do with the owners of the company, you know, whether they believe how they want to run the company or not only how they want to run the company, where do they want to take the company, I guess that's pretty much a shareholder or board meeting issue. And that's sort of done in that, you know, between the founders. Of course we'll obviously listen and look at our employees and outside them. It's not only our internal ideas, but the business as a whole.	ODM
59.	ES	So to what degree do you consider these environmental uncertainties as influential in the adoption of AI decision making?	
60.	R6	I mean, again, look, the only reason to say yes is the legislative issues. So, I mean, for example, data mining is crucial. Data mining is a very crucial aspect of AI and machine learning that's driven models. And there's legislative discussions or the single market that is defining what is acceptable data mining and what is not. And then what there comes the verification, how it's defined, then that will obviously affect a lot. But I think there's black	EC-EU

		business perspective. External issues don't matter that much.	
61.	ES	So that was the whole framework, basically. So now we'll move into a wrap up session. Broad questions basically so you can speak freely and ask us anything if you want to. But after the adoption what has changed after the implementation of A.I. in the organisation? Now, we've just been in the organisation from the start. But if we look at the implementation of a new AI-capability in decision making?	
62.	R6	I mean that well, we did this one, which I think still think it's a cool thing, is that we designed a product data driven product, an internal product that practically tells every person that works what to do and why. So it practically takes, I mean, tons of sales. But does it take the decision making away from employees? Looking at it from the company perspective, life as such, it's a good thing. If you look at from the paper, it's a very AI-driven, you know, tool that tells you to call here to this person, say these arguments and if they say no and then say this, you know, identically. If you did close the deal or are meeting or not, then that data goes back to the database. I mean, it gives us better leads. It sounds good, but what it takes to get that side. I would say of the brains away from the employees, which then is not necessarily a good thing. It's people start to find a lot of excuses why things don't work, because then they can have an extra reason that the product that, you know, this system gives me a wrong leads, which might not be the case, but it's just because the decision making is taken away. They don't, it affects their behaviour, which then it affect your performance in the organisation. I think it is a good reflection of what is not so good about AI in the decision making.	ODM-CS

63.	ES	It's interesting. So would you say that the organisation managed more data today than prior to the adoption? I mean, you have grown as a company, but if we specifically after implementation, new capabilities. Do you manage data?	
64.	R6	I think we manage a much, much more data, but we're not driven. We're sort of in that, we have a new strategy that we are implementing. And it's not very much like I mean, the execution of it's not that much set in stone that the sales prospect thing was four [2] years ago. It was very data driven. You know, you do get person on board, then they do this and this and then they start to be profitable and off it goes. It was very data driven and a lot of participation in management was very much data driven. Here we have more and more data, obviously, because we've collected the decision making is not that much based on data. It's more based the vision of where we want to go and these kind of things. which then also affects the results. We're not performing as well as we were four years ago. But still.	TC-AD OC-TMS
65.	ES	So when it's not already know, who do you think your organisation will consider to be normal and not something that it's new and innovative?	
66.	R6	Yeah. I mean, my dream would be that it would be a company that would be like self-driven by data. That we could find a model in place where the company would be autonomous. And then people who would work for our company would be people that sort of would contribute to that model. So that would be my dream. I don't know if that will ever happen with any company.	TC-AD ODM-CS
67.	ES	We will have to see what the future holds. But what would you say that the staff of the organisation and its members, do they consider AI to be normal today? Since it has been with you since the start?	

68.	R6	Yeah. I mean, I guess a lot of things people don't even think about where AI is being used. You know, I mean, in very various aspects of collecting the data and doing certain decisions, things like this, it's not something that we have a robot telling to do that it's just something that we are a lot of automation, some things that our company run on. People don't even realise that is there. Oh, yeah, definitely I think this is a common thing.	
69.	ES	So now I will go through all of the factors that we've talked about today. And if you just can reflect upon which of these do you think is most were more influential than others from your perspective, basically. So what we've talked about is the perceived direct and indirect benefits prior to the adoption. The amount of data, the technical competence of the organisation, decision making obstacles, top management support, competitive pressure, environmental uncertainty. Yeah, those were all of them.	
70.	R6	All right.	
71.	ES	And so. So which of these do you think is most influential? You can name a few or if you have any that perhaps stick out?	
72.	R6	Yep. Well, I think the competitive advantage for us is the most influential. Not the operation thing as such, I would say in that way of how we actually create our product. So that is definitely a competitive advantage, something that our competition really does not have. So I think the number one thing definitely.	EC-CP

73.	ES	So if we look at the decision making situations and where AI is kind of complemented by a human. Can you please just reflect on how do you see that partnership coming? What kind of types of situations or decisions are these suitable to play a part?	
74.	R6	I think the best combination is exactly that. So a lot of, I think a good example of how this works is that of course when you've got a lot of data in and then you have the classification models and that are training data sets actually that is where web classification models come from. And then, then the classification score gives sort of underscore how likely it is that it's known, it is something you're looking for. I mean, if it's high enough, the score, then it's whole automated and up then that answer is contributing to the training data set, then it becomes better and better. If it's uncertain if the score is like 50 or 70. Then it goes up to almost like a human pool. The human pool can be very global. Like Amazon's global pool of people who sort of make the decisions. Or then it can go to our internal people that make the decision is this actually what we're looking for and they know the answer. Of course, humans know the assets the best. And then when they answer that, yes or no. Then again, that master calls that AI-model, the training data set and it gets better. And this loop is done when it comes to company data thousands of times per day, even more like, you know, it can be hundreds of thousands of times. Not quite. I would say well, thousands of times per day, I would say is the correct answer at this point. But it always gets better and better and better when the model becomes better and better and better. A human is needed less and less and less to make those decisions. But still, there are more and more complicated stuff coming in. There's so much complicated stuff in running the organisation that the decision making by humans will never fade away. But I guess that's bred combinations. The repetitive work will increasingly be done by computers. Now, that's what we want. But I think there will never be a computer looking to be a beauty stand Stand-Up comedian, for example, or a good sales person, you know all or even that I understand the human interaction. So that job will always be done by humans.	ODM-CS AI-C

75.	ES	Mm hmm. Do you have the capability of AI today to deliver several alternatives of an answer or a question that you posed to it?	
76.	R6	Yeah, I mean, yeah. Oh, yeah, we can. So there's like the model I described, I guess that's difficult machine learning. But then there's like I don't know very, very well. But then also on unsupervised learning kind of things that. So that the computer is sort of doing its own unsupervised like answers. I didn't know how we use that. So we're doing some summaries in some way. But I guess in those situations, it's a bit more free the way the computer makes their decisions.	AI-C
77.	ES	Yeah. So do you have anything else regarding adoption of AI or decision making that you want to bring up or?	
78.	R6	No, I think. No, not much. I think that was pretty well summed up everything. You know, I think it's something that will come up and every company will need to adopt to it. And I think also by not so that the. You know, engineering and tech departments will take over the whole company, I think it's the other way, other way around that no commercial people like us need to understand more about, you know, how to work with data and AI and engineering. But I'm like, you know, like the car companies. I mean, it's really something that the CEO needs to know how to drive a car. He cannot say that I do not know how to drive a car but just make cool looking cars.	OC-TMS OC-PTC
79.	ES	Yeah. All right. But that is everything we had for this session. And we, as I said before, were truly grateful that you participated. And this was rewarding for us. And we will continue to write our thesis. And in the middle of June, I think it will be finished. So then you are welcome to read it.	

80.	R6	Ok perfect, looking forward to it! Bye bye!	
81.	ES	Bye!	

References

Acs, Z. J. & Audretsch, D. B. (1987).Innovation, Market Structure, and Firm Size, *The review of Economics and Statistics,* vol. no. 567-574

Ajzen, I. (1985). From Intentions to Actions: A Theory of Planned Behavior. *Action Control.* Springer pp 11-39.

Ajzen, I. (1991).The Theory of Planned Behavior, *Organizational behavior and human decision processes,* vol. 50, no. 2**,** pp 179-211

Alshamaila, Y., Papagiannidis, S. & Li, F. (2013).Cloud Computing Adoption by Smes in the North East of England: A Multi-Perspective Framework, *Journal of enterprise information management,* vol. 26, no. 3**,** pp 250-275

Alter, A. L., Oppenheimer, D. M., Epley, N. & Eyre, R. N. (2007).Overcoming Intuition: Metacognitive Difficulty Activates Analytic Reasoning, *Journal of Experimental Psychology: General,* vol. 136, no. 4**,** pp 569

Arnott, D. & Pervan, G. (2008).Eight Key Issues for the Decision Support Systems Discipline, *Decision Support Systems,* vol. 44, no. 3**,** pp 657-672

Baker, J. (2012). The Technology–Organization–Environment Framework. *Information Systems Theory.* Springer pp 231-245.

Banko, M. & Brill, E. (2001). Scaling to Very Very Large Corpora for Natural Language Disambiguation. *Proceedings of the 39th annual meeting on association for computational linguistics.* Association for Computational Linguistics.

Benbasat, I. & Barki, H. (2007).Quo Vadis Tam?, *Journal of the association for information systems,* vol. 8, no. 4**,** pp 7

Bhattacherjee, A. (2012). Social Science Research : Principles, Methods, and Practices, 2. ed.: A. Bhattacherjee.

Black, N. J., Lockett, A., Winklhofer, H. & Ennew, C. (2001).The Adoption of Internet Financial Services: A Qualitative Study, *International Journal of Retail & Distribution Management,* vol. no.

Bonczek, R. H., Holsapple, C. W. & Whinston, A. B. (1979).Computer‐Based Support of Organizational Decision Making, *Decision Sciences,* vol. 10, no. 2**,** pp 268-291

Bonczek, R. H., Holsapple, C. W. & Whinston, A. B. (1980a).The Evolving Roles of Models in Decision Support Systems, *Decision Sciences,* vol. 11, no. 2**,** pp 337-356

Bonczek, R. H., Holsapple, C. W. & Whinston, A. B. (1980b).Future Directions for Developing Decision Support Systems, *Decision Sciences,* vol. 11, no. 4**,** pp 616-631

Booth, W. C., Booth, W. C., Colomb, G. G., Colomb, G. G., Williams, J. M. & Williams, J. M. (2003). The Craft of Research: University of Chicago press.

Borgman, H. P., Bahli, B., Heier, H. & Schewski, F. (2013). Cloudrise: Exploring Cloud Computing Adoption and Governance with the Toe Framework. *46th Hawaii international conference on system sciences.* IEEE.

Brinkmann, S. & Kvale, S. (2005).Confronting the Ethics of Qualitative Research, *Journal of constructivist psychology,* vol. 18, no. 2**,** pp 157-181

Brynjolfsson, E. & Mcafee, A. (2017).The Business of Artificial Intelligence, *Harvard Business Review,* vol. no. 1-20

Burgess, A. (2018). The Executive Guide to Artificial Intelligence. [Elektronisk Resurs] : How to Identify and Implement Applications for Ai in Your Organization, 1st ed. 2018.: Springer International Publishing.

Cambridge Dictionary. (2020a). Decision. *decision.* dictionary.cambridge.org.

Cambridge Dictionary. (2020b). Decision-Making. *decision-making.* dictionary.cambridge.org.

Chan, S. C. & Ngai, E. W. (2007).A Qualitative Study of Information Technology Adoption: How Ten Organizations Adopted Web‐Based Training, *Information Systems Journal,* vol. 17, no. 3**,** pp 289-315

Chau, P. Y. & Tam, K. Y. (1997).Factors Affecting the Adoption of Open Systems: An Exploratory Study, *MIS quarterly,* vol. no. 1-24

Choo, C. W. (1991).Towards an Information Model of Organizations, *The Canadian Journal of Information Science,* vol. 16, no. 3**,** pp 32-62

Clark, T. D., Jones, M. C. & Armstrong, C. P. (2007).The Dynamic Structure of Management Support Systems: Theory Development, Research Focus, and Direction, *Mis Quarterly,* vol. 31, no. 3**,** pp 579-615

Cohen, M. D., March, J. G. & Olsen, J. P. (1972).A Garbage Can Model of Organizational Choice, *Administrative science quarterly,* vol. no. 1-25

Collins, P. D., Hage, J. & Hull, F. M. (1988).Organizational and Technological Predictors of Change in Automaticity, *Academy of Management Journal,* vol. 31, no. 3**,** pp 512-543

Cragg, P. B. & King, M. (1993).Spreadsheet Modelling Abuse: An Opportunity for Or?, *Journal of the Operational Research Society,* vol. 44, no. 8**,** pp 743-752

Creswell, J. W. & Creswell, J. D. (2017). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches: Sage publications.

Criminisi, A., Pérez, P. & Toyama, K. (2004).Region Filling and Object Removal by Exemplar-Based Image Inpainting, *IEEE Transactions on image processing,* vol. 13, no. 9**,** pp 1200-1212

Crook, C. W. & Kumar, R. L. (1998).Electronic Data Interchange: A Multi-Industry Investigation Using Grounded Theory, *Information & Management,* vol. 34, no. 2**,** pp 75-89

Cyert, R. M. & March, J. G. (1963).A Behavioral Theory of the Firm, *Englewood Cliffs, NJ,* vol. 2, no. 4**,** pp 169-187

Cyert, R. M., Simon, H. A. & Trow, D. B. (1956).Observation of a Business Decision, *The Journal of Business,* vol. 29, no. 4**,** pp 237-248

Daft, R. L. & Lengel, R. H. (1986).Organizational Information Requirements, Media Richness and Structural Design, *Management science,* vol. 32, no. 5**,** pp 554-571

Daft, R. L. & Macintosh, N. B. (1981).A Tentative Exploration into the Amount and Equivocality of Information Processing in Organizational Work Units, *Administrative science quarterly,* vol. no. 207-224

Daft, R. L., Murphy, J. & Willmott, H. (2017). Organization Theory & Design : An International Persepective, 3. ed.: Cengage Learning EMEA.

Dane, E. & Pratt, M. G. (2007).Exploring Intuition and Its Role in Managerial Decision Making, *Academy of management review,* vol. 32, no. 1**,** pp 33-54

Dane, E., Rockmann, K. W. & Pratt, M. G. (2012).When Should I Trust My Gut? Linking Domain Expertise to Intuitive Decision-Making Effectiveness, *Organizational behavior and human decision processes,* vol. 119, no. 2**,** pp 187-194

Davenport, T. H. & Harris, J. G. (2007a).The Architecture of Business Intelligence, *Competing on analytics: The new science of winning,* vol. no.

Davenport, T. H. & Harris, J. G. (2007b). Competing on Analytics: The New Science of Winning. Harvard Business School Press.

Davis, F. D. (1985). A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results. Massachusetts Institute of Technology 1985].

Davis, F. D. (1989).Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, *MIS quarterly,* vol. no. 319-340

Davis, F. D., Bagozzi, R. P. & Warshaw, P. R. (1989).User Acceptance of Computer Technology: A Comparison of Two Theoretical Models, *Management science,* vol. 35, no. 8**,** pp 982-1003

Davis, F. D. & Kottemann, J. E. (1994).User Perceptions of Decision Support Effectiveness: Two Production Planning Experiments, *Decision Sciences,* vol. 25, no. 1**,** pp 57-76

Dietvorst, B. J., Simmons, J. P. & Massey, C. (2015).Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err, *Journal of Experimental Psychology: General,* vol. 144, no. 1**,** pp 114-126

Duan, Y., Edwards, J. S. & Dwivedi, Y. K. (2019).Artificial Intelligence for Decision Making in the Era of Big Data – Evolution, Challenges and Research Agenda, *International Journal of Information Management,* vol. 48, no. 63-71

Duncan, R. B. (1972).Characteristics of Organizational Environments and Perceived Environmental Uncertainty, *Administrative science quarterly,* vol. no. 313-327

Dwivedi, Y. K., Papazafeiropoulo, A., Ramdani, B., Kawalek, P. & Lorenzo, O. (2009).Predicting Smes' Adoption of Enterprise Systems, *Journal of enterprise information management,* vol. no.

Eisenhardt, K. M. & Zbaracki, M. J. (1992).Strategic Decision Making, *Strategic management journal,* vol. 13, no. S2**,** pp 17-37

Entzenberg, L. & Söderqvist, E. (2019).Organisationers Arbete Med Nyutexaminerade Systemvetare-Utvecklingsprogrammens Betydelse, vol. no.

Fisher, S. L. & Howell, A. W. (2004).Beyond User Acceptance: An Examination of Employee Reactions to Information Technology Systems, *Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in alliance with the Society of Human Resources Management,* vol. 43, no. 2 ‐ 3**,** pp 243-258

Gaines-Ross, L. (2016).What Do People–Not Techies, Not Companies–Think About Artificial Intelligence, *Harvard Business Review,* vol. 24, no.

Galbraith, J. (1973). Designing Complex Organizations: Addison-Wesley.

Gangwar, H., Date, H. & Raoot, A. D. (2014).Review on It Adoption: Insights from Recent Technologies, *Journal of Enterprise Information Management,* vol. 27, no. 4**,** pp 488-502

George, G., Haas, M. R. & Pentland, A. (2014).From the Editors: Big Data and Management, *The Academy of Management Journal,* vol. 57, no. 2**,** pp 321-326

Giboney, J. S., Brown, S. A., Lowry, P. B. & Nunamaker Jr, J. F. (2015).User Acceptance of Knowledge-Based System Recommendations: Explanations, Arguments, and Fit, *Decision Support Systems,* vol. 72, no. 1-10

Gill, S. (1995).Globalisation, Market Civilisation, and Disciplinary Neoliberalism, *Millennium,* vol. 24, no. 3**,** pp 399-423

Goodhue, D. L., Klein, B. D. & March, S. T. (2000).User Evaluations of Is as Surrogates for Objective Performance, *Information & Management*, vol. 38, no. 2**,** pp 87-101

Goul, M., Henderson, J. C. & Tonge, F. M. (1992).The Emergence of Artificial Intelligence as a Reference Discipline for Decision Support Systems Research, *Decision Sciences,* vol. 23, no. 6**,** pp 1263-1276

Grover, V. (1993).An Empirically Derived Model for the Adoption of Customer ‐ Based Interorganizational Systems, *Decision sciences,* vol. 24, no. 3**,** pp 603-640

Gummesson, E. (2003).All Research Is Interpretive!, *Journal of business & industrial marketing,* vol. no.

Harrell, E. (2016).Managers Shouldn't Fear Algorithm-Based Decision Making, *Harvard Business Review,* vol. no.

Hayashi, A. M. (2001).When to Trust Your Gut, *Harvard Business Review,* vol. 79, no. 2**,** pp 59-65

Hess, T. J., Rees, L. P. & Rakes, T. R. (2000).Using Autonomous Software Agents to Create the Next Generation of Decision Support Systems, *Decision Sciences,* vol. 31, no. 1**,** pp 1-31

Hilbert, M. & López, P. (2011).The World's Technological Capacity to Store, Communicate, and Compute Information, *science,* vol. 332, no. 6025**,** pp 60-65

Hoffman, R. (2016).Using Artificial Intelligence to Set Information Free, *MIT Sloan Management Review,* vol. 58, no. 1**,** pp 20

Hossain, M. A. & Quaddus, M. (2011).The Adoption and Continued Usage Intention of Rfid: An Integrated Framework, *Information Technology & People,* vol. 24, no. 3**,** pp 236-256

Hsieh, H.-F. & Shannon, S. E. (2005).Three Approaches to Qualitative Content Analysis, *Qualitative health research,* vol. 15, no. 9**,** pp 1277-1288

Iacovou, C. L., Benbasat, I. & Dexter, A. S. (1995).Electronic Data Interchange and Small Organizations: Adoption and Impact of Technology, *MIS quarterly,* vol. no. 465-485

Jarrahi, M. H. (2018).Artificial Intelligence and the Future of Work: Human-Ai Symbiosis in Organizational Decision Making, *Business Horizons,* vol. 61, no. 4**,** pp 577-586

Kahneman, D., Rosenfield, A., Gandhi, L. & Blaser, T. (2016).Noise, *Inconsistent Decision-making. HBR,* vol. no. 38-46

Karahanna, E., Straub, D. W. & Chervany, N. L. (1999).Information Technology Adoption across Time: A Cross-Sectional Comparison of Pre-Adoption and Post-Adoption Beliefs, *MIS quarterly,* vol. no. 183-213

Keding, C. (2020).Understanding the Interplay of Artificial Intelligence and Strategic Management: Four Decades of Research in Review, *Management Review Quarterly,* vol. no.

Keen, P. G. (1981).Value Analysis: Justifying Decision Support Systems, *MIS quarterly,* vol. no. 1-15

Khasawneh, A. M. (2008).Concepts and Measurements of Innovativeness: The Case of Information and Communication Technologies, *International Journal of Arab Culture, Management and Sustainable Development,* vol. 1, no. 1**,** pp 23-33

Kimberly, J. R. (1976).Organizational Size and the Structuralist Perspective: A Review, Critique, and Proposal, *Administrative Science Quarterly,* vol. no. 571-597

King, J. L. & Grudin, J. (2016).Will Computers Put Us out of Work?, *Computer,* vol. 49, no. 5**,** pp 82-85

Klein, H. K. & Myers, M. D. (1999).A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems, *MIS quarterly,* vol. no. 67-93

Kottemann, J. E., Davis, F. D. & Remus, W. E. (1994).Computer-Assisted Decision Making: Performance, Beliefs, and the Illusion of Control, *Organizational Behavior and Human Decision Processes,* vol. 57, no. 1**,** pp 26-37

Kuan, K. K. & Chau, P. Y. (2001).A Perception-Based Model for Edi Adoption in Small Businesses Using a Technology–Organization–Environment Framework, *Information & management,* vol. 38, no. 8**,** pp 507-521

Kurnia, S., Karnali, R. J. & Rahim, M. M. (2015).A Qualitative Study of Business-to-Business Electronic Commerce Adoption within the Indonesian Grocery Industry: A Multi-Theory Perspective, *Information & Management,* vol. 52, no. 4**,** pp 518-536

Kvale, S. (1996).The 1,000-Page Question, *Qualitative inquiry,* vol. 2, no. 3**,** pp 275-284

Kvale, S. (2008). Doing Interviews: Sage.

Kvale, S. & Brinkmann, S. (2009). Interviews: Learning the Craft of Qualitative Research Interviewing: Sage.

Lee, C.-P. & Shim, J. P. (2007).An Exploratory Study of Radio Frequency Identification (Rfid) Adoption in the Healthcare Industry, *European Journal of Information Systems,* vol. 16, no. 6**,** pp 712-724

Lee, S. & Kim, K.-j. (2007).Factors Affecting the Implementation Success of Internet-Based Information Systems, *Computers in human behavior,* vol. 23, no. 4**,** pp 1853-1880

Leyer, M. & Schneider, S. (2019a).Me or Information Technology? Adoption of Artificial Intelligence in the Delegation of Personal Strategic Decisions, *Managerial and Decision Economics,* vol. 40, no. 3**,** pp 223-231

Leyer, M. & Schneider, S. (2019b). Me, You or Ai? How Do We Feel About Delegation. *27th European Conference on Information Systems (ECIS).* Stockholm & Uppsala, Sweden.

Lian, J.-W., Yen, D. C. & Wang, Y.-T. (2014).An Exploratory Study to Understand the Critical Factors Affecting the Decision to Adopt Cloud Computing in Taiwan Hospital, *International Journal of Information Management,* vol. 34, no. 1**,** pp 28-36

Lin, H. F. & Lee, G. G. (2005).Impact of Organizational Learning and Knowledge Management Factors on E‐Business Adoption, *Management Decision,* vol. no.

Liu, Z., Min, Q. & Ji, S. (2008). A Comprehensive Review of Research in It Adoption. *4th International Conference on Wireless Communications, Networking and Mobile Computing.* IEEE.

Logg, J. M., Minson, J. A. & Moore, D. A. (2019).Algorithm Appreciation: People Prefer Algorithmic to Human Judgment, *Organizational Behavior and Human Decision Processes,* vol. 151, no. 90-103

Low, C., Chen, Y. & Wu, M. (2011).Understanding the Determinants of Cloud Computing Adoption, *Industrial management & data systems,* vol. no.

Mallat, N. (2007).Exploring Consumer Adoption of Mobile Payments–a Qualitative Study, *The Journal of Strategic Information Systems,* vol. 16, no. 4**,** pp 413-432

Mansfield, E. (1968).Industrial Research and Technological Innovation; an Econometric Analysis, vol. no.

Mansfield, E., Rapoport, J. & Romeo, A. (1977). E, Villani, S. Wagner, and F. Husic, the Production and Application of New Industrial Technology. WW Norton: New York, l977.

March, J. G. & Simon, H. A. (1958).Organizations, vol. no.

Marler, J. H., Fisher, S. L. & Ke, W. (2009).Employee Self ‐ Service Technology Acceptance: A Comparison of Pre ‐ Implementation and Post ‐ Implementation Relationships, *Personnel Psychology,* vol. 62, no. 2**,** pp 327-358

Maxwell, J. (1992).Understanding and Validity in Qualitative Research, *Harvard educational review,* vol. 62, no. 3**,** pp 279-301

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D. & Barton, D. (2012).Big Data: The Management Revolution, *Harvard business review,* vol. 90, no. 10**,** pp 60-68

McCulloch, W. S. & Pitts, W. (1943).A Logical Calculus of the Ideas Immanent in Nervous Activity, *The bulletin of mathematical biophysics,* vol. 5, no. 4**,** pp 115-133

Meador, C. L., Guyote, M. J. & Keen, P. G. (1984).Setting Priorities for Dss Development, *MiS Quarterly,* vol. no. 117-129

Mello, F. R. & Ponti, A. M. (2018). Machine Learning. [Elektronisk Resurs] : A Practical Approach on the Statistical Learning Theory, 1st ed. 2018.: Springer International Publishing.

Miles, M. B., Saldaña, J. & Huberman, A. M. (2014). Qualitative Data Analysis : A Methods Sourcebook, 3. ed.: Sage.

Mintzberg, H. (1973). The Nature of Managerial Work: Harper & Row.

Mintzberg, H., Raisinghani, D. & Theoret, A. (1976).The Structure of" Unstructured" Decision Processes, *Administrative science quarterly,* vol. no. 246-275

Money, A., Tromp, D. & Wegner, T. (1988).The Quantification of Decision Support Benefits within the Context of Value Analysis, *MIS quarterly,* vol. no. 223-236

Musawa, M. S. & Wahab, E. (2012).The Adoption of Electronic Data Interchange (Edi) Technology by Nigerian Smes: A Conceptual Framework, *Journal of Business Management and Economics,* vol. 3, no. 2**,** pp 55-68

Newell, A. & Simon, H. A. (1972). Human Problem Solving: Prentice-Hall Englewood Cliffs, NJ.

Niederman, F. & March, S. (2015).Reflections on Replications, *AIS Transactions on Replication Research,* vol. 1, no. 1**,** pp 1-16

Nohria, N. & Gulati, R. (1996).Is Slack Good or Bad for Innovation?, *Academy of management Journal,* vol. 39, no. 5**,** pp 1245-1264

Oates, B. J. (2006). Researching Information Systems and Computing: Sage.

Ocasio, W. (2011).Attention to Attention, *Organization science,* vol. 22, no. 5**,** pp 1286-1296

Oliveira, T. & Martins, M. F. (2011).Literature Review of Information Technology Adoption Models at Firm Level, *Electronic Journal of Information Systems Evaluation,* vol. 14, no. 1**,** pp 110

Oxford Dictionary. (2020). Artificial Intelligence. lexico.com.

Pan, M.-J. & Jang, W.-Y. (2008).Determinants of the Adoption of Enterprise Resource Planning within the Technology-Organization-Environment Framework: Taiwan's Communications Industry, *Journal of Computer information systems,* vol. 48, no. 3**,** pp 94-102

Panetta, K. (2017). *Gartner Top 10 Strategic Technology Trends for 2018* [Online]. Available online: https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2018/ [Accessed April 1 2020].

Parry, K., Cohen, M. & Bhattacharya, S. (2016).Rise of the Machines: A Critical Consideration of Automated Leadership Decision Making in Organizations, *Group & Organization Management,* vol. 41, no. 5**,** pp 571-594

Patton, M. Q. (2015). Qualitative Research & Evaluation Methods: Integrating Theory and Practice, Thousand Oaks, California: SAGE Publications, Inc.

Piccinini, G. (2004).The First Computational Theory of Mind and Brain: A Close Look at Mcculloch and Pitts's “Logical Calculus of Ideas Immanent in Nervous Activity”, *Synthese,* vol. 141, no. 2**,** pp 175-215

Power, D. J. (2007).A Brief History of Decision Support Systems, *DSSResources.com,* vol. 3, no.

Prahl, A. & Van Swol, L. (2017).Understanding Algorithm Aversion: When Is Advice from Automation Discounted?, *Journal of Forecasting,* vol. 36, no. 6**,** pp 691-702

Pyke, J. (2009).Now Is the Time to Take the Cloud Seriously, *White Paper, at: www. cordys. com/cordyscms_sites/objects/bb1a0bd7f47b1c91ddf36ba7db8 8241d/time_to_take_the_cloud_seroiusly_online_1_. pdf,* vol. no.

Rai, A. & Bajwa, D. S. (1997).An Empirical Investigation into Factors Relating to the Adoption of Executive Information Systems: An Analysis of Eis for Collaboration and Decision Support, *Decision Sciences,* vol. 28, no. 4**,** pp 939-974

Randolph, J. (2009).A Guide to Writing the Dissertation Literature Review, *Practical Assessment, Research, and Evaluation,* vol. 14, no. 1**,** pp 13

Ransbotham, S., Kiron, D., Gerbert, P. & Reeves, M. (2017).Reshaping Business with Artificial Intelligence: Closing the Gap between Ambition and Action, *MIT Sloan Management Review,* vol. 59, no. 1**,** pp

Recker, J. (2013). Scientific Research in Information Systems. [Elektronisk Resurs] a Beginner's Guide: Springer Berlin Heidelberg.

Ritchie, J., Lewis, J., Nicholls, C. M. & Ormston, R. (2013). Qualitative Research Practice: A Guide for Social Science Students and Researchers: sage.

Rogers, E. M. (1995). Diffusions of Innovations, Forth Edition. New York: Tree Press.

Rometty, G. (2016).Digital Today, Cognitive Tomorrow, *MIT Sloan Management Review,* vol. 58, no. 1**,** pp 28

Russell, S. J. & Norvig, P. (2010). Artificial Intelligence-a Modern Approach. 3rd international edition ed.: Pearson Education.

Russell, S. J. & Norvig, P. (2016). Artificial Intelligence: A Modern Approach. Malaysia: Pearson Education Limited.

Russom, P. (2011).Big Data Analytics, *TDWI best practices report, fourth quarter,* vol. 19, no. 4**,** pp 1-34

Ryen, A. & Torhell, S.-E. (2004). Kvalitativ Intervju: Från Vetenskapsteori Till Fältstudier, 1: Liber ekonomi.

Rzepka, C. & Berger, B. (2018). User Interaction with Ai-Enabled Systems: A Systematic Review of Is Research.

Saaty, T. L. (2008).Decision Making with the Analytic Hierarchy Process, *International journal of services sciences,* vol. 1, no. 1**,** pp 83-98

Sabherwal, R. & Grover, V. (1989).Computer Support for Strategic Decision ‐ Making Processes: Review and Analysis, *Decision Sciences,* vol. 20, no. 1**,** pp 54-76

Salwani, M. I., Marthandan, G., Norzaidi, M. D. & Chong, S. C. (2009).E ‐ Commerce Usage and Business Performance in the Malaysian Tourism Sector: Empirical Analysis, *Information management & computer security,* vol. no.

Seale, C. (1999).Quality in Qualitative Research, *Qualitative inquiry,* vol. 5, no. 4**,** pp 465-478

Searle, J. R. (1990).Is the Brain's Mind a Computer Program?, *Scientific American,* vol. 262, no. 1**,** pp 25

Shieber, S. M. (1994). Lessons from a Restricted Turing Test.

Simon, H. A. (1960).The New Science of Management Decision, vol. no.

Simon, H. A. (1965). The Shape of Automation for Men and Management: Harper & Row.

Simon, H. A. (1972).Theories of Bounded Rationality, *Decision and organization,* vol. 1, no. 1**,** pp 161-176

Snead, K. C. & Harrell, A. M. (1994).An Application of Expectancy Theory to Explain a Manager's Intention to Use a Decision Support System, *Decision Sciences,* vol. 25, no. 4**,** pp 499-510

Soelberg, P. (1966). Unprogrammed Decision Making. *Academy of Management Proceedings.* Academy of Management Briarcliff Manor, NY 10510.

Starbuck, W. H. (1976).Organizations and Their Environments, *Handbook of industrial and organizational psychology,* vol. no.

Stenzelius, V., Morey, M. & Boström, J. (2019).Information Overload-Ett Problem För Näringslivet Och Folkhälsan, vol. no.

Stewart, R. (1988). Managers and Their Jobs: Springer.

Tornatzky, L. G. & Fleischer, M. (1990). Processes of Technological Innovation: Lexington books.

Tshilidzi, M. (2015). Causality, Correlation and Artificial Intelligence for Rational Decision Making: World Scientific.

Tung, R. L. (1979).Dimensions of Organizational Environments: An Exploratory Study of Their Impact on Organization Structure, *Academy of Management Journal,* vol. 22, no. 4**,** pp 672-693

Tushman, M. & Nadler, D. (1986).Organizing for Innovation, *California Management Review,* vol. 28, no. 3**,** pp 74-92

Tushman, M. L. & Nadler, D. A. (1978).Information Processing as an Integrating Concept in Organizational Design, *Academy of management review,* vol. 3, no. 3**,** pp 613-624

Wade, M. & Hulland, J. (2004).The Resource-Based View and Information Systems Research: Review, Extension, and Suggestions for Future Research, *MIS Quarterly,* vol. 28, no. 1**,** pp 107-142

Wang, D., Khosla, A., Gargeya, R., Irshad, H. & Beck, A. H. (2016). Deep Learning for Identifying Metastatic Breast Cancer.

Wang, Y.-M., Wang, Y.-S. & Yang, Y.-F. (2010).Understanding the Determinants of Rfid Adoption in the Manufacturing Industry, *Technological forecasting and social change,* vol. 77, no. 5**,** pp 803-815

Watson, H. (2017).Preparing for the Cognitive Generation of Decision Support, *MIS Quarterly Executive,* vol. 16, no. 153-169

Watson, H. J. (2014).Tutorial: Big Data Analytics: Concepts, Technologies, and Applications, *Communications of the Association for Information Systems,* vol. 34, no. 1**,** pp 65

Weller, S. (2017).Using Internet Video Calls in Qualitative (Longitudinal) Interviews: Some Implications for Rapport, *International Journal of Social Research Methodology,* vol. 20, no. 6**,** pp 613-625

Wen, K.-W. & Chen, Y. (2010).E-Business Value Creation in Small and Medium Enterprises: A Us Study Using the Toe Framework, *International Journal of Electronic Business,* vol. 8, no. 1**,** pp 80-100

Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D. (2003).User Acceptance of Information Technology: Toward a Unified View, *MIS quarterly,* vol. no. 425-478

Williams, M. D., Dwivedi, Y. K., Lal, B. & Schwarz, A. (2009).Contemporary Trends and Issues in It Adoption and Diffusion Research, *Journal of Information Technology,* vol. 24, no. 1**,** pp 1-10

Vogelsang, K., Steinhüser, M. & Hoppe, U. (2013).A Qualitative Approach to Examine Technology Acceptance, *Association for Information Systems,* vol. no.

Wood, R. & Bandura, A. (1989).Impact of Conceptions of Ability on Self-Regulatory Mechanisms and Complex Decision Making, *Journal of Personality & Social Psychology,* vol. 56, no. 3**,** pp 407-415

Vroom, V. H. & Yetton, P. W. (1973). Leadership and Decision-Making: University of Pittsburgh Pre.

Yarowsky, D. (1995). Unsupervised Word Sense Disambiguation Rivaling Supervised Methods. *33rd annual meeting of the association for computational linguistics.*

Young, T., Hazarika, D., Poria, S. & Cambria, E. (2017). Recent Trends in Deep Learning Based Natural Language Processing.

Zahra, S. A. & George, G. (2002).Absorptive Capacity: A Review, Reconceptualization, and Extension, *Academy of management review,* vol. 27, no. 2**,** pp 185-203

Zhu, K., Kraemer, K. & Xu, S. (2003).Electronic Business Adoption by European Firms: A Cross-Country Assessment of the Facilitators and Inhibitors, *European journal of information systems,* vol. 12, no. 4**,** pp 251-268

Zhu, K. & Kraemer, K. L. (2005).Post-Adoption Variations in Usage and Value of E-Business by Organizations: Cross-Country Evidence from the Retail Industry, *Information systems research,* vol. 16, no. 1**,** pp 61-84

Zhu, K., Kraemer, K. L. & Dedrick, J. (2004).Information Technology Payoff in E-Business Environments: An International Perspective on Value Creation of E-Business in the Financial Services Industry, *Journal of management information systems,* vol. 21, no. 1**,** pp 17-54

Zins, C. (2007).Conceptual Approaches for Defining Data, Information, and Knowledge, *Journal of the American society for information science and technology,* vol. 58, no. 4**,** pp 479-493