THE AI REVOLUTION

A study on the present and future application and value of AI in the context of ERP systems

*Jacob Bergdahl*
Abstract

Business leaders around the world are expressing equal amounts of excitement and urgency for implementing artificial intelligence (AI) technologies. Yet the upcoming AI revolution is clouded with uncertainties and misconceptions. In this thesis, the business value and application potential of AI were studied in a context of enterprise resource planning (ERP) systems through a case study at a consultancy firm with small- to midsize clients. Three research questions were posed and answered: how can, or do, organizational processes covered by ERP systems benefit from AI, what AI features do customers typically request when ordering ERP systems, and is AI adopted with the purpose of reducing costs or increasing revenue?

Using a framework for data analysis, multiple organizational processes covered by ERP systems were explored through interviews with ERP experts. The results indicated that small- and midsize companies were still primarily requesting and working to implement basic, incremental AI with the purpose of reducing costs through automations. Future leaders may instead need to implement AI that fundamentally reinvents their business processes, with the purpose of increasing revenue through augmentations. Overall, while some organizational processes have already been improved with AI solutions, many processes have yet to be AI-powered in the ERP solutions sold by the consultancy firm examined in this study. However, the consultants of the firm express great positivity for the untapped potential of AI, and many further AI solutions are being developed.

Keywords: artificial intelligence (AI), enterprise resource planning (ERP) system, business value

Sammanfattning

Affärsledare världen runt upplever såväl entusiasm som brådska för att implementera artificiell intelligens (AI). Men den kommande AI-revolutionen är fyld av osäkerheter och missuppfattningar. I denna uppsats undersöks det affärsvärde och den användningspotential som AI har i en kontext av affärsystem (enterprise resource planning system, ERP) genom en fallstudie på en konsultfirma med små- och mellanstora kunder. Tre forskningsfrågor ställdes och besvarades: hur kan organisatoriska processer som täcks av affärsystem komma att gynnas av AI, eller hur gynnas de redan, vilken typ av AI efterfrågar kunder när de beställer affärsystem, och införskaffas AI i syftet att minska kostnader eller öka intäkter?

Med hjälp av ett ramverk för dataanalys utforskandes ett flertal organisatoriska processer som täcks av affärsystem genom intervjuer med affärsystemsexperter. Resultatet tyder på att små- och mellanstora företag fortfarande primärt efterfrågar och jobbar med enkla, inkrementella AI-utvecklingar, med syftet att minska kostnader genom automatiseringar. Framtidiga ledare kan istället komma att vilja implementera AI som fundamentalt återuppfinner organisationens affärsprocesser, med syftet att öka inkomsterna genom att göra personalen kraftfullare. På det stora hela har endast än så länge endast ett mindre antal organisatoriska processer blivit förbättrade med AI-lösningar i de affärsystem som säljs av konsultfirma som undersöktes i denna studie. Företagets konsulter uttrycker dock starkt positivitet för den outnyttjade potentialen som kan hittas i AI, och fler AI-lösningar för affärsystemen håller på att utvecklas.

Nyckelord: artificiell intelligens (AI), affärs-system (ERP), affärsvärde
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1 Introduction

In this introductory chapter, the background for the thesis will lead the way to the problem formulation, ultimately resulting in the presentation of the research questions. At the end of the chapter, research demarcation and a brief disposition are presented.

1.1 Background

“No business can avoid the AI reality […] Remember those diehards who swore they weren't going to use the Internet? Now they're running ads on Google or Facebook. To run a business, you need information and insight. The Internet gives you information but not insight. AI gives you both.” – Daniel Wu, chief technologist for data systems and data science at Hewlett Packard Enterprise (Hopkins 2017).

A revolution is starting.

All aspects of daily life for people and companies alike are radically changing. Innovations discovered and progress made in digitization, internet of things, cloud storage and big data have provided new means and superior solutions to previously upheld standards. Yet the digital revolution has sparked an even greater such. Following the unlimited access to computer power granted by the cloud and the massive growth in big data (Purdy & Daugherty 2016, p. 11), a previously discovered technology has been reborn: artificial intelligence (AI).

While AI is not a new concept, the AI revolution has only recently become popularized. Major companies are predicting great things for the future of AI. Consultancy giant Accenture (2017a, p. 33) believes that customers will soon select a company’s services based on their AI, rather than their traditional marketing. Accenture (ibid.) argues that, in seven years, most UI’s will exist without a screen, instead opting to be built entirely by AI-powered voice recognition features. In an additional three years, they argue, digital assistants will be active at all times. Consultancy firm Gartner also predict great things for AI. The company argues that using AI correctly will result in big digital business payoffs, and that AI in general will be making numerous objects intelligent (Panetta 2017). Experts at Hewlett Packard Enterprise compare AI to the Internet, saying those who initially laughed at the Internet, are now running ads on Facebook and Google (Hopkins 2017). The father of CRM systems, Tom Siebel, argue that AI will downright replace the market for CRM and ERP systems (Woodie 2017).

Business leaders agree. In a survey executed by Accenture (2017a, p. 24), 85% of managers claimed they would invest heavily in AI-related technologies over the coming three years. IT consultancy firm Avanade received nearly identical numbers when they asked Swedish managers: 86% of these believe their company must implement AI to remain competitive (Djurberg 2017). When software developer giant Oracle (2016, p. 5) surveyed marketing leaders, 80% responded that they already have or soon will implement AI-powered chatbots.
MIT researchers Brynjolfsson and McAfee (2017, p. 2) argue that the fundamental drivers of economic growth are technological innovations, and highlight that the most important general-purpose technology of our era is artificial intelligence. The two authors explain how most big opportunities in the area of AI have yet to be explored, even though many companies are already using AI-powered technologies.

Clearly, there is a lot of buzz surrounding artificial intelligence. Yet this sparks a great question:

How does one even begin their AI revolution?

1.2 Problem

The purpose of AI technologies is likely to somehow provide business value, be it through automation, greater insights, superior call to actions, or other means. As AI will soon be applicable to every part of a company’s business, questions concerning prioritizations are rising in equal part with the general lack of understanding for the actual benefits of AI. What more, large companies such as technology giants and major banks are common examples used in discussions of AI, rather than small- to midsize companies.

Artificial intelligence is not a new field of research. The concept has been around for hundreds of years, and has been actively researched since the 20th century (Purdy & Daugherty 2016). The advancements made in the last few years, however, with cognitive abilities and machine learning as leading stars, have drastically changed the view, understanding, and urgency of AI. An early literature study made it clear that while a fair amount of research has been done on low-level – that is, technical levels – of AI, much to the benefit of engineers and developers, my literature very little organizational research exists. Rather, private companies have gained a great lead over researchers in the understanding of the topic, putting clients at the mercy of companies with proprietary knowledge. More academic reports on AI are clearly needed.

Examining artificial intelligence on an organizational level can be made easier by putting it in an appropriate context, such as enterprise resource planning (ERP) systems. As an enterprise-spanning system, ERP systems touch upon up to all areas of a company’s processes, from customer relationship management to human resources, from accounting to sales, and from corporate performance to production. Thus, it is the ideal context in which to explore AI implementation. What better way to see what artificial intelligence can do, than by applying it in an organization-spanning context?

Nordic companies express more concerns over AI technologies than the global average, according to a study by consulting giant Accenture (2017b, p. 3). Data quality, lack of maturity in technologies and wider concerns over the use of AI technologies are all expressed in more
concern in the Nordics (ibid.). They argue that one reason for this increased amount of concerns is the fact that many AI technologies are not yet available in Nordic countries. However, Accenture (2017b, p. 3) concludes, Nordic businesses are starting to identify AI’s ability to generate revenue, and the demand will inevitably increase. This increased concern does provide an extra layer of interest, as this study will indeed be performed in a Nordic country; Sweden.

As a nation-wide Swedish deliverer of such ERP systems, consultancy firm Exsitec experience curiosities for AI and calls for further exploration of the topic. As ERP manufacturer Visma’s biggest partner, Exsitec is an enterprise with long experience in the delivery of ERP systems, and like many other companies, the firm is curious on how they can provide greater business value for their clients, who are small- and midsize companies. Their clientele being small- to midsize companies is particularly interesting, as companies of this size presumably have less organizational capabilities, thus this thesis hopes to provide an alternate perspective to those who focus merely on corporate giants. In this thesis, I will perform a case study at Exsitec to discover the potential of AI.

1.3 Research Purpose

The purpose of this thesis is to examine artificial intelligence and its potential business value in the context of enterprise resource planning systems, from the perspective of a midsize consultancy firm with small- to midsize clients. The following research questions will be answered:

- How can, or do, organizational processes covered by ERP systems benefit from AI?
- What, if any, AI features do customers typically request when ordering ERP systems?
- How is the value of AI perceived: Are AI technologies adopted with the purpose of reducing costs or increasing revenue?

This is to be done through a case study at Exsitec – a company that handles the delivery of ERP systems. By constructing questions out of already established theories for AI, I aim to find out how the ERP consultants at Exsitec believe AI already is, or is not, and how it can, or cannot, be applied to ERP systems. The goal is to identify an organizational perspective on the perceived value that AI can bring to companies through ERP systems.

The theoretical contribution that the thesis aims to provide is a greater understanding of how AI is, can, and will be used in an organizational context. The practical contribution, meanwhile, is a concrete presentation of how organizations use AI in the present, and may use it in the future, as based on the results gained from the respondents. The research questions are thus made specifically to fill the identified research gap.
1.4 Demarcations

This thesis will examine AI in a high-level organizational context, rather than a low-level technical such. The thesis does not explore general-purpose strong AI (see 2.1.1), instead examining modular use cases of narrow AI. In other words, the ethical and moral aspects of AI are not explored, and neither are concepts of general-purpose AI. Instead, AI is viewed as a modular technology (see 2.1.1) that serves a specific purpose.

As the case study is performed at Exsitec, all interviewees will naturally be limited to Exsitec employees. Furthermore, the interviewees are mainly accustomed to using Visma’s ERP systems. The interview questions will for that reason to some extent be formulated around Visma’s terminology for processes (see 3.3.2), however the results are intended to be relevant regardless of which ERP system is in question. Finally, as the company being examined operates in Sweden, another demarcation is made as the interviewees will presumably be primarily experienced with working in Sweden.

1.5 Disposition

The disposition of the thesis is as follows.

Chapter 2: Theoretical Background
In the theoretical background, key concepts surrounding AI and ERP systems are explained. Previous research in the organizational impact and business strategies of AI is also explored.

Chapter 3: Method
Based on the theories and key concepts of the second chapter, interview questions are formulated and a framework for data analysis established. The research strategy and research method are presented.

Chapter 4: Results
Through interviews performed in accordance with the method established in the previous chapter, the present and future use of sixteen processes and four AI models are presented. The insights gathered lead to the creation of three trends, which are then analyzed in the following chapter.

Chapter 5: Analysis
The three trends identified in the results chapter are analyzed in greater detail in this fifth chapter.
Chapter 6: Discussion
In the discussion, the three aforementioned trends are combined and elevated to explain a greater trend: the AI revolution.

Chapter 7: Conclusion
Finally, the thesis is concluded in the seventh chapter.
2 Theoretical Background

In this chapter, I will thoroughly explain key terms, using a combination of academic research and corporate whitepapers. Theories from academic researchers, corporate researchers, as well as books will be presented. The inclusion of corporate whitepapers is critical to this thesis, as academic research is lagging behind the research of major corporations. For example, one major whitepaper (Accenture 2017a), surveyed outlooks for 31 countries (Accenture 2017a, p. 89), using a team of 250 researchers and analysts that span 23 countries (ibid., p. 94). High-level research on AI on this scale in the academic world appears to be non-existent.

I searched for literature through Uppsala University’s library portal¹, which aggregates the databases to which the university has access². Searches were made using different combinations of the keywords AI, ERP, value, applications, strategies, and enterprise, with encompassing synonyms³ from December of 2017 through February of 2018.

A severe lack of research on the organizational level of AI, outside of primarily brief MIT papers, was discovered. Most research for AI covered the phenomenon on a technical level. What little research covered AI on an organizational level did so in very specific contexts that would be impossible to generalize or to apply to this thesis. Theories on how AI can be implemented into organizational processes were practically non-existent. Instead, private research appears to dominate the field. That presumption was confirmed by AI researcher Corea (2017, p. 23), author of a book on AI and business models. The author argues that universities are losing relevance to the private sector, as the latter can provide higher salaries, more interesting problems, large and unique datasets, and more resources. Indicating the cross-fertilization of industry and academia, an article published by Accenture researchers Plastino and Purdy (2018) based on an Accenture survey, was peer-reviewed by academics and published in the academic journal Strategy & Leadership. Even still, private research also proved to be lackluster, as previous research found was limited even in the private sector.

However, the dominance of corporate research suggests a major need for more academic studies of these topics, in particular due to the recency and potential urgency for AI in an organizational context. This gap is one of the motivating factors behind this thesis, and its research questions, which discuss AI on an organizational level.

¹ [http://www.ub.uu.se/?languageId=1](http://www.ub.uu.se/?languageId=1)
2.1 Artificial Intelligence

Artificial intelligence (AI) is a term with a long history. Authors Flasiński (2016) and Corea (2017) have both written books on the topic, which detail the rich history of the phenomenon. Flasiński (2016, p. 3) proposes that the history of AI stretches as far back as to classic philosophers e.g. Aristotle and Thomas Hobbes, who asked philosophical questions such as what the basic cognitive operations are and if reasoning could be automatized. However, according to the author, it was not until the 20th century that these fundamental questions could finally be answered, as the first computers were being created.

More precisely, Flasiński (2016, p. 4) and Corea (2017, p. 4) both suggest that artificial intelligence was born in 1956, following a famous conference at Dartmouth College. Six years earlier, Alan Turing had published his famous paper, which discussed whether a machine could show intelligence, Corea (2017, p. 4) explains.

Throughout the years, AI would go through multiple optimistic and pessimistic waves. Corea (2017, p. 5) argues that the current wave of optimism began in late 2012, when a group of researchers presented detailed information of their convoluted neural networks, which could reach great accuracies in prediction.

Today, that optimistic wave is growing ever stronger. Corea (2017, p. 6) suggests three reasons why AI is a hot topic in the present: it has great potential applications, it receives large amounts of media and public attention, and there is an immense amount of funding fueling interest in the phenomenon. Accenture’s Purdy & Daugherty (2016, p. 11), meanwhile, suggest two key factors as enablers for the current AI growth: unlimited access to computing power, and the growth in big data. Data storage has become abundant, and the amount of data around the world is increasing exponentially, the authors explain. AI feeds on data, in the same way that humans feed on food, thus AI has been enabled by this massive recent growth.

Machines are still far away from exceeding human intelligence, so-called singularity. Corea (2017, p. 7) emphasizes, as he explains that while AI is certainly advancing quickly, it is not advancing quite as quickly as many had previously predicted. Largely a philosophical question, technological singularity refers to the invention of a superintelligence that radically changes human society through its rapid self-development. It must be emphasized that this view of AI, sometimes referred to as strong AI, and commonly perceived as either a utopia or dystopia, is not relevant for this thesis. This thesis will not discuss AI as a general-purpose technology, will not explore the ethical or moral aspects of AI, will not examine the philosophical debate, and will not discuss singularity.

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4 In this thesis, the term “machine” is used synonymously with “device”. Examples of machines could be computers and smartphones.
2.1.1 The Definition of AI

As the previous introduction would suggest, AI is a phenomenon with many definitions.

Ertel (2011) presents a number of historically significant definitions of AI. First, a 1955 definition by John McCarthy: “The goal of AI is to develop machines that behave as though they were intelligent” (Ertel 2011, p. 13), which Ertel argues as an insufficient definition. He also discusses the definition of AI formulated by encyclopedias, which he suggests have many weaknesses. Ultimately, he lands on a 1989 definition by Elaine Rich: “Artificial [i]ntelligence is the study of how to make computers do things at which, at the moment, people are better” (Ertel 2011, p. 14), which he describes as elegant and forever relevant. For this thesis, however, the definition is too broad, as it encompasses virtually every feature of a computer, and a somewhat more precise definition is needed when discussing AI with a consultancy firm.

On the other side of the spectrum, Corea (2017, p. 1 – 2) defines AI as “[a] system that can learn how to learn, or in other words a series of instructions (an algorithm) that allows computers to write their own algorithms without being explicitly programmed for” (Corea 2017, p. 2). For the purpose of this thesis, Corea’s definition is instead too narrow. This definition revolves solely around machine learning (see chapter 2.1.2), while AI for this thesis needs to be more encompassing to be applied to an organizational context.

Flasiński (2016) does not present a single definition of AI. Instead, he presents a number of fundamental concepts and approaches, illustrating the many complexities and varieties of AI. For instance, Flasiński (2016, p. 236) discusses strong AI and weak AI. He defines both of these variants of artificial intelligence: “[s]trong [a]rtificial [i]ntelligence, which claims that a properly programmed computer is equivalent to a human brain and its mental activity” (Flasiński 2016, p. 236), while “[w]eak [a]rtificial [i]ntelligence, in which a computer is treated as a device that can simulate the performance of a brain. In this approach, a computer is also treated as a convenient tool for testing hypotheses concerning brain and mental processes” (Flasiński 2016, p. 236).

Ayoub and Payne (2016, p. 795), meanwhile, distinguish between the two terms of AI by using the terms “modular AI” and “general AI”, where the former has a narrow, domain-specific expertise while the latter uses knowledge more flexibly.

Strong AI is closely related to the previously described theory of singularity. Again, it is urgent to stress that this thesis takes the approach of weak AI. As a case study examining AI as perceived by a consultancy firm, any definition of AI used in this thesis must also be of a context where AI has a use case for corporations, which general-purpose AI presently does not.

Brynjolfsson and McAfee (2017, p. 8) also emphasize that AI systems are often trained to do very specific tasks. A machine that can perfectly translate English to Chinese, they exemplify,
cannot necessarily give recommendations on where to eat in Beijing. When humans perform a task well, they naturally presume that they also have some competence in related tasks. This is a common fallacy and source of exaggerated trust in AI, the authors argue. “We are far from machines that exhibit general intelligence across diverse domains,” Brynjolfsson and McAfee (2017, p. 8) conclude.

Finally, Accenture’s Bataller & Harris (2016) argue that AI “consists of multiple technologies that enable information systems and applications to sense, comprehend and act. That is, computers are enabled (1) to perceive the world and collect data; (2) to analyze and understand the information collected; and (3) to make informed decisions and provide guidance based on this analysis in an independent way” (Bataller & Harris 2016, p. 6). This definition of AI as presented above is shared across Accenture’s whitepapers. Accenture’s Purdy & Daugherty (2016), for example, also use the same definition. Their definition has a suitable balance between narrowness and breadth. It is a contemporary definition made to be used in an organizational context. Therefore, it is a definition well worth a closer examination. The authors specify three components of the definition:

**Sense**

Bataller & Harris (2016, p. 6) exemplify AI’s ability to sense with how border controls use facial recognition to identify characteristics, or how AI can help retailers recognize customers as they enter a store and provide personalized service. There are many forms of vision and audio processing, Purdy & Daugherty (2016, p. 10) argue, including processing of images, sounds and speech.

**Comprehend**

Artificial intelligence can also comprehend through technologies such as natural language processing (commonly shortened as NLP; technologies that can comprehend natural languages through text or speech) and expert systems, Bataller & Harris (2016, p. 6) argue. AI systems can thus, for example, help doctors identify diseases (Bataller & Harris 2016, p. 6) and power language translation features (Purdy & Daugherty 2016, p. 10).

**Act**

An AI system acts independently, Bataller & Harris (2016, p. 6) argues. AI systems can take action, either through technologies or in the physical world, Purdy & Daugherty (2016, p. 10) elaborate. Autopilot features and assisted-braking capabilities are such examples, the latter duo proposes. Factory robots that assemble products on the production line and virtual assistants that act by responding to inquiries are two other examples of AI systems acting, Bataller & Harris (2016, p. 6) conclude.

The three capabilities above are all underpinned by an additional ability: the ability to learn (see figure 1).
Bataller & Harris (2016, p. 6) argue that a distinctive feature of all true AI systems is their ability to adapt their capabilities based on experience, rather than having all its rules be hardcoded. This is done through a technology called machine learning, which will be explained shortly. AI systems are self-learning, the authors argue, much like students given educational material can learn by themselves.

Self-learning AI solutions are already in use, Bataller & Harris (2016, p. 7) argue, for example at banks in order to detect credit fraud. By letting machines study spending patterns of customers and predicting future transactions, it can flag unusual activity, the duo explains. The systems also learn from real examples, and evolve as fraudsters discover new tactics. Self-learning solutions are also prevalent at consumer level, for example with Google Now, a personal assistant. Google Now learns from user’s activities and interactions, the authors suggest, to find, collect and present relevant information. The system also constantly improves based on feedback and its own learning methods.

AI systems ability to learn is only improving, Bataller & Harris (2016, p. 7) conclude, as new technologies such as deep learning are being used to mimic the structure of a human brain. Deep learning will also be explained shortly.

According to Bataller & Harris (2016, p. 6), AI solutions ultimately help humans, regardless of application, through one out of two means: automation (relieve humans of tasks) and augmentation (empower humans to execute tasks). These two means will be further highlighted in chapter 3.3.1, where a framework for data analysis is presented.

Since the purpose of this thesis is to investigate AI in an organizational context, the definition suggested by Bataller and Harris is especially useful, given its strong focus on the corporate aspects of AI, along with its detailed components and its contemporary nature, which fits perfectly with this thesis. However, extending it with the means through which AI, according
to the same authors, contributes to corporations (i.e. augmentation and automation), further strengthens its value as an analytical tool. Therefore, in this thesis, the definition of AI that will be used is:

AI is a technology that can sense, comprehend and act, in order to empower humans through automation or augmentation.

This definition encompasses all forms of automation and augmentation, both basic and advanced. It is important to bear this definition in mind throughout the results and analysis.

2.1.2 The Technologies Powering AI: Machine Learning and Deep Learning

The ability for computers to learn is powered by machine learning (ML) – an umbrella term for many advanced techniques of AI. Machine learning is a technique that AI systems may adopt to quicker learn from past data. ML is a popular technique today, but for the definition of AI as used in this thesis, ML is not a necessity for AI, as basic AI can also be taught by humans rather than by itself. First coined by Samuel (1959), ML is one of the main drivers of AI today. Though the term is technologically complex, it will be presented in a simple general overview in this chapter, with the purpose of providing a better understanding of AI and its possibilities.

![Figure 2. A simple diagram showcasing the order in which technologies were invented, and their relation to each other. The year symbolizes which decade the technology began to gain major traction, rather than the year it was invented. Source: Copeland (2016).](image)

While there is much debate concerning the definition of AI, there appears to be a rather strong consensus surrounding the definition of machine learning. On the contrary, all literature
background found on machine learning discuss the technology with similar fundamental ideas. The aforementioned Corea (2017) provide extensive knowledge in machine learning and pattern recognition, including its many methods and techniques, though he explains it in a quite technical manner. Instead, Agrawal, Gans and Goldfarb (2017), Brynjolfsson and McAfee (2017) and Louridas and Ebert (2016) provide simple explanations and demonstrate use cases of the technology. Agrawal et al. (2017, p. 1) describe ML as programming computers which learn from example data or previous experience. Brynjolfsson and McAfee (2017, p. 2) describe AI as the most important general-purpose technology of our time, while emphasizing machine learning as particularly important for AI. They refer to ML as a “machine’s ability to keep improving its performance without humans having to explain exactly how to accomplish all the tasks it’s given” (Brynjolfsson & McAfee 2017, p. 2). Louridas and Ebert (2016, p. 110) describe machine learning as the “major success factor in the ongoing digital transformation across industries”.

Agrawal et al. (2017, p. 1 – 2) use objects in a basket of groceries as an example to explain machine learning. If one can describe the way an apple looks to a computer, then one can easily program a computer to recognize apples based on their color and shape. The issue, however, is that there are many objects that are apple-like in both color and shape. One would have to describe apples in greater detail, but as the real world is very complex, such descriptions would, according to the authors, quickly become unfeasible to create manually. This is where ML is useful. Rather than telling machines what apples look like, providing a machine with a million photos of apples with an accompanying short description, allows the machine to learn the correlations by itself.

Deep learning is a further advancement within the field of machine learning. Brynjolfsson and McAfee (2017, p. 11) argue, with superior algorithms. Deep learning uses a technique referred to as neural networks, allowing them to make better use of much larger data sets, they continue. Some large systems are trained by as many as 36 million examples. In any given situation in which one has a lot of data on behavior and are trying to predict an outcome is a potential use case for supervised learning, the authors conclude.

Brynjolfsson and McAfee (2017, p. 14) emphasize that, contrary to popular belief, one does not need much data to start using machine learning. While the performance of machine learning systems improves the more data they are given, companies can still improve their performance with smaller amounts of data – a sufficient amount of which is easily obtained, the authors argue.

Machine learning create new approaches to occupations, business processes, and business models, Brynjolfsson and McAfee (2017, p. 15) suggest. The two authors argue that machine learning complement human activities, rather than replace them. For instance, workflows and layouts are being reinvented to provide more efficient service, and business models are being reworked around ML to sell music and movies to customers based on their preference.
2.1.3 The Organizational Impact of AI

Agrawal, Gans and Goldfarb (2017) have written a paper on how AI delivers value in the workplace for a journal from the Massachusetts Institute of Technology. They argue that the key value of AI is its ability to predict. Agrawal et al. (2017, p. 2) highlight many recent advances that have brought the quality and speed of tasks, such as image recognition and language translation, to have gone from inconsistent performance to very consistent such. These advances have been made in the areas of sensors, computational speed, data retrieval, and algorithms. The authors describe autonomous driving as an example of a collection of predictions that have made previously manual tasks automatic.

Thus, Agrawal et al. (2017, p. 2) argue that the cost of prediction has decreased, while the value it provides has increased. As large amounts of data in great variety has become easily accessible, so too has prediction gained value.

Human work therefore moves from prediction to judgment, Agrawal et al. (2017, p. 3) suggest. They argue that while the AI discussion is usually framed as a battle between machine and human, they see it in terms of understanding the level of judgment that is necessary to pursue actions. In some tasks, once more autonomous driving as an example, which is filled with rules and routines, machines can replace humans, while some tasks require more complex judgment. However, the authors emphasize, as the cost of prediction decreases, so too will the number of tasks that cannot be done by machines decrease. In many contexts, AI can provide predictions that then require human judgment. Agrawal et al. (2017, p. 3) highlight Google’s Inbox by Gmail as an example. As the user is reading an email, Gmail proposes numerous short responses, which the user can then choose based on their own judgment. Selecting from a list of options is faster than typing a response, thus augmenting the human.

Finally, Agrawal et al. (2017, p. 3 – 4) present three interrelated insights that managers must understand in order to prepare for the AI future. The first insight is that prediction is not the same thing as automation. A task is made up of data, prediction, judgment, and action, the authors argue, while machine learning only involves prediction — thus only a single component of a task.

The second insight, proposed by Agrawal et al., is that the most valuable workforce skills involve judgment: “Employers will want workers to augment the value of prediction” (2017, p. 3 – 4). The authors use an analogy of golf balls to explain. The demand for golf balls increases when the price of golf clubs decreases, as they are complementary goods. In a similar way, judgment skills are complementary to prediction. If the demand for prediction skills decreases, then the value for judgment skills increases. Judgment skills come in many forms, from ethical to artistic, and which form of such skills will be the valuable is, incidentally, difficult to predict, the authors conclude.
Finally, the third insight proposed by Agrawal et al. (2017, p. 4) is that management may require a new set of talents and expertise. Tasks such as hiring and promoting are prediction based. This results in the task to figure out which job applicant would be the most likely to succeed in a job becoming more easily automated. In its place, judgment skills such as the ability to mentor and provide support, become more valuable managerial skills, the authors argue. Furthermore, finding out how to best apply AI by finding opportunities for prediction, becomes a key task for managers.

2.1.4 The Business Strategies of AI

In a peer-reviewed article published in an academic journal, Accenture’s Plastino and Purdy (2018, p. 16) argue that all industries they studied can benefit from AI, though organizations must adopt new approaches.

Plastino and Purdy (2018, p. 16 – 18) propose that AI can lead growth through intelligent automation, labor and capital augmentation, and innovation acceleration. For instance, they argue that AI can augment low-value adding or supporting tasks and thus enable workers to focus on high-value work.

The two authors suggest a number of strategies for handling AI. One such strategy was a proposition to measure the value of AI through return on algorithms, rather than the old-fashioned approach of measuring value through return on investment. Plastino and Purdy (2018, p. 21) argue that this is due to the fact that AI assets have self-learning technologies, and therefore gain value as time passes, while traditional assets typically depreciate over time. Thus, the authors argue that it is difficult to estimate the future value of AI when investments are made, as the majority of the costs and benefits will not appear until some amount of time after the AI has been adopted.

Ayoub and Payne (2016) have also explored business strategies of AI. They argue that AI will bring profound and radical change: "[…] in health, education, manufacturing, finance, social care and a host of other human activities, AI is already reshaping human activity and society" (Ayoub & Payne 2016, p. 794). The two authors (ibid. 2016, p. 806 - 807) argue that modular, i.e. domain-specific, AI can be used on tactical, operational and strategic levels alike. The authors propose that AI will improve the quality of human decision-making at strategic levels, using military efforts as a context to exemplify such strategies. The duo argues that AI does not feel fatigue or experience stress, and will not employ any emotions, unless programmed explicitly to do so. This makes AI excellent at creating strategies, Ayoub and Payne (2016, p. 807) propose.
2.1.5 The Untapped Potential of AI

Attempting to describe the potential of AI, its practical implications and the barriers to its adoption, Brynjolfsson and McAfee (2017) argue that, although AI is already in use in thousands of companies around the world, most big opportunities have yet to be tapped. They argue that the effects of AI will be magnified in the coming decade, as manufacturing, retailing, transportation, finance, healthcare, law, advertising, insurance, entertainment, education, and practically every other industry transform their business models to take advantage of machine learning. While AI has generated many unrealistic expectations, Brynjolfsson and McAfee (2017, p. 4) emphasize, it has also created many practical uses.

Brynjolfsson and McAfee (2017, p. 4) argue that the biggest advancements in the field of AI have been made in perception and cognition. The biggest advancements in the category of perception have been in regard to speech. One study that the authors mention found that speech recognition is currently three times as fast, on average, as typing on a cell phone. Image recognition is another area where AI has made many advancements, the authors suggest. The social media Facebook, for example, can recognize the user’s friends faces in photos they upload, and automatically tag them.

Cognition, then, has also seen great improvements, Brynjolfsson and McAfee (2017, p. 7) suggest. Machines have beaten the best human players in games of poker and Go, cybersecurity companies use AI to detect malware, and e-payment giant Paypal uses cognition to prevent money laundering. Many companies are using machine learning to decide which trades to perform on Wall Street, and Amazon uses the very same technology to improve product recommendations to customers, the authors argue.

Accenture (2017a, pp. 19-20) suggests that AI is also about to become a digital spokesperson for companies. Following the rise of AI-powered conversations, they suggest that AI will become the face of companies.

2.2 Enterprise Resource Planning Systems

Typically shortened as ERP, an enterprise resource planning system is a complete package that implements an enterprise architecture of an organization, according to Beynon-Davies (2013, p. 189). Hsu (2013, p. 1) argues that ERP systems are large commercial systems that digitize business processes. He explains that its purpose is to integrate an enterprise’s data, in order to transform it into useful data that support business decisions. It is an information and communication system that spans an entire organization with different features split up into modules (Beynon-Davies 2013, p. 189). Typically, a buyer of an ERP system may choose which modules to implement.
2.2.1 The Components of ERP Systems

A typical ERP package consists of modules that support a common range of organizational functions. These are functions such as customer relationship management (CRM), management reporting, inventory management, production control, human resource management (HRM) and supplier relationship management (Beynon-Davies 2013, p. 190). These modules all interact with a centralized database, and they can be implemented in an integrated manner across the organization, the author argues. They typically have a consistent look and feel, and the data contained within an ERP system can be updated and accessed in real-time (Beynon-Davies 2013, p. 189).

The author argues one major driver of an ERP package to be interoperability. When an organization adopts information systems, a common issue is that data and information become fragmented, redundant and inconsistent. By implementing a complete ERP solution, such issues become non-existent, as all modules are integrated into the same database.

2.2.2 The Business Value that ERP Provides

Much research has been conducted on the business value that ERP systems provide. Hsu (2013) examined 150 ERP and e-business adopters in the US in order to understand with what organizational resources, and by building what firm-specific capabilities ERP systems may bring competitive advantage to firms.

Hsu (2013, p. 413) argues that the IT productivity research has produced contradictory results, arguing that studies in ERP value have similarly produced inconsistent findings. For example, while ERP implementation has a positive effect on productivity measures and market value, it has no effect on profitability measures. The author argues that big differences can be observed between ERP adopters, even within the same industry or same country. Thus, Hsu (2013, p. 413) describes and dismisses ERP research that examines critical success factors. He argues that critical success factors are not necessarily related to improvements in firm performance, opting to instead focus on another view: the resource-based view. This view is a framework that argues that firms possess resources, Hsu (2013, p. 413 – 414) argues, a subset of which enable them to achieve competitive advantage.

Using the resource-based view, he discovered that managerial skills and organizational change management are more important factors than IT resources in generating business integration capability, though neither provided a competitive advantage. Instead, business integration capability built from both resources had a mediating role in which businesses could achieve a competitive advantage, Hsu (2013) argue.
Ruivo, Oliveira and Mestre (2017), meanwhile, found ERP systems to be an important asset to business value. Their paper examines the value of both ERP and CRM systems, discovering that the latter only has a positive impact on business value if it is well integrated with the former. The authors argue that, as ERP systems support critical parts of a firms’ value chains, operations, and sales processes, they therefore have a big impact on business value. Ruivo et al. (2017, p. 1624) also suggest that there may be other systems besides ERP and CRM systems that contribute to business value, such as e-commerce systems.
3 Method

In this thesis, I have performed a qualitative case study at Exsitec through interviews, the result of which were analyzed in conjunction with the literature. The methodology presented in this chapter is based on a method book by Oates (2006), which explains how to research information systems and computing. For the chapter on Data Analysis, Elo and Kyngäs (2008) was used alongside Oates (2006).

Thus, in this chapter, I will present my research strategy, research method, and method for data analysis.

3.1 Research Strategy

The aim of the thesis is to gain a deep understanding of how organizational processes covered by ERP systems can, or already do, benefit from AI, with small- and midsize clients in focus. An appropriate research strategy for discovering this knowledge is through a case study; performing interviews at a specific consultancy firm and gaining as much insight as possible in the matter.

Oates (2006, p. 35) argues that a case study lets the researcher obtain detailed insights into a situation and its processes, which matches what the research purpose of this thesis aims to answer. The case that is approached in this thesis is that of consulting firm Exsitec, a company with long experience in the delivery of ERP systems. As a nation-spanning company, Swedish firm Exsitec (2018) is the biggest partner of ERP manufacturer Visma. At Exsitec, I aimed to study the views and experiences of employees within the fields of consultancy and sales in order to gain deep insights into how consultants perceive the potential for AI in small- and midsize companies.

A case study is characterized by investigating a topic in its natural setting, Oates (2006, p. 142) argues. By performing this study at Exsitec, I aimed to get as close to a natural setting as possible. Finally, Oates describes how researchers typically use a wide range of sources when performing case studies, e.g., interviewing as many people as possible at a department if a department is being studied. Accordingly, I interviewed nine consultants at Exsitec, including one pre-study interview, for this study.

Oates (2006, p. 143) argues that there are three types of case studies: exploratory, descriptive and explanatory. He argues that an exploratory case study is used to define the questions to be used in a subsequent study, a descriptive case study provides a rich, detailed analysis of a phenomenon in a given context, and an explanatory case study is one that goes a step further than the descriptive type, seeking to explain why events happened in the way they did. This study is of the descriptive nature, as insights on AI are described in detail. Furthermore, the
study is contemporary, described by Oates (2006, p. 144) as an examination of what is happening now, rather than exploring an event of the past. Exsitec was chosen as case as it represents a typical instance of a consulting firm, while having deep knowledge of ERP systems, that to some degree can be generalized to consultancies as a whole.

Finally, I followed an interpretative paradigm, the key aim of which is an attempt to identify, explore and explain how various factors in a given setting are related (Oates 2006, p. 292). This paradigm is characterized by the belief of multiple subjective realities, which means that the thesis is written under the presumption that there is no single version of truth (Oates 2006, p. 292). For instance, different companies and cultures work differently, and this thesis examines one interpretation of reality for one company. The interpretative paradigm is a common choice for case studies (Oates 2006, p. 300).

### 3.2 Research Method

I collected empirical data through interviews with Exsitec employees within the departments of consultancy and sales, in particular the former, who are very well experienced within the field of ERP systems. The first interviewee, who was selected for the pre-study, was selected through a recommendation from my contact person at Exsitec. The other eight interviewees were chosen from the company’s HR portal, which lists all of its employees. The first six consultants and the first two salespeople listed in their portal, who were employed in Stockholm and who worked in the department of ERP systems, were asked through emails to be interviewed individually in person. All eight employees responded that they were available for interviews.

As an interviewer only gets to interview an interviewee for the first time once, it was crucial to formulate the questions correctly before performing the large chunk of interviews. The questions had to be formulated in a somewhat explorative nature, where the interviewer had as little influence on the answers as possible, while also ensuring that the correct information was collected. I therefore chose semi-structured interviews as format, which would allow me to explore the mind of the interviewee, while also steering him or her in the direction of AI, should the interviewee get side-tracked.

The balance between openness and narrowness was tested through a pre-study. In this first interview, I asked questions by using the interview sheet found in appendix C. The pre-study gave me interesting findings, which are described in chapter 4 alongside the other interviewees, but moreover it further gave me good insights into how I could improve my questions. I realized that my questions were too broad, and the interview format was slightly too explorative. I also gained insights from the pre-study which I wanted to expand upon in upcoming interviews, thus I updated the questions for the study.
The final interview sheet, which was used for all interviews but the first, can be found in appendix F. The interview is separated into four parts.

In part one, I gain a quick but important understanding of the interviewee. I asked questions about their role at the company, and what their day-to-day tasks are. I asked these questions to get an early idea of their unique expertise, which may influence the answers they provide.

In part two, I presented the material that would be used as basis for the next part of the interview. I presented printed versions of appendix D and E. Appendix D presents a list of common organizational processes that a typical ERP system may encompass. I built this figure in Microsoft Visio, with the content based on Visma (2018) solutions, as well as a generic framework of enterprise functionality by Shtub and Karni (2010, p. 38–40). The reason why I wanted to present this figure, was to allow the interviewee to have something concrete to manifest their thoughts onto, considering that the questions were highly explorative in nature. I presented this figure rather quickly, emphasizing that the interviewee may use this figure as they wish, even breaking processes down into even smaller processes, should he or she prefer.

After that, also in part two, I presented appendix E. This figure is a simplified version of the framework for data analysis which is presented under 3.3.1. In this framework, the four models through which AI can create business value is explained. However, in the version I showcased, the data variables had been removed, and keywords for each model were presented. I dedicated more time to explaining this appendix than I did with the previous, as appendix D contains processes that the interviewee would be familiar with, while I could only presume that this framework would be unfamiliar to him or her. I therefore dedicated around two minutes to walk the interviewee through the four models which this framework contains. Naturally, this appendix most likely influenced the respondents’ line of thinking, though it was crucial to ensure a common baseline and a unified language. The full figure presented in 3.3.1, with the two parameters data complexity and work complexity, was not presented to the respondents, though questions concerning data and work complexity were asked in the next part.

In part three, I asked the bulk of my questions. The questions were intentionally organized in a way that they started with highly explorative questions, to later move on to more narrow such, before ultimately ending up with broad questions once more. The reason why, was that I wanted to see what processes and models the interviewee’s mind would be drawn to first, based on the appendixes, with as little influence from my specific questions as possible.

Finally, in part four, I asked a small amount of final, broad questions, in order to allow the interviewee to summarize his or her thoughts. Even over a brief interview such as this, the interviewee’s thoughts could have changed or adapted over the course of the interview, thus I wanted to collect these final thoughts. Each interview lasted for between 50 to 70 minutes.
3.3 Data Analysis

As the area being examined in this thesis does not have much prior research, and this thesis as such has a research purpose that has not been tested before, I was first inclined to adopt an exclusively inductive approach for analyzing the data, which Elo and Kyngäs (2008, p. 1) describe as an excellent choice in cases when there is no previous research dealing with the phenomenon. However, to provide validity in general and structure in particular, I instead opted to combine a deductive approach with an inductive approach. What this essentially means is that the two of the three categories for data analysis were deductively created before the interviews were performed, while a third was inductively created thereafter, to catch unpredicted insights. This not only allowed me to ask more concrete questions, but it also allowed for a more structured analysis.

After each interview, I transcribed them in their entirety, and made notes of the main insights from each paragraph along the way. Next, I began to categorize the data into three main categories: the first being models, the second being processes, and the third being other insights. The first two categories are deductive categories with a number of subcategories. These two categories are explained in detail in 3.3.1 and 3.3.2 respectively, with findings presented in 4.2 and 4.1. The first category, consisting of four sub-categories, was chosen through the framework. The second category was chosen to simplify the applying of AI to ERP systems. The third category, meanwhile, allowed for an inductive approach for insights and trends that may not fit into either of these categories, but that still provide value for the research purpose. These sub-categories were discovered by extracting themes from the interviews. Categories were extracted by looking at key topics brought forward by the respondents. The findings of this third category are presented in 4.3.

3.3.1 The Framework for Creating Business Value with AI

This framework, presented by Bataller and Harris (2016, p. 8 – 10), was created specifically for analyzing the business value of AI. It was chosen in order to have a concrete framework upon which to base the analysis. In essence, the framework describes how AI can create value either through automation or augmentation, and presents two variables and four models through which one can achieve this value.

The two variables are data complexity and work complexity (see figure 3). Tasks with high data complexity are represented vertically in the diagram, and tasks with high work complexity are represented horizontally. Data with low complexity is typically well structured, stable and/or of low volume, while data with high complexity is typically unstructured, volatile, and/or of high volume. Work of low complexity is typically routine work, predictable and/or rules-based, while work of high complexity is typically ad hoc, unpredictable and/or judgment-based (Bataller & Harris 2016, p. 9).
Tasks with low data complexity and low work complexity, such as credit decisions (Bataller & Harris 2016, p. 9), can easily be automated. This means that the machines can either fully or partly perform the task themselves, and thus allowing humans to perform more meaningful tasks. Meanwhile, tasks with high data complexity and high work complexity, such as music composing (Bataller & Harris 2016, p. 9), can be augmented. In these tasks, AI is used to empower humans to better execute the task. Thus, automation is placed in the lower left corner, and augmentation in the upper right (see figure 3). The higher the data- and work complexity of a task, the more likely it is that augmentation is the correct approach to using AI to support the task.

![Figure 3](image)

**Figure 3.** The two uses of AI: automate and augment, as appropriate per variable.

The authors further elaborate the figure by categorizing entries into four primary types of activity models, through the creation of a matrix (see figure 4). These four models are efficiency, effectiveness, expert and innovation (Bataller & Harris 2016, p. 8).
Figure 4. The complete version of the framework. A modified and simplified figure made by myself, based on Accenture’s original figure (see Appendix B). All variables and models of the framework remain the same in my figure as in the original, though the colors and shape of the figure has been altered, and keywords have been removed for clarity. Source: Bataller and Harris (2016, p. 9).

**Efficiency Model (Low data complexity, low work complexity)**

The efficiency model revolves around providing consistent, low-cost performance (Bataller and Harris 2016, p.10). As the tasks found in this model are routine activities based on defined rules and procedures, machines can take over through their ability to sense, comprehend and act, allowing humans to monitor the machines and change their rules as the business environment evolves.

These systems can translate decisions into action quickly, accurately and efficiently, Bataller and Harris (2016, p. 10) argue, highlighting automated credit decisions and package delivery via drones as two examples.
**Effectiveness Model (High data complexity, low work complexity)**
The goal of the effectiveness model is to improve the ability of workers and companies to produce a particular desired result (Bataller and Harris 2016, p. 10). Their success heavily relies on communication and coordination, as their work involves several interconnected activities. In these solutions, technology acts as an assistant to help people, the authors suggest. Cognitive tools that assist in scheduling, communicating, monitoring and executing activities are prime duties of AI in this model.

Personal assistants such as Google Now and Alexa are excellent examples of AI solutions in this model: “Only when questions are not resolvable from an automated knowledge base would a user be referred to a live agent,” (Bataller and Harris 2016, p. 10).

**Expert Model (Low data complexity, high work complexity)**
The expert model attempts to leverage expertise (Bataller and Harris 2016, p. 10). Work in this model is likely to rely on individual expertise and judgment. These are activities performed by lawyers, financial advisors and engineers, according to the authors. Decision-making and action is often taken by the humans themselves, while the technology’s role is to augment the decision-making of humans; offering advice and support.

Expert systems, as their name implies, are examples of AI solutions within the expert model (Bataller and Harris 2016, p. 10). Such systems can search through large data volumes and make recommendations, which humans can then use their better judgment to decide upon. Expert systems for medical diagnosis, or legal or financial research are examples of such expert systems, the authors propose. Sometimes expert systems speak directly to a customer autonomously, such as car configurator on a manufacturer’s website, but often they go through an expert to a customer, in order to form a personal, trusting relationship, as is the case in a medical diagnosis.

**Innovation Model (High data complexity, high work complexity)**
In the final model, AI can be used to enable creativity and ideation (Bataller and Harris 2016, p. 10). While humans make decisions and act, technology helps to identify recommendations and alternatives. Fashion designers, biomedical researchers, musicians, chefs and entrepreneurs use tools that fall into this model, the authors suggest. A music-making software may recommend changes to make a song even better, for instance. AI can be used to allow humans to experiment, explore and be creative more easily by augmenting them with the knowledge and speed they need to move their craft to the next level.

**How the Framework Was Applied**
I applied the framework to the context of ERP systems, by mapping out various processes (see 3.3.2), which a typical ERP system covers onto the diagram, through insights gained from the interviews. This explained how these various processes, at a high level, could or already do
benefit from AI technologies. The interviewees were asked questions concerning the models and processes (and the data and work complexity of the latter), with the processes being mapped out by myself based on these findings.

Note that the framework is used as a method for data analysis, and is not in itself used as literature background. On the same note, additional validity for the variables used for the framework can be corroborated in the literature background, where theories from Agrawal, Gans and Goldfarb (2017), which proposed a correlation between prediction and judgment, were discussed. In the same manner, the leftmost models are prediction-based while the rightmost are judgment-based.

3.3.2 The Organizational Processes

In each interview, I briefly presented a paper (see appendix D) featuring 16 processes to be used as support for contemplating the use and potential of AI in the context of ERP systems. These processes are, in no particular order: marketing, invoice management, purchasing, retail management, recruitment, inventory and warehouse management, knowledge management, service and support, business intelligence, human resource management, customer relationship management, research and development, procurements, time and project management, asset management, and finally enterprise management and business development.

As the interviewees work primarily with ERP systems developed by Visma, the processes were chosen based on the list of ERP solutions that Visma (2018) provides. This was done to create familiarity among the interviewees in order to receive more answers. In order to ensure the validity of the processes gathered from Visma (2018), an independent generic framework of enterprise functionality, created by Shtub and Karni (2010, p. 38 – 40), was used as a reference point. Ultimately, the processes chosen were natural for this context, as they are the processes that ERP systems sold by Exsitec cover.

3.4 Validity and Reliability

Through a comprehensive literature background with established definitions of key terms, validity was attempted to be secured through interviews with ERP experts analyzed in conjunction with findings from previous research. The validity and reliability were also attempted to be strengthened through a powerful framework made to be used in an organizational context, created by one of the leading consultancy firms, whose customers include 95 of the Fortune 100 companies\(^5\).

Parts of the theoretical background consist of private research. Naturally, private companies have monetary interests, and do not necessarily aim to showcase reality, but rather reality as it suits them. Despite this, the private research that was presented in the theoretical background is that of major companies that are looked up upon for their advancements in AI. Moreover, the theories born of private research was never treated as unconditional proof in this thesis. Rather, their theories were compared with the results from the respondents, and then analyzed in conjunction with it. Indeed, this thesis is not primarily a literature study. No stance was taken as to whether any of the literature is right or wrong. Indeed, all topics concerning strategies, business potential, and organizational impact are contemporary, speculative and subjective by nature, and have been treated as such throughout this entire thesis. Therefore, the mixture of books along with academic- and private research should not prove a hinderance with regards to validity.

As the purpose of the thesis is explorative in nature, it was important to use a framework for data analysis to provide reliability. Though the study is qualitative and inherently subjective, it attempts to convey a perception of reality in an organizational context. Indeed, as a case study, the thesis delves deep into perceptions of a phenomenon.

The results are not meant to be understood as an absolute or general truth, but rather AI as it is understood in the context of ERP among experts at one organization. Further, the results are contemporary, providing an understanding of the phenomenon as it is perceived in the present.

3.5 Critical Review

Though validity and reliability are attempted to be established (see 3.4), all findings are ultimately subjective. As an interviewer conducting semi-structured interviews, I naturally influenced the way the interviewees formulated their thoughts through the use of my questions and appendixes. However, measures were taken to influence the interviewees as little as possible while also establishing a common baseline (see 3.2). Further, while a case study was perceived to be an appropriate research strategy for this thesis, one could suggest that another approach would have been to perform interviews at a number of different organizations to get wider results that could potentially be more generalized for the industry. However, even within the same company, interviewees proved to have varied skillsets and personalities, as some interviewees appeared to prefer discussing the present while other preferred to discuss future potential. Moreover, some interviewees were experts on a few specific processes, while others had general knowledge across a broad spectrum of processes. This means that performing merely one or two interviews at a number of organizations could have generated skewed results – a larger quantity of interviews would be necessary for each organization, which would have been out of scope for this thesis. Thus, a case study remains the best option for the research purpose and scope as observed in this study.
The choice of Exsitec as case was made due to the fact that the company is ERP manufacturer Visma’s largest partner. As an expert in the areas of selling, implementing and integrating ERP systems, they were an optimal choice for the study with their knowledge in organization-wide use of information systems.
4 Results

Nine Exsitec employees were interviewed, seven of which are ERP consultants and two of which work with ERP sales. The interviewees are all involved with the implementation, integration and/or selling of ERP systems, with interviewees having a varied skillset. In this thesis, the interviewees have all been given fictional names, from the interviewee first interviewed to the last: Anton, Birgitta, Cristopher, Daniel, Edward, Fredrick, Gunilla, Hans, and Isak.

Thus, in this chapter, the findings from these nine interviews will be presented and organized as follows. First, I describe the respondents’ view on each process and argue for its present place in the framework. Next, I present the findings for each model (i.e. efficiency, effectiveness, expert and innovation) in a broader scope, exploring the present and future of the models based on the respondents’ views. Last, I present and discuss other relevant findings from the interviews.

4.1 The Present and Future of The Processes

In this section, the processes (introduced in 3.3.2) will be placed in the framework for data analysis (introduced in 3.3.1). For each process, the discussed usage of AI in the context of the process in the present as well as the future will be presented. In reference to the future, both actual future use and envisioned future use is presented. Further, for each process, a final motivation is given for its placement in the framework, based on insights gathered from the respondents. As noted in the method chapter, the processes are placed in the framework based on findings gathered from the interviews. Thus, naturally, this chapter is also an analysis, though the upcoming chapter 5 presents a deeper such.
Figure 5. A reminder of the framework used as support for data analysis. The reader ought to also be reminded that low data complexity was one where the data was typically structured, stable and/or of low volume, while high data complexity was typically unstructured, volatile and/or of high volume. For work complexity, low such was typically routine, predictable and/or rules-based, whereas tasks with high work complexity are typically ad hoc, unpredictable and/or judgment-based. These descriptions are crucial in the process of determining in which model the respective processes should be placed.

4.1.1 Invoice Management

Present: As one of the most frequently mentioned processes in this study, invoice management was mentioned as a basic example of automation by Anton, Birgitta, Cristopher, Daniel, Gunilla, Hans, and Isak. Hans argued that much of the work of a company’s economic department is being simplified or ultimately removed by ERP systems, as he highlighted automated invoice management as the most common and simple such example. He described it as a basic AI with rather trivial rules. Daniel described automatic invoice management as a “no-brainer”, as he argued that every company should have it. Fredrick too mentioned that it is the most common of customer requests, though he highlighted that customers only ask for automation of invoices when they have more invoices than they can handle. If a customer spends 80% of their time manually handling invoices, they do not perceive there to be a reason to automate the process, he explained. However, he continued, if a customer has so many invoices that they no longer have the time to handle them all, they will ask to automate the process entirely. The point, Fredrick concluded, is that customers generally only ask for a solution when they perceive they have a problem, even if it would benefit them before the problem has shown itself. Anton, Birgitta, Cristopher, Gunilla and Isak all simply argued that the process is typically automated.
Future: Cristopher suggested that more intelligent automation will become necessary, for two reasons. One reason is that simplifies the handling of anomalies, such as unusual invoices. The second reason is that AI, through the power of machine learning, can self-learn to read invoices by itself. Fredrick also noted the latter. Today, invoice management systems must be manually implemented and integrated for each firm and their unique invoices. An AI-powered system could automatically learn to read new invoices, he suggested, meaning that consultants would not need to manually configure automated invoice management for each unique organization. Anton argued that much progress is indeed being made in efforts to make the automation of invoices intelligent. Technology that automatically figures out how to better handle a particular invoice, for instance, is currently being developed, he concluded.

Model: efficiency. All respondents accordingly mentioned this process as one with simple data and work complexity, thus placing the process in the efficiency model. This process has already become automated but could benefit from a further developed intelligent automation.

4.1.2 Inventory & Warehouse Management

Present: Another commonly discussed process, inventory and warehouse management, was always noted as a process within the efficiency model. Anton explained that there are already examples of warehouses that are fully automated through robotics integrated with ERP systems. AI is here being used entirely with the purpose of automation. Daniel argued that the optimization of warehouses is the simplest AI-powered task of ERP systems today. Hans argued that it is very common amongst customers to ask Exsitec for this service. Cristopher argued that the data and work associated with warehouses is generally simple, a fact that Fredrick corroborated, as he argued that the data associated with warehouses is indeed basic.

Future: Birgitta argued that inventory management would benefit from having more intelligent systems, and Gunilla argued that the associated systems are not automatic enough today, as she explained that most work must be configured manually. Isak speculated that warehouse management systems will become smarter in the future, providing suggestions on, for instance, what shelves to put certain wares on, depending on their size and weight. AI could perform these tasks faster and more efficiently than humans. This is rather basic automation – not necessarily using machine learning – but nonetheless important AI for increasing efficiency. Hans also expressed similar thoughts, explaining that they already sell a system that helps customers optimize the flow of their warehouses. Edward proposed that the status of a company’s inventory should be more easily accessible to management, suggesting that warehouse systems should place relevant data in the centralized database that BI systems can then use.

Model: efficiency. Overall, it became overwhelmingly clear that this process belonged in the efficiency model as every technological advancement already made, and already envisioned,
revolves around optimizing flows and determining routine tasks. Further, both data and work complexity were noted to being low. The process could benefit from further optimizations to allow for more efficient flows and management, and where applicable, robotized warehouse management.

4.1.3 Retail Management

Present: A common process, retail management includes payment channels and payment solutions. Both Cristopher and Daniel mentioned it as having simple data and work complexity, as the process follows a simple flow. Cristopher explained that much of the work surrounding retail management in the present has been automated through basic flows.

Future: Hans suggested that the process is currently being redeveloped in accordance with marketing solutions such that the retail system presents suggestions of products to purchase. Anton highlighted difficulties concerning retail management, difficulties which primarily revolve around legal regulations. Retail management systems have not seen as many advancements as other systems in the efficiency model, he said, due to concrete regulations that must be followed. Regardless, he added, it is a process of simple complexity.

Model: efficiency. The process was placed in the efficiency model as it is completely rules-based with routine tasks. Many optimizations have already been made, but the process could, much like invoice management, benefit from intelligent automation.

4.1.4 Knowledge Management

Present: As a process that customers do not frequently request, knowledge management was seldom mentioned by the interviewees, though one consultant, Cristopher, had much insight into knowledge management systems. He argued that knowledge management is a big struggle for many companies. Senior employees can do a junior employee’s work in much less time, thus senior employees will often get put on work that otherwise would have been great learning experiences for the junior, he argued. Finding the balance between when to give a job to juniors versus when to give a job to seniors is a massive challenge, he proposed. Furthermore, Cristopher added, creating schedules and coordinating activities between employees and company work is another major challenge. He noted that no AI work has been done in the present with this process.

Future: Cristopher proposed that AI could solve many of the challenges of knowledge management, though he made it clear that AI is not currently being used in such a fashion. Fredrick also expressed interest in the opportunity of AI supporting knowledge management systems. He suggested that such developments would be interesting not only for their
customers, but in particular for the consultancy firm itself. Daniel briefly mentioned knowledge management as a process with complicated data, yet he was uncertain of the work complexity.

**Model:** effectiveness. Though none of the respondents explicitly argued for the work complexity of the process, it was clear that it was a process of high data complexity. Cristopher highlighted the issues surrounding knowledge management as tasks revolving around scheduling and coordinating, which is precisely the issues that the effectiveness model attempts to solve. These are not tasks of high work complexity, but rather something that AI-powered assistants can accomplish. This is a process where little AI-work has been done in the present, meaning the untapped potential is great.

### 4.1.5 Service & Support

**Present:** Service and support was a slightly divisive module in terms of work complexity. Cristopher proposed that much of the work in this process consists of routine tasks that can be automated through basic FAQ’s, while Birgitta, Daniel, Edward and Hans argued that it is a complex process at heart, as queries can reach virtually any level of complexity. Birgitta argued that while any customer support has systems providing them with information, it nonetheless requires human interaction to solve complicated issues. Edward too argued that, while the data is simple, support is not possible to automate due to the number of ad hoc requests. Daniel also argued that the data is structured, while the work is complex. This process has not yet seen any AI developments in the ERP systems that these consultants work with.

**Future:** Hans proposed that support processes will become even more complicated moving forward, as other tasks rise in complexity, which indirectly results in more knowledge being necessary for the support employees. Thus, he suggested service and support systems will need to provide more intelligent information in the future.

**Model:** expert. Only one respondent proposed service and support as a process with easy work complexity, while four others argued for it as a complicated process in terms of work, but with simple data. Hans also argued that support employees are experts who make use of an expert system, which further emphasizes its position as an expert system. Thus, the process was placed in the expert model.

### 4.1.6 Purchasing

**Present:** This process was frequently highlighted as one with simple data complexity but questionable work complexity. The process of purchasing from wholesalers was debated both in the efficiency model as well as the expert model. Hans highlighted that automatic purchases from wholesalers presently exist in ERP systems, though these systems are not very intelligent, he argued, as they are largely configured manually. Every company that is handling purchases
are trying to optimize it to some extent, Hans continued, pointing out that customers usually approach Exsitec when they have reached a point when they no longer have a clear overview of their purchases, i.e. when the purchases are too many for them to handle manually. Meanwhile, purchases can of course only be made automatic when there are large quantities of similar products, he explains, thus companies with largely ad hoc purchasing or with great variety in stock may find themselves unable to automate. In these scenarios, an expert system would be of preference, though he has never encountered such a clearly defined system in the present.

Cristopher argued that the process of purchasing from wholesalers exists just as much in the efficiency model as it does in the expert, suggesting that automation of purchasing is easy, while tasks such as purchasing non-routine items and collecting trends are too complicated for automation. Isak also argued for its place in both the efficiency and expert models, proposing that within the next few years, many clients will ask for a combination of the two. Gunilla argued that automated purchases still have to be manually set, which somewhat defeats the point.

**Future:** While the automation of routine purchases of wares already exists, assistance for purchasing of non-routine wares, finding new products and wholesalers, as well as assessing products and wholesalers, do not presently exist, as explained by Hans, Cristopher, and Isak above. Isak also added that a purchasing system should be able to both inform and warn its users when certain wares are running out, or the opposite, when they run a risk of not getting sold, and accordingly propose appropriate solutions. Overall, Isak argued that the system should, and probably will, make many more suggestions in the future. Furthermore, the automation of routine purchasing is still largely manual, Gunilla argued, as she hoped that future versions of purchasing systems would be able to automatically order products without having a human first set minimum/maximum levels. Thus, there are large amounts of potential to use AI-powered tools in both of these models.

A cautious approach was taken by Daniel and Ted, who urged for the organizational difficulties that the expert model of purchasing might face. Daniel expressed concerns that people would not want an AI to help them decide what products to order, as a company’s assortment is closely tied to its identity. Ted also argued that in the present day, small- to midsize customers do not want to give away the power of influence of what to purchase to a computer.

**Model:** efficiency and expert. It became overwhelmingly clear that the process of purchasing had to be split and placed into both the efficiency model and the expert model. Automatic purchasing is presently far too simple; forcing its users to manually set min/max-levels. More intelligent algorithms to automatically handle purchasing, rather than forcing employees to manually decide upon orders, will be an important feature going forward. Simultaneously, businesses with irregular or varied purchasing processes will benefit from an expert system,
though consultants should apply caution and emphasize that the purpose of the expert system is to empower the user, rather than taking the control away from him or her.

4.1.7 Business Intelligence

**Present:** The process of business intelligence (BI) was unanimously put into the expert field, as Anton, Birgitta, Cristopher, Daniel, and Fredrick argued for it being a process with low data- and high work complexity. Birgitta argued that it provides the very foundation for judgment-based decisions. The data, she suggested, has to be presented in an understandable, structured, systematic manner, either through reports or dashboards, thus being simple. Birgitta argued that BI is a process at the forefront of innovations, though she could not provide any examples of how AI is currently being used within these systems.

**Future:** Daniel argued that BI has grown in popularity and will greatly continue to do so. He speculated that BI will become the most requested feature from their customers in the near future, as he argued that good decisions can only be taken with good decision-making support, and that this is the key to defeating competitors. He proposed that AI-powered BI will become important in the future. Not through automatizations, he emphasized, but through providing more intelligent suggestions.

**Model:** expert. BI was unanimously discussed within the expert model for its low data complexity but high data complexity by Anton, Birgitta, Cristopher, Daniel, and Fredrick.

4.1.8 Marketing

**Present:** Daniel noted that marketing has become split into two categories. One that involves great complexities and human judgments, and one that is structured and rules-based. He referred to the latter as demand generation, a term that refers to the combination of marketing processes and structured sales processes. Anton explained that demand generation technologies can automatically suggest when and what a marketer needs to read and learn. Meanwhile, both Daniel and Cristopher highlighted that a majority of marketing work is still judgment-based and uses data that can reach any level of complexity. Neither of these categories of marketing has seen any major advancements in AI.

**Future:** While Daniel noted that marketing can be automated today through demand generation tools, he made it clear that it is very clunky and limited. He proposed that better tools must, and will, be developed. Hans argued that rules-based marketing can greatly help people figure out who should receive what advertisements, which would relieve much of the workload that is put on marketers today. On the other side of the spectrum, the difficult marketing work must be assisted through other means, though the consultants were uncertain how.
Model: efficiency and innovation. Following the information gathered, I split the process into two and presented it under both the efficiency and innovation models. The innovation model was chosen as Daniel and Cristopher noted that the process is one of both high data complexity and high work complexity. The rules-based marketing could be further developed through machine learning algorithms to more easily reach out to potential and prospective targets, while judgment-based marketing should be empowered.

4.1.9 Recruitment

Present: Though Daniel, Anton, Hans, and Cristopher were interested in the possibilities of recruitment, they acknowledged that no AI-powered work has been done for the process of recruiting in ERP systems. Instead, they had major visions for the future of the process.

Future: Hans argued that the work of recruitment is very complicated and must be simplified. Daniel, meanwhile, proposed that early steps of recruitment can be automated. He argued that the initial phase of any recruitment process can be automated through algorithms that in part scan career networks such as LinkedIn, and in part scan resumes and cover letters. On the other end, Daniel, Anton and Cristopher argued for the complexities involved in recruitment, which revolves around highly complicated data, and judgment-based skills that require human recruiters to be a part of the process. Cristopher argued that wrongful recruitment – the selection of the wrong candidate – is an issue that AI could solve. The AI could, Cristopher envisioned, scan the interviewees’ voice during interviews, and provide insights to the recruiters, presenting information such as “this person is so-and-so analytical versus emotional”.

Model: efficiency and innovation. Based on the thoughts of Daniel, Anton, Hans, and Cristopher, it became clear that recruitment is another process that must be split into two: one rules-based, and one judgment-based. Rules-based recruitment can be powered by machine learning algorithms which scan and learn from keywords, while judgment-based recruitment should empower recruiters through AI-powered assistance.

4.1.10 Human Resource Management

Present: Cristopher, Hans, Edward, and Daniel made it clear that very little AI work has been done in human resource management (HRM), as it was seldom requested by customers and likewise was perceived as a complicated process where no one really knew how, in practice, AI can be used to develop it.

Future: Both Cristopher and Daniel noted that the process requires intense human judgment, though Cristopher proposed that this judgment could be made much easier with AI-powered assistance. He suggested that AI can be used to tailor benefits and solutions to distinctive employees, though he acknowledged that no such work is being developed in the present. Hans
believed HRM would greatly rise in importance, primarily as he speculated that the process of employment will fundamentally change at some point in the future, from long-term employment to management of a network of talent.

**Model:** innovation. Human resource management was exclusively referred to as one with both complex work and data, and was thus placed in the innovation model. Though the process will likely not be at the top of any given company’s priority list in terms of AI development, AI should ultimately be used to empower the management of human resources.

### 4.1.11 Customer Relationship Management

**Present:** Anton, Cristopher, Edward, and Daniel acknowledged customer relationship management (CRM) much in the same vein as HRM: as a complicated process that also revolves around humans. All primary activities related to CRM must be handled through human interaction. Further, much for the same reasons as HRM, Cristopher noted that there are currently very few AI technologies supporting CRM systems.

**Future:** Cristopher proposed that AI could be used to provide insights and decision-making support to users of CRM systems. Daniel suggested that AI could scan keywords of customer’s websites and social media, to empower CRM users with insights. Edward also argued that judgments can be empowered through the use of AI, as he highlighted the importance of being able to compare customers.

**Model:** innovation. Consistently referred to as a model of high data and work complexity that revolves around humans, it was very clear that CRM should be placed in the innovation model. Empowering users of CRM systems with customer insights along with frames for comparison appears to be an excellent direction in the development of this process.

### 4.1.12 Other processes

There were five additional processes that I asked the interviewees about: enterprise management & business development, time & project management, research & development, procurements, and asset management. There was too much uncertainty surrounding these five processes to attempt to properly classify them, due to the fact that Exsitec does not work with these processes in their ERP solutions. Nonetheless, these processes were briefly discussed by the interviewees.

Anton expressed great interest in enterprise management and business development, as well as research and development, stating that these two processes will be very interesting in an AI-assisted future. He argued that both of these processes in particular are very interesting as there are few regulations one is forced to follow, and that those who are quick to realize the best
practice for these processes will gain a great competitive advantage. Overall, these two processes were proposed to have a high work complexity and an uncertain data complexity, though again, as the respondents were far too uncertain, I decided to exclude the processes.

A few interviewees expressed great interest in time and project management, though rather than discussing it in the context of ERP systems, they discussed these processes in an internal context. Fredrick proposed that an AI for internal project management would be immensely useful, as an AI that could support the act of organizing and planning projects would make their day to day life much more convenient.

Asset management and procurements were the least discussed processes, barely getting any mentions. Again, this could largely be due to the fact that these processes are not a part of the solutions that Exsitec’s customers typically ask for.
4.2 The Four Models of the Framework Explored

**Figure 6.** The processes as placed in the framework. The placement of the processes inside each model is arbitrary, i.e. *marketing* *(rules-based)* does not necessarily have a higher work complexity than *purchasing* *(automatic)*, even though the former is placed to the right of the latter. Such finetuning is not possible when looking at processes on a high-level as done here.

Figure 6 above illustrates the processes as placed within the framework. In addition to being asked about the processes in particular, the interviewees were also asked questions concerning the four models in particular. The four models will thus be presented below, with findings based on the insights gathered from the figure above, coupled with the results gained from questions asked concerning the models.
4.2.1 Efficiency

Throughout the interviews, processes relating to the efficiency model were generally more frequently discussed, and respondents perceived that they have more experience with this model. Anton argued that efficiency is the model where they have made the most advancements, regardless of which business process is in question. Birgitta explained that efficiency is the easiest model to work with, and Cristopher, Daniel, Edward, Fredrick, and Hans all highlighted processes relating to efficiency as the most commonly requested from customers. “Customers typically call us and say ‘hi, can you help us optimize this thing’”, Daniel explained in our interview. Fredrick explained that customers contact Exsitec when they have a routine-heavy process that the customers perceive that a computer would be able to do just as well. Anton elaborated that the efficiency model is by far the easiest to work with, as it is the easiest to understand in practice. He also highlighted that most customers still have much to automate, noting that customers thus prioritize such features.

Anton explained that there is still much progress to be made in this model. For instance, he highlighted the handling of invoices as a process that customers often want automated, and while that is a process the consultants can easily automate, the automation is not particularly intelligent. Thus, the automation technology powering this process is being further developed by their partners in order to make the automation intelligent, i.e. using technology that automatically figures out how to better handle a particular invoice.

Hans and Fredrick presumed that the efficiency model would still be the most requested model in the next few years, as customers have much yet to optimize, and as optimizations themselves are getting more advanced year over year.

4.2.2 Effectiveness

The model of effectiveness was given very little attention by the interviewees, as very few concrete examples were brought forward in our interviews. Aside from a few minor occurrences and a few moments of visionary general-purpose AI that would theoretically assist the organization as a whole. Birgitta proposed that AI could be used at stores for creating schemes for cashiers, as each cashier would provide their preferences for the AI, which would then create the working hours based on when each employee would rather work. Alas, Birgitta highlighted, this is not something the company works with. Instead, Cristopher highlighted knowledge management as a key area where AI does not currently, but absolutely could, provide great value. Several interviewees expressed interest in the effectiveness model when considering the internal organization. For the consultancy firm itself, using AI-powered assistants for project and knowledge management was highlighted as a great opportunity by a number of consultants.
4.2.3 Expert

Several of the interviewees expressed great interest in expert systems for purchasing of wholesaler wares and simultaneously stressed the importance of business intelligence systems. Birgitta argued that the expert model is easier for customers to adopt in terms of organizational difficulties, as jobs being empowered feel safer than jobs being automated. Despite this, there were but three examples of expert systems being used in ERP systems, and the respondents were unable to provide examples of how, or if, AI is currently being used in these processes.

4.2.4 Innovation

As the most difficult model to explore, the creativity-enabling innovation model was nonetheless envisioned with great enthusiasm during my interviews. Very little work appears to have been made in the innovation model in the context of ERP systems, thus every process that in this thesis got placed in this model possess untapped potential. Making advancements in this model is complicated and demanding, thus it is not likely to be a priority in the next few years, though early adopters are sure to gain a competitive advantage. However, among the consultancy firm’s small- to midsize customers, Fredrick argued that most customers do not want systems in the innovation model. Customers do not presently want to give away control of such vital creative processes, as they lack trust in IT systems. Most interviewees, however, confidently acknowledged the innovation model as the future, uttering with certainty that this model will ultimately gain great importance.

4.3 Other Insights

Many additional interesting insights were discovered from the interviews.

The respondents proposed organizational difficulties as some of the most problematic. These issues include change communication, incorrect understandings of the anatomy of tasks, problematic rules and regulations, lack of clearly defined routines, and lack of monetary resources. Isak and Birgitta argued that change communication is an enormous challenge. Isak noted that everyone says that they like change, while in reality, no one truly wants to change. Fredrick noted that customers are happy to automate when it removes tasks that they see as a burden, such as invoice management, though only when the customer themselves have actually conceived of it as a burden. Combating change could prove to be an even greater challenge than the technical such, as humans are difficult to work with, Edward also argued.

Gunilla explained that customers not understanding the anatomy of their tasks is another great organizational challenge. She argued that it was common that a customer would explain a process incorrectly, leading to an incorrect configuration. Anton, meanwhile, highlighted rules and regulations as a great hindrance for general automation, emphasizing that variety in
regulation results in solutions having to be tailor-made. He also expressed the lack of clearly defined routines as problematic: many smaller companies do not have clear routines for how they do things, which makes automation troublesome.

Building trust in AI is perceived as an additional challenge, Birgitta argued, as she emphasized that expert systems are perceived as safer as they do not take away any control from the people. Further, Hans argued that while CEO’s may often be visionaries, their customers are often contacting the consultancy firm from the company’s economic department, where, Hans suggested, employees may not be as trusting in technology.

Outside of the aforementioned organizational challenges, many other interesting insights were gathered.

Daniel argued that unstructured data will rise in importance. He proposed that unstructured data is what gives any given company its competitive advantage, as he noted the importance of the innovation model. Fredrick too believed ERP systems would benefit greatly if the systems collected more data of the unstructured kind.

Every interviewee was asked directly if they believed the main goal of AI was to reduce costs or increase revenue, to which every respondent answered that the primary goal of adopting AI technologies is to reduce costs, though Daniel proposed that this mentality is bound to change. He argued that the future corporate leaders are those who focus on using AI technologies to grow, rather than to merely optimize their processes, something Edward also proposed. Edward suggested that many processes are rapidly and extensively being reshaped by new innovations.

Fredrick argued that ERP systems are preparing companies for emerging technologies, as they have been made modular thanks to the cloud. Fredrick and Hans elaborated that one of the ERP systems they sell and implement is fully cloud-based, which makes it easy for customers to swap individual systems for newer whenever new advancements are made.

Hans proposed that tasks and processes that were previously complicated are becoming simpler, highlighting recruitment as such a task. As more ways to systematically execute jobs are being discovered, so too are the tasks becoming simpler. On the other side of the spectrum, Hans noted, simple jobs may in turn become complicated, as more data for decision-support is made easily available. He noted service and support as a job that may become even more complicated as new innovations are made.

Finally, Edward noted that many processes will soon need to be fundamentally reinvented, as artificial intelligence paves the way for superior ways of performing virtually every task. In our interview, Edward argued: ‘The ones who know today’s way to work, and are kings in their industry, will be the newcomers and become farmers in the future. Someone within the company will ask: ‘Do you want to become a farmer again?’ ‘No’. ‘Good, then let us continue
for another year and hope that it all works out’. This is why companies will collapse, because they do not want to change.” He proposes that major companies will fall as they will be unable to redefine their processes quick enough. On a similar note, Daniel confidently argued that AI will eventually outperform humans in virtually every process. He would often recommend customers to reinvent their processes, though the customers were often too scared to do so, he explained. Hans argued that some companies could be fully automated already in the present, not requiring any human resources.

4.4 Conclusion

The results have provided insights into the present and future use of processes and models in the context of ERP systems, along with additional insights into organizational factors, future reinvention of processes, and more. It has become clear that the efficiency model is the most common model among small- to midsize companies, though several consultants believe the innovation model to rise in importance. Meanwhile, most efforts on AI are made to reduce costs, rather than to increase revenue. Additionally, the organizational difficulties have proven to be many; perhaps even overshadowing the technical issues.

Throughout the results, three particularly interesting trends can be distinguished. These trends encompass all of the results found, and were discovered through examining the results:

1. Vision versus Reality: Efficiency is still the Most Prioritized Model
2. Costs versus Revenue: Providing Value through AI
3. The Technical versus The Organizational: Organizational Issues are a Major Obstacle

The deductive categories – i.e. the processes and the models – were collected and summarized into the first trend, which analyses why the efficiency model is the most prioritized. The second trend was discovered when asking the respondents for the value of AI. The third and final trend was discovered through the inductive categories, where many organizational factors were discovered. The purpose of analyzing the third trend is to discover the challenges that must be overcome before AI can be applied to the processes of an organization.

These three trends will be further analyzed next.
5 Analysis

The three trends discovered in the results will be further analyzed in this chapter, with the purpose of providing deeper insights into the use of AI in the context of ERP systems.

5.1 Vision versus Reality: Efficiency is still the Most Prioritized Model

Throughout all nine interviews, processes relating to the efficiency model was dominantly highlighted as the model which the consultants most often work with, with automatization and optimization being features most typically requested by customers. Moreover, it was perceived to remain the most requested model for the next few years, as many companies are still struggling with optimizing their backend surrounding routine tasks. This is an interesting clash with the grand visions of university researchers and corporate giants alike. While both academic and corporate researchers seem to make the innovation model appear immediately urgent, the reality appears to be that small- to midsize companies not only lack the preparation, resources, and understanding of how to utilize these models, but have yet to even AI-power their essential routine-based processes. A few respondents guessed that the innovation model could become vital already within the next few years, but several of the respondents proposed that the efficiency model will be the most frequently requested model for several years still. Many customers have yet to digitize the backend of their organization, and many previously made automations could be developed further. For instance, invoice management was perceived as a process that was easy to automate. The respondents argued that it should be an obvious decision to automate the process, as it ensures scalability, and more importantly relieves resources to be put on more demanding processes. Meanwhile, the task of automating invoices can be made even easier with machine learning algorithms that can learn the specifics of invoices and intelligently learn how to handle new forms of invoices, along with anomalies. This simplifies integration and implementation of invoice management systems, as it can be configured automatically, rather than manually.

Thus, the efficiency model appears to be the easiest to work with. It is perhaps also the model with the least amount of risk involved for companies not yet ready to perform substantial changes to their business.

Interestingly, some companies may not even need to implement AI from models outside of the efficiency model to empower their entire business. Agrawal, Gans and Goldfarb (2017) argued that AI’s main function is prediction. According to them, AI is excellent at predicting, but less capable of judging. This theory is closely related with the underlying concept of the framework used in this thesis, where the leftmost two models revolve around tasks that are easy to predict, while the rightmost two models are judgment-based. Agrawal et al. (2017) argued that the developments done in AI are leading to AI being able to predict increasingly more difficult tasks. For instance, the process of driving a car was previously one that required humans with
judgment-based skills, but is now a process that has been fully automated through prediction-based routines. This was accomplished by creating clearly defined rules where none previously existed, and thus adopting AI for automation, rather than for augmentation. Driving a car is therefore a process that was moved from one of the rightmost models into the efficiency model. Note that the process was not moved from one model to another due to AI, but rather due to AI strategy. It is not technology that dictates the position of a process inside of the framework, but rather the data- and work complexity associated with the process itself. Therefore, one can only presume that the moving of processes from one model to another can happen to other processes as well. In particular, processes currently found in the expert- and innovation models are likely to be moved to the efficiency- and effectiveness models as more routines are discovered that AI can adopt. Thus, companies choosing to stay in the efficiency model rather than venturing beyond may find themselves satisfied, as the technology may come to them, rather than vice versa.

Daniel also noted that machines will eventually become better than humans at performing virtually every task. Plastino and Purdy (2018) noted that processes are being reinvented, as did Ayoub and Payne (2016) and Brynjolfsson and McAfee (2017). Hans, one of the respondents, proposed the same trend, as he noted that complex jobs appear to become simpler. Interestingly, he also noted that some previously simple tasks are becoming more complicated, as they are empowered with more data and decision-making capabilities.

This does not reduce the legitimacy of the framework; however it does confirm that the framework is contemporary – which reasonably everything practical in AI research is.

This creates an interesting but uncertain situation. When adopting an AI strategy – that is, a strategy for how to implement AI, be it through automation or augmentation – for a process with a high work complexity, one following the framework must decide whether to implement AI based on the complexities of the process today, or to simplify the process by establishing routines. The difference is large. As an example, assume that you are deciding on an AI strategy for a subprocess of recruiting, an early step in the process: examining cover letters and resumes. Assume that your recruiters are hiring for a position with three hundred applicants, and also assume that your organization lacks clearly defined rules for examining such documents. Due to the fact that your recruiters, surely experts in their field, need to manually examine the cover letters and resumes, judging each candidate and assessing whether they may be qualified to proceed to the next step in the process, you consider the process to be of high work complexity. In this scenario, your organization has two options for adopting AI to help in executing the task. Either your organization could adopt AI in the purpose of augmentation, perhaps developing an expert system that extracts valuable keywords and insights and present them in a simple fashion. Or perhaps an innovative system that provides real-time guidance while the recruiter is examining the documents, highlighting details that the AI finds of particular interest for decision support. Or, instead, the organization could attempt to build routines (or alternatively buy routines or rules from a company that has already established such), and use these routines
to adopt AI in the purpose of automation. In this scenario, the AI could perhaps automatically scan the cover letters and resumes, and either provide an aggregated presentation of the candidate’s traits and skills, placing the candidates that the AI perceives to be top candidates at the top of a list, or go even further and automatically decide which candidates get to come for an interview, completely eliminating human recruiters from this step of the recruitment process.

The possibilities of turning judgment-based tasks into prediction-based tasks through the creation of routines could ultimate make it cheaper and easier to adopt AI technologies.

Naturally, many judgment-based processes are not as easily converted into predication-based processes as driving. While car drivers follow clearly defined rules, such as stopping at red lights and driving on a specific lane, many processes do not follow such clearly defined rules.

Two such processes, which were left out of the framework due to insufficient data but nonetheless presented in 4.1.12, are enterprise management and business development and research and development. The former is a good example of a process without clearly defined rules: there are countless of ways to run and develop a business. Yet if we continue with the presumption that AI can help humans with all processes, either through automation or augmentation, we must either acknowledge a best practice for automation or find a way to support creativity and/or ease decision-making in this kind of process. Anton found these two processes to be the most interesting for the future, and indeed argued that the finding of best practices for these processes would be both interesting and exciting. Certainly, realizing the best AI strategy for these processes could lead to a competitive advantage.

Daniel posed an interesting argument, as he proposed that companies should ask themselves (or consultants, I add) how they can improve their business, rather than how they can simply make it more effective. He urged companies to take one large step, rather than a small such, proposing that technology ought to be used as more than a basic supporting tool for existing processes. Indeed, reinventing processes may not only be difficult, it may also be downright frightening, as it may be an irreversible change. Once a company has reinvented themselves, they may find it hard to go back.

Edward argued that the reinvention of processes is inevitable, and even proposed that it would result in the downfall of many top organizations. Industry leaders have become leaders because they have streamlined their processes, he argued; they have become as cost-effective as is possible in present day. Yet as AI offers new ways of redefining processes, industry leaders may find themselves forced to fundamentally change the way they do things, which, during the process, may allow companies born in the AI era to claim their throne.

Regardless, for small- to midsize companies, it has become clear that the most important model in the present is the efficiency model. Attempting to empower employees related to tasks in the innovation model would certainly provide a competitive advantage, but the value compared to
cost may not be sufficient for companies other than large corporations. Finding or building routines where none exist could greatly simplify the adoption of AI technologies.

5.2 Costs versus Revenue: Providing Value through AI

All respondents noted that the primary purpose of adopting AI technologies, in the present, is to reduce costs. This is usually done by automating routine tasks, typically those perceived as boring and time-wasting, and instead allowing the human resources to employ more challenging and fulfilling tasks. While this is certainly an appropriate way to adopt artificial intelligence, Daniel argued that companies ought to ask themselves how technology can empower their revenue-facing activities. Hans suggested that some modern businesses could be fully powered by artificial intelligence, without the need for any human resources, as the entire value chain, both the revenue-facing and the cost-facing sides, could be automated. Often, however, the revenue-facing activities involve complicated ad hoc tasks, which makes it more difficult to build AI solutions for empowering them.

Agrawal, Gans and Goldfarb (2017) argued that AI is excellent at predicting, but not so good at judging. According to them, AI can increasingly predict things faster and more accurately than humans. In doing so, AI is providing organizations with more predictions than before, which, the authors suggested, increases the value of prediction, while lowering the cost of it. This, in turn, means that judgment has instead increased in cost, as there are more predictions that need to be judged, the trio argued. The authors’ ultimate point was that companies will need to hire staff with judgment-based skills rather than prediction-based such.

Indeed, this should prove to be the direction that companies are facing, as the rules-based backend of organizations is increasingly becoming automated. I would argue that AI-powering the revenue-facing activities of any firm will provide the greatest competitive advantage. The product and/or service offered by any company ought to be its competitive advantage, and is naturally the component that brings in money for the organization. Therefore, adopting AI with the intention of increasing revenue, rather than decreasing costs, is a perspective that ought to provide more value for the organization, though it is certainly more challenging to realize how AI can empower revenue-facing processes.

Plastino and Purdy (2018) proposed that the value that AI provides cannot be measured through traditional means, as classic goods depreciate over time, while a self-learning AI instead improves over time. This is a major change in investment tactics, as it is difficult to estimate the value that advanced AI provides. Not only is the initial value difficult to estimate, but the fact that self-learning AI provides additional value the more it learns makes it harder to predict.

In order to measure the value that AI provides, Plastino and Purdy (2018) proposed that organizations should measure return on algorithm, rather than return on investment. They
argued that it is difficult to estimate the costs and benefits that an advanced self-learning AI will bring, acknowledging that such benefits will become apparent only sometime after the AI has been adopted. This could perhaps prove a further challenge for small- to midsize companies, as the return on their investments becomes uncertain. Learning to measure on algorithm could therefore become a competitive advantage for consultancy firms who can provide guidance to small- and midsize businesses. This ought to be particularly true in the context of ERP systems, where modules are off-the-shelf, rather than built from scratch. Realizing the return on algorithm for each self-learning AI used in ERP systems would prove to be an immense advantage. As ERP systems are now often cloud-based, and therefore no longer necessarily a one-time investment but instead a subscription service, investing in AI should not be a large, uncertain investment for small- and midsize customers.

Indeed, as Fredrick and Hans noted, many systems are cloud-based – one of the ERP systems offered by Exsitec is in fact entirely cloud-based. This creates modularity and allows firms to tailor solutions based on the needs of each company. AI technologies could therefore be tried in a system, their return on algorithm tracked, and algorithms then potentially swapped, depending on whether the algorithms lived up to expectations in the long run.

As targeting revenue-facing processes become easier and cheaper over time, so too may it become a necessity. In the same way that e-commerce giant Amazon built its value chain on the foundations of the World Wide Web, challenging traditional retailers, so to may a company born in the AI era challenge older companies. It can only be presumed that targeting revenue-facing activities will provide an early advantage that for some business models could turn into a major competitive advantage long term. Learning to estimate the value of advanced AI will surely become a key skill moving forward.

5.3 The Technical versus The Organizational: The Greater Challenge

Chapter 4.3 included an array of organizational challenges that were discovered during the interviews. As noted in the chapter, these challenges include change communication, incorrect understandings of the anatomy of tasks, problematic rules & regulations, lack of clearly defined routines, and lack of monetary resources.

Clearly, advanced artificial intelligence already exists, as machine learning algorithms are readily available, alongside cheap technologies such as IBM’s Watson and Amazon’s Alexa. Small- to midsize companies are thus clearly lagging behind technological advancements. The organizational issues may therefore prove to be even greater than the technical. The potentially small amount of data produced by small- to midsize companies is neither a large concern. Brynjolfsson and McAfee (2017) suggested that, contrary to popular belief, organizations do not need much data to begin working with machine learning. Thus, while this thesis has not studied such organizational and communicative issues in detail, or included any literature
discussing such issues in detail outside of the sole exception of Hsu (2013) who discussed the value of ERP systems – which, he suggested, was tied to organizational aspects rather than technical such – this is nonetheless an important trend to include for the purpose of the thesis. There are undoubtedly great studies already done on such challenges outside of the AI context, so instead, I would like to explore the implications that these challenges may have on organizations in the alleged AI revolution.

As noted in 5.1 and 5.2, AI can provide great value to organizations. For instance, when routines are discovered, judgment-based processes can turn into prediction-based such, and therefore be performed faster and cheaper. However, this is obviously a great organizational challenge. As Gunilla noted, companies themselves often do not understand their own work processes, which makes it impossible to establish routines. Many companies completely lack clearly defined routines for their day-to-day operations altogether. Anton also discussed the difficulties of clearly defining processes. This is especially challenging in small- to midsize companies, as jobs may not be as clearly defined as they are in larger companies.

Furthermore, the organization itself must have a positive attitude and trust in AI in order for it to be successfully implemented. This was also described as a challenge in our interviews. Daniel noted that one progressive company has already adopted AI as a stakeholder, something he suggested as showcasing great trust and positive attitude in AI.

Artificial intelligence introduces a new era for corporations, much like the Internet did. Companies born before the so-called dot-net bubble, which spawned alongside the mainstream use of the Internet, were slow to adopt the new technology, often lacking trust and understanding for the new technology. In the same way, companies born during the upcoming AI era may find themselves with a staff that trusts and understands the use cases of AI, thus placing themselves with an easier outset for preparing for AI-powering their processes.

Overcoming these organizational challenges is an important step in implementing AI technologies.
6 Discussion

The present and future of eleven processes and four models were analyzed, and three subsequent trends were discovered and further analyzed: vision versus reality, costs versus revenue, and the technical versus the organizational. These trends collectively make up a much larger trend, one we can refer to as the AI revolution.

As every business process already can or soon will benefit from AI, the reality of organizations will likely fundamentally change. In this speculative chapter of presumptions, I will propose that the AI revolution will be the biggest revolution since the industrial such, even outweighing the impact that the Internet had on organizations.

6.1 The Grand Scope of The AI Revolution

It has clearly become justified to refer to AI as a revolution. It allows for the utter reinvention of not just business processes and business models, but business environments and societies at large. Activities that could previously only be performed by humans are now automatically being handled by AI, and other activities are being empowered by it. As the cost of prediction decreases, as more businesses are overcoming organizational challenges, and as mindsets change, the usage of AI in organizations will inevitably grow. No business will be able to avoid this revolution, as their competitors would otherwise gain a competitive advantage.

Indeed, Daniel argued that artificial intelligence will ultimately outperform humans in every process. Hans suggested that some organizations can already become fully automated, not requiring any human resources to perform their business. Edward proposed that kings will become farmers.

Though small- and midsize companies have been in focus for this thesis, let us begin the discussion with larger corporations, in line with Edward’s proposition. Industry leaders have become “kings” by optimizing their processes as far as possible. Their value chains are extraordinarily cost-effective. This is true almost regardless of the industry one chooses to observe, be it clothing retailers, fast food restaurants or grocery stores. Leaders in these industries have some of the world’s strongest revenues thanks to their solid routines and strict optimizations. However, as every process is being reinvented, these major companies will face great challenges. Surely they possess the monetary resources to handle change, but are they reactive enough to change their routines, standards, and workforce in compliance with the changes that AI brings to their business models? Corporate giants will find themselves forced to choose between continuing to work the same way they have done before or start over with new AI-powered processes. An industry giant with factories, personnel and/or stores in the hundreds or thousands may not be able to change its processes quickly enough, thus allowing smaller companies to claim their throne. In the same vein that revolutions have shattered the
standings of those in power in the past, so too may the AI revolution change the hierarchy of organizations.

Many large companies have crumbled throughout history. Some did not take the Internet seriously and in consequence lost their throne. Indeed, the Internet too introduced new business opportunities, from e-commerce to digital marketing. Before the World Wide Web was created, no one could have imagined the impact that e-commerce would have. For a vast majority of people, the phenomenon of buying items on the Internet, something that we today would surely consider obvious, was a concept unheard of. E-commerce is still growing year over year, as classic retail stores are struggling versus their online competition. Imagine, then, a company born in the AI era that similarly reinvents the market of commerce. Such an entirely new phenomenon may be difficult to conceptualize, which is precisely why its inventors will gain enormous advantages. Many of the commonplace services of the future will be conceptualized in the next decade.

The AI era is a product of the aforementioned Internet era, yet the AI era presents larger consequences than the Internet era ever could. As the AI era is fundamentally reinventing business models and human labor, it will ultimately lead to enormous changes in organizations. Companies born in the AI era will surely possess a competitive advantage over older companies, much like companies born in the Internet era possess natural advantages over companies that were formed before it, in particular those whose business model did not revolve around technology. As business models and value chains will be built from the ground up for AI, newly born organizations will adapt far quicker than older giants.

Companies born in the AI era will use AI technologies as an integral part of their business model. They will use the technology to empower their entire value chain, naturally including their revenue-facing processes. They will understand the power of augmentation – not just automation. The intention of AI will not be to remove jobs, but rather to empower employees.

When exactly the AI era will take off is impossible to estimate. One could argue that the world has already entered the AI era, as powerful AI technology already exists and is to some degree in use by large companies, and as AI technologies are being researched at many top organizations. However, one could also argue that the world has yet to truly enter the AI era, as AI has not yet seen widespread practical adoption, and likewise companies do not appear to have been fundamentally redeveloped through the technology yet, instead cautiously and incrementally adopting basic AI tools. Regardless of one’s precise definition of the term “AI era”, the point is that the world is far from its AI climax.
6.2 The Modest Scope of The AI Revolution

Yet this discussion does not necessarily mean to instill a fear of urgency. As this thesis has made evident, small- to midsize companies show little urgency to suddenly reinvent their processes or redevelop their business models. Naturally, these things cannot, and should not, be rushed overnight. Additionally, while one should remain optimistic for AI, it is also important to note that improper AI strategies could lead to a company’s collapse. Irreversibly implemented technologies that ended up destroying successful business processes and replacing them with dysfunctional such is absolutely a potential risk.

While the AI revolution will bring with it fundamental changes, it may take many more years before the large changes start becoming apparent. Furthermore, there is no evidence to believe that AI will not be easier to adopt over time, as its value for a specific industry or process could become clearer and solutions more widespread as early adopters pave the way for late adopters.

For organizations wanting to start their AI journey, there are many possibilities to gain an early advantage. First, naturally, the organizational challenges must be overcome. In particular, issues surrounding change communication and routine management must be resolved. Of utmost importance is that the upper management of the organization understands the strategic value of AI as applied to their business, and that the management can motivate and inform their employees of this value. Next, the framework which was used for data analysis in this thread is an excellent tool for any organization wanting to understand how AI can benefit their organization. By applying the framework to their businesses, they can discover how their concrete processes can be helped through the use of AI. When applying the framework to a specific company, it will be important to break processes down into subprocesses until there is no doubt of its position in the framework. Next, appropriate actions should be taken based on its position in the model, be it automation or augmentation, through the formation of business strategies.

The successful companies of the future will likely be those who aim for a fundamental change, rather than an incremental such. Though small optimizations may appear more tempting and safe, substantial redevelopments will nonetheless be what separates the great corporations from their competitors. Further, as has been stressed many times, companies who apply AI technologies to their revenue-facing activities will experience greater success than those who do not. In total, establishing AI across the organization, rather than on small parts of it, will establish greater synergy. This is indeed also the power of ERP systems and AI in the context of it. AI implemented into ERP systems can surely more easily be developed to be compatible in unison with systems across the organization.

It is only natural that small companies experience skepticism and uncertainty towards AI. A small company may have been made successful through the hard work of a small team who have full control of the entire organization. They may not experience any form of urgency or
any real interest in adopting AI technologies. What more, adopting AI in a fundamental manner as expressed above may be a one-way ticket. Once the value chain has been redefined to be AI-powered, it may not be possible to go back to the way the processes were previously organized, which results in increased fears.

Consultancy firms, then, will face great challenges in helping small- to midsize companies overcome these fears and challenges. It will be important for consultants to gain deep knowledge concerning the impact and reality of AI. Learning to implement and integrate AI, while also being able to measure its value, will become a key skill. These challenges may be easier for ERP consultants to solve, as ERP systems are off-the-shelf packages where solutions can be generalized, and thus AI could more easily be tried, and a general conception of its value created. Furthermore, as ERP systems become increasingly cloud-based, so too increase the possibilities for modular, interchangeable systems where new algorithms can be tested.
7 Conclusion

While studies showcased that there is great interest, excitement and urgency in AI, the reality for small- to midsize companies is far from as exciting. Yet the AI revolution is slowly approaching, and companies wanting to become future leaders must overcome organizational challenges in order to fundamentally reinvent their business processes through the use of AI technologies. Companies will need to find ways to adopt AI to their revenue-facing activities, either through automations or augmentations.

Yet there is a significant lack of academic research done on AI on an organizational level, which has put smaller clients at the mercy of larger corporations with proprietary knowledge. This thesis aimed to help fill this research gap. The purpose of this thesis was thus to examine AI and its potential value in the context of ERP systems, from the perspective of a midsize consultancy firm with small- to midsize clients. The following research questions were posed:

- How can, or do, organizational processes covered by ERP systems benefit from AI?
- What, if any, AI features do customers typically request when ordering ERP systems?
- How is the value of AI perceived: Are AI technologies adopted with the purpose of reducing costs or increasing revenue?

Using a framework for evaluation, I examined typical organizational processes in order to explore how they benefitted in the present and/or how they may benefit in the future. I also investigated what small- to midsize companies request when ordering ERP systems in the context of AI, and how their requests may further change in the future. Finally, I determined whether AI was used for the purpose of decreasing costs or increasing revenue.

The present and future of eleven organizational processes covered by ERP systems were identified in chapter 4. These processes were placed in the aforementioned framework in order to identify the AI strategy for working with them (see figure 7). Overall, there is little AI technology implemented in the present ERP systems offered by Exsitec, though the untapped potential is enormous. The respondents expressed great interest and excitement into the opportunities of AI.

Processes relating to the efficiency model are the most frequently requested by customers in the present, with features such as automatization and optimization being typical requests. Simple processes such as invoice management and inventory and warehouse management are often automated, while most other processes had yet to be automated or augmented at Exsitec’s customers, who are small- to midsize companies.

Yet both the literature review as well as the interviews proposed that AI will have a massive impact on organizations, to the point of ultimately redefining virtually every business process. This massive change, bringing with it new business ideas, value chains, and business models,
is referred to as the AI revolution, which was discussed in chapter 6. Three trends leading up to the AI revolution were identified in chapter 4, and subsequently analyzed in chapter 5. The first trend showed that the efficiency model was currently the model seeing the most investments, requests, and developments. Meanwhile, activities previously judgment-based are becoming prediction-based, suggesting that the efficiency model could remain vital. The second trend showed that AI is generally being implemented with the intention of reducing costs, rather than increasing revenue, which shows a lack of maturity in mindset for using AI solutions. Moreover, calculating the return on investment for self-learning AI is challenging, due to the fact that typical investments depreciate over time, whereas advanced AI becomes better over time. Finally, the third trend showed that organizational challenges are major obstacles that must be overcome to implement AI. The lack of clearly defined routines, along with issues relating to change communication, are some of the issues that must be resolved.

**Figure 7.** The processes as they were placed within the framework.
The three trends were finally combined into the greater trend: the AI revolution. The AI era will create major changes across industries, which could lead to a change in hierarchy amongst competitors. Companies born in the AI era may reinvent entire business models with new unprecedented ways of running businesses, forcing older companies to be reactive and accordingly update their own processes. Present companies will need to overcome organizational challenges and make their upper management understand the strategic value of AI. Companies aiming to be future leaders will need to fundamentally change their businesses with AI, though the risks involved must be calculated. The faster a company can implement AI, the larger their early advantage, however those who wait will be able to observe best practices and successful reinventions, and thus learn from the success of others. Regardless, realizing how AI can fundamentally benefit the organizations’ revenue-facing processes through augmentations will provide the biggest competitive advantage for any organization.

In conclusion, then, the research questions were answered through extensive interviews and a deep analysis. While some organizational processes have already been improved with AI solutions, many processes have yet to be AI-powered. Through the means of automation or augmentation, every process can ultimately benefit from AI. Today, customers are typically not requesting AI features when ordering ERP systems, though they generally ask for optimizations or automations, without specifically mentioning AI. The purpose of using AI in the context of ERP systems in the present is almost always to reduce costs, though several respondents noted that a shift is likely to happen, where customers will begin to ask for AI features with the purpose of increasing revenue.

Much more academic research on AI in an organizational context is needed to prepare organizations and society at large for the AI revolution. Further research on the managerial challenges in the context of AI would be valuable. Additionally, while this thesis aimed to provide an overview of the value that AI provides in the context of ERP systems, studies focusing on how one particular industry or market can benefit from AI technologies would provide valuable insights. Research on how to estimate returns on algorithm in practice will also be crucial. This study has taken one step in filling this massive research gap by contributing an overview of the AI revolution for organizations, but a lot more research into specific components is necessary.

Though the AI revolution does not appear quite as urgent as media may imply, it is nevertheless approaching, and organizations large and small alike must be prepared. The first step in the preparation for this upcoming AI era is a simple one. Stop asking yourself how AI can make your business incrementally more effective – ask yourself how AI can make your business fundamentally better.

For no business can avoid the AI reality.
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Appendix A: Sense, Comprehend, Act & Learn (Original)

Source: Bataller & Harris (2016, p. 6).
Appendix B: The Framework (Original)

Source: Bataller & Harris (2016, p. 9).
Appendix C: Pre-study Interview Sheet

Namn:
Roll:

Del 1: Skapa förståelse för intervjuobjektet.
   a) Vad skulle du säga är din expertis?

Del 2: Presentera intervjuverktygen och försäkra basförståelse för AI.
- [Presentera bild 1 (bilaga D)]. Ponera att en organisation vill införskaffa ett organisationstäckande ERP. För generaliseringens skull ignorerar vi organisationens exakta affärsidé och storlek, men ponera att deras verksamhet täcker dessa klassiska processer. De vill helt enkelt ha ett kompletterande ERP. Samtidigt har de hört att artificiell intelligens är framtidens, och de vill gärna hamna i framtiden.
- [Presentera bild 2 (bilaga E)]. Det finns många definitioner av AI, men enligt en teori kan AI hjälpa människor och organisationer enligt dessa fyra modeller. [Presentera kortfattad de fyra modellerna].

Del 3: Utforska AI applicerat på ERP.
   - [Intervjuobjektet väljer ett moment]
   - [Rekursiv punkt]
     a) Hur kan denna modul gynnas av AI? Genom vilken modell?
     b) Anser du att datan i denna modul är avancerad eller enkel? Är arbetet för kunden svårt eller enkelt när de själva använder denna modul?
     c) När du ser dessa teorier om hur AI kan hjälpa, tror du att de skulle ha en stor påverkan på denna modul, eller en mindre sådan?
   - [Fortsätt från rekursiv punkt tills alla moduler har diskuterats.]

Del 4: Reflektion och utforskning av tankar från intervjuens gång.
3. I efterhand, efter att ha gått igenom alla moduler, är det någon av dessa som du tyckte var extra intressant? Varför?
4. I efterhand, är det någon av dessa fyra modeller för AI som du tycker är extra intressant för ERP?
5. Rent generellt, var går dina tankar kring maskininlärning, alltså maskiner som lär sig själva? Påverkar det ERP?
6. Vad tänker du om personliga assistenter, såsom Amazons Alexa för Business? Tror du att sådana verktyg kommer ha en större påverkan på organisationer?
Appendix D: Interview Material 1
Appendix E: Interview Material 2

**Effektivitet**
- Kommunikation
- Koordination
- Schemaläggning
- Monitoring

Exempel:
- Google Now
- Amazon Alexa

**Innovation**
- Augmentering
- Kreativitet
- Människor fattar beslut, Al hittar alternativ och rekommenderar
- Kläddesigners, musiker, entreprenörer

Exempel:
- Mjukvara för att skapa musik
- Rekommendationer i text

**Optimering**
- Rutiner
- Konsistens
- Skapa låga kostnader
- Automatisering

Exempel:
- Automatiserade kreditbeslut
- Drönarleveranser

**Expert**
- Göra bedömningar
- Advokater, finansrådgivare, ingenjörer
- Människor fattar beslut, Al hjälper dem att fatta dem

Exempel:
- Medicinska diagnoser
- Efterforskningar inom finans
Appendix F: Interview Sheet

Namn: 
Roll: 

Del 1: Skapa grundläggande förståelse för intervjuobjektet.
1. Kan du berätta lite kort om din roll på Exsitec? Hur ser din vardag ut?
   a) Vad skulle du säga är din expertis?

Del 2: Presentera intervjuverktygen och säkerställ basförståelse för AI.
- [Presentera bild 1 (bilaga D)]. Det här är en bild på ett antal klassiska organisationsprocesser som ERP system vanligen täcker.
- [Presentera bild 2 (bilaga E)]. Det finns många definitioner av AI, men enligt en teori kan AI hjälpa människor och organisationer enligt dessa fyra modeller. [Presentera kortfattat de fyra modellerna].
- Under intervjuens gång kommer jag att ställa frågor med detta ramverk för AI som underlag. Du får gärna bryta ner dessa processer i mindre processer om du vill.

Del 3: Utforska AI applicerat på ERP.
   a) Följfråga: Hur kan denna process gynnas av AI? Genom vilken modell?
3. Vi tittar närmare på modellen optimering. Finns det några processer där optimering är extra intressant? Är de automatiserade redan idag, eller kommer de att bli det?
4. Vad tänker du om modellen effektivisering? Var kan den appliceras, eller appliceras den redan idag?
5. Finns det några exempel på expertsystem i ERP-lösningar? Använder de AI-tjänster idag?
7. Tror du att någon av modellerna medför sig organisatoriska svårigheter? Till exempel att någon modell framförallt kräver att man måste genomföra personalutbildning? Eller är det tvärtom?
8. I en studie genomförd av Avanade ansåg 86% av företagsledarna i Sverige att deras företag måste implementera AI-teknologier för att fortsatt vara konkurrenskraftiga. Är det något ni känt av från kundsidan?

65
a) Vad är era kunder intresserade av? Vad efterfrågar de just nu, och tror du att
det kan förändras i framtiden? Frågar de specifikt om AI?

9. I en kontext av AI, vad är ni själva intresserade av? Är det samma som det kunderna är
ute efter, eller kikar ni explorativt mot framtiden? Med andra ord: fokuserar ni helt på
att möta det kundbehov som finns idag, eller försöker ni också förbereda er för
framtiden?

10. Data kan ibland vara ganska enkel och ibland ganska komplex. Den kanske är
strukturerad, stabil och i små volymer, eller så är den ostrukturerad, volatil och i stora
volymer. Ett vanligt exempel på det tidigare är siffror, såsom antal produkter sålda,
medan det senare kan vara data från sociala medier eller sensorer. Bland dessa
processer, finns det någon eller några där du skulle säga att datan är väldigt enkel eller
väldigt komplex?

11. Arbete kan också vara enkelt och komplex. Men medan datakomplexitet kanske säger
sig självt, kan arbetskomp lexitet ses som lite svårare att definiera. Om vi tänker oss att
enkelt arbete är sådant som är regelbaserat, rutinartat och förutsägbart, oavsett hur
mycket arbete det är eller hur lång processkedja det är, och att komplex arbete är mer
ad hoc, oförutsägbart, och som kräver mänsklig bedömning, kan du då se några
processer där arbetet är enkelt respektive komplex?

12. Tror du att AI kan underlätta vid implementation av ERP system? Det vill säga om det
can underlätta direkt för konsulter som er själva?

13. Maskininlärning har beskrivits som en av våra tids viktigaste teknologier. Det handlar
om att maskiner lär sig själva från exempel, snarare än att programmeras för specifika
resultat. I vissa maskininlärningsmetodiker kan AI till och med reparera och
vidareutbilda sig själv. Ser du exempel på maskininlärning i ERP redan idag? Tror du
att det är relevant? I vilka processer?

14. Personliga assistenter har som mål att i någon mån ersätta användargränssnitt. Allt
mer och mer försöker de smyga in på arbetsplatsen. Tror du att de kan skapa värde i
ett ERP-system? Kan en personlig assistant agera som assistent till ett helt ERP-
system? Är det vissa processer som kan stödas särskilt av dem?

15. Vad tror du själv om affärsvärdet bakom AI? Tror du att AI-teknologi har stor
påverkan på värde eller en mindre sådan?

Del 4: Slutlig reflektion och utforskning av tankar från intervjuens gång.

17. I efterhand, är det någon av dessa fyra modeller för AI som du tycker är extra
intressant för ERP?

18. Samma fråga för processerna. Är det någon som är extra intressant?

a) Vilka processer är extra intressanta för framtiden?
19. Med allt detta i åtanke, rent generellt, om en organisation idag skulle fråga dig var de bör börja sin AI-satsning, vad skulle du svara? Vad tror du att du hade svarat om fem år?

20. Till sist, finns det något jag inte frågat – som du inte fått möjlighet att nämna – som du tycker är viktigt eller intressant att ta upp i denna kontext?