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CRITICAL SUCCESS FACTORS IN IMPLEMENTING ARTIFICIAL INTELLIGENCE - BUSINESS VALUE VIEWPOINT

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Tekoäly on noussut tasaisin väliajoin informaatioteknologian megatrendiksi. Tällä hetkellä tekoälytoteutuksia yritetään implementoida yritysten ja organisaatioiden liiketoimintaan enemmän kuin koskaan, mutta usein myös tuloksetta – moni tekoälytoteutus ei päädy pilottivaihetta pidemmälle. Tekoälyn saavuttama noste on luonut tilanteen, jossa tekoälyä yritetään implementoida laaja-alaisesti liiketoiminnan eri osa-alueille. Tekoälytoteutuksien epäonnistumisiin ja peruttuihin projekteihin on olemassa monia syitä, mutta onnistumisen juurisyitä ja menestystekijöitä ei myöskään tarkkaan tunneta. Tässä pro gradu -tutkielmassa selvitetään, mitkä tekoälyprojektissa ja tekoälyn implementoinnissa ovat kriittisiä menestystekijöitä projektin onnistumisen kannalta tekoälyn tuottaman liiketoiminnallisen arvon näkökulmasta, ja mikä näiden suhde on toisiinsa. Tutkielman tarkoituksena on luoda parempi ymmärrys siitä, mitkä tekijät johtavat tekoälyprojektin todennäköisempään liiketoiminnalliseen onnistumiseen. Tutkimus toteutettiin kaksiosaisena, systemaattisena kirjallisuuskatsauksena ja empiirisenä haastattelututkimuksena. Systemaattisessa kirjallisuuskatsauksessa pohjustettiin kirjallisuuden perusteella tutkimuksessa käytetyt keskeiset käsitteet, jonka pohjalta empiiristä osiota varten luotiin teoreettinen viitekehys tutkimuskysymyksiin vastaamiseksi. Tutkimus toteutettiin kvalitatiivisena tutkimuksena, puolistrukturoituina ja teemoitettuina asiantuntijahaastatteluina. Haastatteluita järjestettiin yhteensä 9 kappaletta. Empiirisen tutkimuksen tulokset analysoitiin teemoittelun keinoin, ja tuloksia verrattiin kirjallisuuskatsauksessa luotuun teoriapohjaan. Tuloksien ja teoreettisen viitekehyksen pohjalta luotiin malli tekoälytoteutuksien kriittisistä menestystekijöistä liiketoiminnallisen arvon luonnin näkökannalta. Tutkimus ja tulokset vahvistivat olemassa olevan tutkimuksen tuloksia tekoälytoteutuksien kriittisistä menestystekijöistä, mutta tuloksissa tunnistettiin myös uusi kriittisten menestystekijöiden teema. Tutkimuksessa tunnistettiin myös toteutuksen kriittisten menestystekijöiden suhde haluttuun liiketoiminnalliseen vaikutukseen. Tutkimus täydentää tunnistettua tutkimusaukkoa tekoälytoteutuksien kriittisistä menestystekijöistä ja tarkastelee niitä liiketoiminnallisen arvon tuottamisen näkökannalta. Tutkimus ja sen tulokset tarjoavat näkemyksiä ja keinoja käytännön tekoälyprojektien valmisteluun ja toteutukseen antamalla valmiudet tarkastella haluttua liiketoiminnallista vaikutusta ja siihen liittyviä kriittisiä menestystekijöitä.

Asiasanat: tekoäly, koneoppiminen, kriittiset menestystekijät, liiketoiminnallinen arvo, liiketoiminnallinen vaikutus

ABSTRACT

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Artificial Intelligence has risen from time to time to being an information technology megatrend. At this moment, organizations try to implement artificial intelligence into their business functions more than ever, but also without results – a great amount of artificial intelligence implementations do not reach beyond the pilot stage of the project. Artificial intelligence project failures and cancellations may have a myriad of reasons, but the factors of artificial intelligence project success are not either known for sure. This master's thesis researches the artificial intelligence critical success factors from a business value viewpoint – and what's the relationship between the critical success factors and achieved business value. The purpose of this study is to create a better understanding of which factors lead to a more probable business value success. The study was conducted in two separate parts: a systematic literature review and an empirical interview study. The systematic literature review created the theoretical basis and the theoretical framework for the empirical part of the study. The empirical study was conducted as a qualitative study, in the means of semi-structured, thematic expert interviews. The study includes a total of 9 held expert interviews. The results of the empirical study were analysed thematically and compared to the theoretical framework conducted in the literature review. Based on the results of the empirical study and the theoretical framework, the framework for artificial intelligence critical success factors for business value creation was made. The research and the results confirm the critical success factors and business value defined in the earlier research, as well as present a new theme regarding artificial intelligence critical success factors. The study also identified the relationship between artificial intelligence critical success factors and business value impact. The study answers the identified research gap of artificial intelligence critical success factors and observes them from the viewpoint of business value impact. The research and the findings provide insight and tools for planning and execution of artificial intelligence implementations by improving the ability to observe and evaluate the pursued business value and the related critical success factors.

Keywords: artificial intelligence, machine learning, critical success factors, business value, business value impact

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1 INTRODUCTION

Artificial intelligence has once again risen as a disrupting megatrend – not only in the field of information technology but also in everything it affects. With the rise of large language models (LLMs) and especially the introduction of the chat-GPT, artificial intelligence and its capabilities have been brought to the attention of the end user. As artificial intelligence was before mostly a technology-improving process somewhere inside the depths of the software, the impact of artificial intelligence and a variety of different kinds of implementations can be seen all around the world. However, as often in emerging and potentially disrupting technologies, organizations face a myriad of difficulties in the adoption and implementation of artificial intelligence (Alsheibani et al., 2020). Understandably, the business value of artificial intelligence and the potential competitive advantage makes it intriguing for organizations to adopt, which unfortunately often leads to unprofitable and insufficient results. In the end, artificial intelligence applications have been adopted and deployed beyond pilot projects by only a small percentage of those who have tried. (Enholm et al., 2022; Mani et al., 2020). This leads to a question; how can artificial intelligence be successfully adopted, and what are the underlying conditions of successful implementations?

The conditions, or critical success factors for successful information system implementations have been previously studied widely from a variety of viewpoints, starting from the information system project success, to underlying factors of aforementioned project success. However, these have not yet been studied widely in the context of artificial intelligence; as we can conclude from the organizational success of artificial intelligence implementations in real-life scenarios, more advanced observations are greatly needed on the subject. Not only do we need more information about the successful implementation of artificial intelligence and the factors leading to successful artificial intelligence projects, but also information about the business value generation of artificial intelligence. This thesis aims to answer some of those questions and generate more understanding of artificial intelligence project success, from a business value viewpoint.

This thesis consists of two distinct parts of the study; the systematic literature review and the qualitative empirical study performed as a set of semi-structured, thematic expert interviews. By creating the qualitative study on the theoretical basis created in the literature review, this thesis aims to produce credible conclusions and answer the research questions. The main research questions state as follows:

- What are the critical success factors in implementing artificial intelligence from the business value viewpoint?
- What is the relationship between the critical success factors of artificial intelligence implementation and artificial intelligence business value?

The research question is approached with existing literature and answering the following supporting sub-questions:

  - What are the potential artificial intelligence critical success factors previously identified in the existing literature?
  - What is the business value of artificial intelligence?

The literature review of this study was conducted as a combination of systematic literature review following Okoli and Schabram's (2010) instructions for systematic literature review in the field of information systems sciences, and snowball sampling. As the subjects of the study, artificial intelligence and critical success factors have been studied for decades (and due to the popularity of artificial intelligence) the criteria for included literature was narrowed down to achieve coherent and high-quality results and provide a trustworthy and up-to-date theoretical basis for the study. First, the included studies should be published in trusted journals in the field or other credible sources. Second, the publication of the article, paper, or book should be recent, otherwise relevant, or widely accepted in the field. Finally, the relevancy of the included literature was evaluated by examining the abstract of the observed article, paper, or book. The databases used in this study include electronic libraries such as Scopus, IEEE Xplore, ScienceDirect, JYKDOK, and Google Scholar. The searches included "artificial intelligence" and "critical success factors" both together and separately, as well as "artificial intelligence" and "business value" both together and separately. Due to the wide definition of artificial intelligence and its intertwined nature with machine learning, some searches were conducted combining the aforementioned terms with "machine learning".

The qualitative empirical study was conducted as a set of semi-structured expert interviews with 9 participants from various backgrounds, organizations, work descriptions, and experience levels. The goal was to find the most suitable candidates for the interview based on the background and expertise of the subject; the criteria for the interviewee for participation in the study was that the interviewee should have experience from artificial intelligence projects and implementations and professional understanding from not only technical implementation but also the business viewpoint of the information system project management. To eliminate the "elite bias" phenomenon, the interviewees include individuals from various expertise levels and backgrounds following the instructions presented by Myers and Newman (2007).

The study is conducted in two distinct sections. The first section provides the theoretical background and addresses the findings of the literature review, and the second section discusses the empirical interview study and its findings. After the Introduction chapter, the thesis proceeds as follows: the second chapter, Artificial Intelligence, defines artificial intelligence from the philosophical standpoint and from the technical implementation method viewpoint to build a coherent understanding and definition of the subject. The third chapter, Critical success factors, not only defines information system project success and critical success factors but also answers the research sub-question about previously defined artificial intelligence critical success factors. The information system success is important to define for the scope of this project; to narrow down the definition of critical success factors in the scope of this thesis, it is needed to conduct a coherent definition of project success itself, which in this, case means the business success of the artificial intelligence implementation. The fourth chapter defines business value and answers the research sub-question about artificial intelligence business value. The fifth chapter, Literature review summary, summarizes the essential findings of the literature review and presents the theoretical framework of the study. The sixth, Methodology, presents the methodology and information about the execution of the empirical study, whereas the seventh and eighth chapter provides the findings and discussion of the study along with the contribution, limitations, and potential topics of further scientific research. The ninth chapter, Conclusion, presents the conclusion of the study.

2 ARTIFICIAL INTELLIGENCE

This chapter introduces the definition and basic concepts of artificial intelligence and how it relates to machine learning, neural networks, and deep learning. Artificial intelligence is defined in Chapter 2.1, machine learning is defined in Chapter 2.2 and further categorized in Chapter 2.3. Neural networks as well as deep learning are defined and discussed further in Chapter 2.4, "Implementation approaches for more complex learning problems".

2.1 Artificial intelligence definition

Artificial intelligence is an umbrella term for a variety of applications, and currently, the term itself has no clear definition of what kind of technological approaches would be classified as artificial intelligence. Generally, artificial intelligence is described as a system capable of performing tasks that typically would require human intelligence. The problem with the term artificial intelligence arises from the very meaning of the term itself – the reference to human intelligence is troublesome since a variety of aspects of human intelligence are undiscovered.

As a field of study and as a subfield of computer science, artificial intelligence is a multidisciplinary field utilizing not only information technology but also mathematics and statistics. As a technical application, artificial intelligence usually refers to an algorithm or set of algorithms that are used to solve a complex problem, for example in currently popular applications, speech recognition and written text generation. Single methods of artificial intelligence are suitable for solving simpler problems, but more complex use cases require either more complex models or a set of different methods of artificial intelligence. With more complex tasks, machine learning as a subfield of artificial intelligence has become a popular method for applications such as computer vision, speech recognition, and natural language processing (Jordan & Mitchell, 2015).

As a wide concept, artificial intelligence contains a variety of different, broad concepts of information technology implementations. This has led to an academic discussion on a more philosophical level, on what to define under the umbrella term of artificial intelligence, and John McCarthy (2004) describes artificial intelligence as follows:

> " It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable."

Further, artificial intelligence has been attempted to define also in a philosophical level by Russel & Norvig (2016) comparing the goals or definitions of artificial intelligence into four different segments of definition by human versus ideal approach and thinking versus acting.

Thinking Humanly	**Thinking Rationally**
"The exciting new effort to make computers think...machines with minds, in the full and literal sense." (Haugeland, 1985) "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem solving, learning..." (Bellman, 1978)	"The study of mental faculties through the use of computational models." (Charniak and McDermott, 1987) "The study of the computations that make it possible to perceive, reason, and act." (Winston, 1992)
Acting Humanly	**Acting Rationally**
"The art of creating machines that perform functions that require intelligence when performed by people." (Kurzweil, 1990) "The study of how to make computers do things at which, at the moment, people are better." (Rich and Knight, 1991)	"Computational Intelligence is the study of the design of intelligent agents." (Poole et al., 1998) "AI... is concerned with intelligent behavior in artifacts." (Nilsson, 1998)

Table 1: Some definitions of artificial intelligence categorized by Russel and Norvig (2016)

Russel & Norvig further emphasize that the human approach is to think and behave like humans, and the ideal or rational approach involves a combination of mathematics and engineering, measuring the ideal performance of a task. Neither of the approaches indicates a perfect approach or perfect performance of a task, nor could a performance ever be perfect; to perform as well as possible is to perform most ideally.

More practically, artificial intelligence can be understood in a nested set of concepts; artificial intelligence is a general term for algorithms or computational implementations that can solve complex tasks that normally require a human or superhuman level of understanding and capability to learn from the environment. Machine learning is a subcategory of artificial intelligence that contains algorithms and methods designed to imitate learning, and deep learning is a subcategory of machine learning implementing multiple layers of neural networks. This categorization is illustrated in Figure 1 (Artificial intelligence subcategories and hierarchy). Machine learning categorization is further discussed in Chapter 2.3, neural networks, and deep learning in Chapter 2.4.

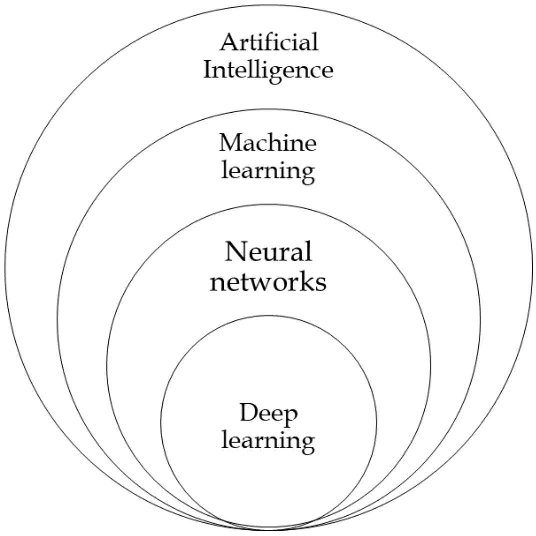

Figure 1: Artificial intelligence subcategories and hierarchy.

2.2 Machine Learning

Machine learning is a subfield of artificial intelligence that can be defined as a program that's aim is to provide preferred results from learning based on past data or experience (Alpaydin, 2020). Machine learning methods can be further categorized into different segments based on the algorithms used in the methods, or by the preferred outcome of utilizing the method. These machine learning classifications are further discussed in subsections of this chapter.

The basis of computer science relies on algorithms that are created to automatically solve problems and tasks given to the computer. Usually, in simple problems that have clear outcomes based on simple parameters, computer scientists and information technology professionals have been able to solve those problems in the past decades. However, when the problem, the outcome, and the parameters themselves are not unambiguous and require more complex consideration, traditional algorithmic problem-solving is not sufficient. As Alpaydin (2020) mentions, in tasks such as image recognition, the human mind can solve effortlessly without even being aware of the task or the problem-solving itself.

Machine learning aims to create algorithms and programs that can solve these kinds of problems.

Usually, in simplicity, the traditional algorithms provide some sort of output based on the input data provided for the algorithm. The basic idea remains the same for the machine learning algorithm, with the addition that the machine learning algorithm or application should be able to improve the outcome through the training experience. According to Jordan & Mitchell (2015), this is referred as the "learning problem", which states as "the problem of improving some measure of performance when executing some task, through some type of training experience". In this training experience, the machine learning model can utilize theory on statistics and other mathematical models to make inferences from the sample data, which makes machine learning closely related to computational statistics in some viewpoints. However, it is noteworthy to state that not all machine learning models utilize statistical learning.

2.3 Machine learning classification

Machine learning models are usually classified by how they process data, whether the inputs and outputs of the algorithms are supervised, and the desired outcome of the algorithm (Alpaydin, 2020). Commonly, in literature machine learning methods are organized as follows:

- Supervised learning
- Unsupervised learning
- Semi-supervised learning
- And reinforcement learning.

Typically, all of the machine learning methods can be categorized under these subcategories of machine learning methods. In addition to the aforementioned classes of machine learning methods, e.g., Ayodele (2010) mentions "transduction" and "learning to learn". These subcategories, however, can also be classified into the aforementioned subcategories since method types do not necessarily differentiate from the other subcategories by the way they process data, but the outcome of the method itself. In transduction, the algorithm does not produce a function but predicts new outputs based on training inputs, outputs, and new inputs (Ayodele, 2010). Further on learning to learn type of machine learning methods, Ayodele describes the algorithm's objective to learn "its own inductive bias based on previous experience". As both transduction and learning to learn are implementations of the aforementioned classifications' methods, they will not be discussed further here.

The selection of the machine learning method relies on the use case of the method and data available to train the model with, and of course, the data available to use in production.

2.3.1 Supervised learning

In supervised learning, the goal is to find out the mapping between the input and output data of the model (Alpaydin, 2020) and produce a function that generates outputs as close to the preferred outcomes as possible. As the name of the category implies, the output is supervised, and the results of the machine learning algorithm are compared to the desired outcome of the algorithm. Supervised learning algorithms are often used in classification problems, where classifications of the data are known, and the classification is easy to determine (Alpaydin, 2010).

Supervised learning is an appropriate approach when the data available for the machine learning algorithm to use is labelled, in other words, known to the supervisor of the machine learning algorithm. This makes it relatively easy to teach the model the preferred outcome of the algorithm – whether it is to classify images by the containing elements or recognize patterns from audio, as in speech recognition. That is one of the reasons the supervised learning strategies are at least right now most popular approach to machine learning (LeCun et al., 2015).

2.3.2 Unsupervised learning

In supervised learning the learning problem seems quite difficult, since in supervised learning the approach is to make the computer learn something it is not told how to be done. In opposition to supervised learning, there is no supervisor, and we have only input data, and the goal is to find regularities and patterns in that provided data. The aim is to find structures that occur more often than others, which in statistics is known as "density estimation" (Alpaydin, 2020) and in machine learning literature and discussion also known as "knowledge discovery" (Murphy, 2022).

According to Ayodele (2010), there are two approaches to unsupervised learning. In the first approach, the learning of the algorithm does not happen by giving categorizations to the agent, but by introducing a reward system to indicate success to the system. Another approach is known as "clustering", where the goal is to find similarities in the training data and cluster the data into groups (Ayodele, 2010; Murphy, 2012).

In addition to the aforementioned approaches to unsupervised learning, Zhu & Goldberg (2009) mention novelty detection and dimensionality reduction. In novelty detection, the goal is to identify instances of the data that differentiate from the majority. Dimensionality reduction on the other hand aims to "represent each instance with a lower dimensional feature vector while maintaining key characteristics of the training sample" (Zhu & Golberg, 2009).

2.3.3 Semi-supervised learning

In semi-supervised learning, as the name implies, the learning method of the system is somewhere in between supervised and unsupervised learning. According to Zhu & Goldberg (2009), most semi-supervised learning strategies are built by first utilizing either supervised or unsupervised learning strategies and then extending the learning process with additional information that is usually typical to the other learning paradigm. By utilizing both of the learning paradigms, it is possible to utilize both labelled and unlabelled data and create machine learning strategies and models that can perform better than the supervised or unsupervised learning strategies and models by themselves alone (Zhu & Goldberg, 2009). In addition to the aforementioned perks of using a semi-supervised learning approach, it is possible to achieve desired outcomes with fewer labelled instances in opposition to utilizing only supervised learning approaches. Generally, semi-supervised learning can enable a way of learning the structure of the provided unlabelled data, reducing the need for labelled data altogether (Goodfellow et al., 2016).

2.3.4 Reinforcement learning

When the desired output of the machine learning algorithm is not available, but it is possible to determine the success criterion and measure the performance of the algorithm, reinforcement learning is a suitable learning strategy. The goal of the learning process is not to predict the outcome values, but to achieve an outcome that performs sufficiently within the given success criteria. Reinforcement learning models can also be described as an algorithm learning a "policy", or guideline, on how to act based on the data available for the algorithm on the environment (Ayodele, 2010). Ayodele further describes that on reinforcement learning, every action has an impact on the environment and the environment acts as feedback for the algorithm to guide the learning process. Kaelbling et al. (1996) also describe the reinforcement learning model as an agent connected to the environment via "perception and action".

2.4 Implementation approaches for more complex learning problems

Simple machine learning algorithms are usually designed to handle relatively simple problems. But when the complexity of the problem and the variety of the possible input variables increases, the traditional and simple machine learning methods are not sufficient enough. In the situation where the complexity of the system increases, additional measures are needed, and in machine learning, this also means that the complexity of the machine learning system increases. This is usually solved by the means of neural networks and deep learning.

2.4.1 Neural networks

A neural network is a set of artificial, algorithmic neurons, that are built to solve more complex problems than standard machine learning processes are unable to perform well with. Neural networks are, as a concept, a part of machine learning methods utilizing a myriad of different, more simple machine learning methods. As we can deduce from the concept of neurons, the inspiration of the architecture of neural networks has been inspired by the most complex organism known so far - the human brain. The idea behind neural networks is to create so-called neurons, that are connected to a network to solve more complex problems that simple artificial intelligence or machine learning algorithms could not otherwise solve. This means that neural networks are capable of solving multiple tasks, such as regression and/or classification tasks simultaneously, although usually neural networks are built to solve one problem at a time (Ayodele, 2010).

As stated previously, neural networks consist of multiple simple processors called neurons, which produce each a sequence of “real-valued activations” (Schmidhuber, 2015). The neural network system aims to mimic a human-like cognitive process, that similarly utilizes a network of neurons – but of course, in a much more sophisticated manner. When comparing the learning processes of human cognition and artificial neural networks, the human mind is capable of learning to actively perceive patterns from the available data by focusing on the relevant available information (Schmidhuber, 2015).

2.4.2 Deep learning

As previously defined, artificial neural networks are a set – or more specifically, a layer – of neurons, that create the network to solve complex problems in a computational setting. Deep learning is a set of artificial neural network layers, and the “depth” of the deep learning implementation comes from the number of layers in the deep neural network. For example, when considering a popular implementation method of deep neural network, a feed-forward neural network, the network consists of an input layer of neurons, a set of hidden layers, and an output layer. In this type of setting, information is fed to the deep neural network on the input layer, where data is being forwarded to the inner layers, and finally to the output layer producing the outcome of the deep neural network process.

For example, in a supervised learning strategy, deep learning can provide a powerful implementation to solve complex problems. As the problem’s complexity increases, it is possible to introduce more layers to the deep neural network to enable it to perform well in the increasingly difficult setting (Goodfellow et al., 2016). As deep neural network architecture enables a variety of ways of connecting neurons and layers, it is possible to approach learning problems in many different ways. As the complexity arises and the neurons may even influence the environment where the learning agent operates, it is crucial for the success of the model to figure out what layers or parts of the model improve the outcome and how. As deep learning approaches usually include hidden layers of neural networks, often the solutions are at least partly "black box" implementations where the model's functionalities could be difficult to understand.

It is noteworthy to state that even though deep learning models can achieve human or even super-human levels of success on certain tasks (Goodfellow et al., 2016), the variety of functions that one model can perform is quite narrow and the models are designed for simple tasks, at least comparing to the human mind's cognitive capabilities. However, as these kinds of large models require large, labelled datasets, it can turn out to be difficult to teach properly. As most of the time the needed amount of labelled data is not available to utilize efficiently, the adoption of deep learning techniques is limited in a widespread manner (Goodfellow et al., 2016).

3 CRITICAL SUCCESS FACTORS

This chapter defines information system project success and critical success factors. The chapter further discusses identifying critical success factors and critical success factors in artificial intelligence. Information system project success is defined in Chapter 3.1 and critical success factors in Chapter 3.2. Critical success factor identification is discussed in Chapter 3.3. and artificial intelligence critical success factors in Chapter 3.4.

3.1 Definition of information system project success

Project success has been studied widely, and project success itself has various definitions based on the definition and the viewpoint of success. Project, however, has a quite accepted definition; a project has certain characteristics, such as specific time setting (e.g., begin and end date), specific goals, a set of related activities, and a limited budget (Pinto & Slevin, 1988). In past studies, project success has been observed greatly from the managerial viewpoint of project success, but later many authors have made a distinction between project management success and project success (De Wit, 1988). Baccarini (1999) also states that project success itself has two components, one being project management success and the other being product success. This is an important distinction, since even though the management of the project could be seen as successful, the outcome of the project could be seen as failure, and vice versa (Rolstadås et al., 2014).

From the project success viewpoint of project management success, the project success can be seen as how well the project management has been executed. In terms of traditional project management success criteria - such as time, budget, and performance - the project success is reached if the project reaches the thresholds defined in the aforementioned criteria. Therefore, the project success from the managerial point of view can be measured only at the end of the project (Andersen, 2014). From the project success viewpoint of product success, project success can be seen as the success of the developed result of the project (Andersen, 2014; Munns & Bjeirmi, 1996). On the contrary to the project management viewpoint of project success, product success is measured by the achieved company goals, the purpose of the project, and customer satisfaction of the project outcome. Customer satisfaction does not necessarily define in its entirety the success of the product for the customer, but Baccarini (2019) states that additionally, the end product should provide value to the end users for the developed product.

Not only the outcome of the project defines project success – according to Cooke-Davies (2002) the distinction should be made between project success that can be measured after the project completion and the project performance that can be measured in any project state. Traditionally in the literature project success criteria have been defined by time, cost, functionality, and quality goals (Savolainen et al., 2012). However, in the domain of software development, there has been debate about whether these success criteria are suitable for software development projects. For example, Bakker et al (2010) argue that in software development projects the traditional project success criteria such as time and budget are poor performance criteria, because it is usual for software development projects to change the project scope and requirements. This leads to changes in budget and time expectations, thus leading to project failure when observing the aforementioned criteria. Therefore, software projects need alternative, or at least more flexible project success definitions and criteria.

DeLone and McLean (1992) developed a model for information system success motivated by years of research on critical success factors, which was still lacking a coherent definition of information system success. Delone and McLean started to develop a taxonomy for information system success, which combined many reviewed aspects of the subject, dividing them into three sections: quality, use, and impact. In this model, quality includes system quality and information quality. System quality is defined as more engineering and performance-oriented approach quality in a manner of e.g., reliability, response time, data accuracy, and so on. Information quality, on the other hand, includes information system output and the quality of the information the system produces. The use section includes the usage of the system and the output, and the user satisfaction or "recipient response to the use of the output of an information system", the successful interaction with the information system (DeLone & McLean, 1992). Impact, on the other hand, is more ambiguous and based on the context can be understood as performance or usefulness on the information system, first on the individual level and second, on the organizational level. The relationship between the aforementioned aspects of information system success is illustrated in Figure 2, "Information system success model by DeLone and McLean (1992)".

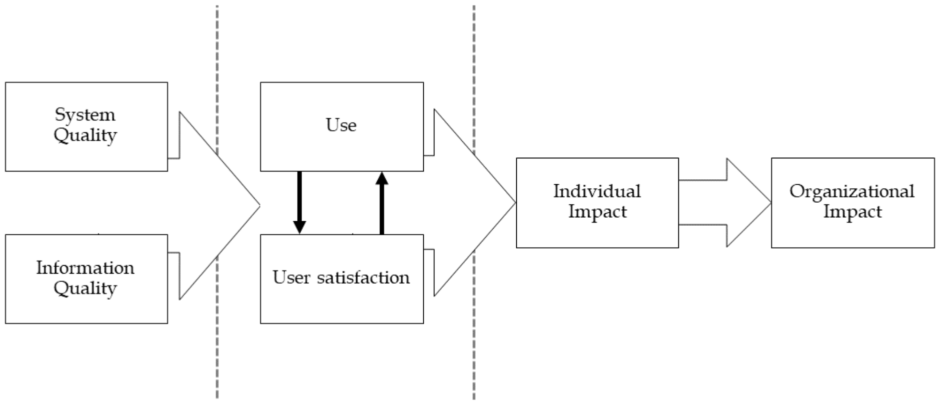

Figure 2: Information system success model by DeLone and McLean (1992)

DeLone and McLean (2002) revisited their model a decade later to improve their model of information system success based on research contributions and changed management of information systems. As the nature of information systems has developed greatly since the first implementation of the information system success model, it was needed to review the literature and scientific findings to further bring the model up to date.

In the updated version DeLone and McLean (2002) added a quality measurement as "service quality" and split the use into "intention to use" and "use" as the distinction between attitude and behaviour in information system usage. The outcome of the system is defined as "net benefits" which can, of course, be either positive or negative net benefits contributing to system use in a feedback loop, impacting the continuation or discontinuation of the information system development.

The information system model by DeLone and McLean has been widely discussed in scientific literature either validating, applying, developing, or challenging the model, and thus making it a relevant subject when discussing the success of information systems. However, it is noteworthy to state that even though the information system success model in its updated version may have been relevant when it was published, it is debatable how much the model applies in modern information systems; as the authors themselves state, the information systems and their relationship to business and society have seen tremendous progress in the past, it is safe to assume that the progress will not stop in the future and the models will require additional reviews in the future. In addition, based on the characteristics of the information system under observation, the model might need adjustments to better describe the environment itself.

3.2 Critical success factor definition

Critical success factors have quite a broad definition – as the name suggests, a group of factors that are necessary for the project to ensure the success of the observed entity. In literature, critical success factors have been approached from various perspectives, such as from the point of view of success or failure, individual, manager or organizational level, or even strategic viewpoint of the organization. Bullen and Rockart (1981) defined critical success factors as the "limited number of areas in which satisfactory results will ensure successful competitive performance for the individual, department or organization".

Bullen and Rockart further observe the critical success factors from a managerial viewpoint by defining critical success factors as "few key areas of activity in which favourable results are absolutely necessary for a particular manager to reach his goals". The managerial viewpoint was later observed by other authors such as Boynton and Zmud (1984), however, in later studies the scope of critical success factors observations has widened as the definition of project success in more recent studies has been separated from managerial success (De Wit, 1988).

As critical success factors can be defined via multiple viewpoints, there are no general success factors that would apply to any proposed setting. Critical success factors have been defined for projects, fields, individuals, and organizations, and used widely – from a management perspective to observing project success outcomes. According to Boynton and Zmud (1984), critical success factors are effective approaches in supporting the planning process and communicating the information technology role to management. In another approach in a more recent study, Sudhakar (2012) states that critical success factors can be used for project governance and communication in the project itself. In his critical success factors term defining article, Rockart (1979) also states that critical success factors can be useful not only in information systems design but also in the planning and management process. This is an interesting and important viewpoint regarding this thesis in terms of artificial intelligence implementation.

3.3 Identifying critical success factors

As previously stated, there are no general principles for defining critical success factors in a global setting. However, critical success factors can be defined on e.g., certain fields or project settings, such as software development projects. This has been researched widely and discussed in multiple studies defining different approaches and models for defining success factors in information system or software development projects. As there exist multiple variations of applying critical success factors, there are also multiple approaches for building an information system success model – with a variety of viewpoints from development to strategical aspects. However, it is noteworthy to state that these models also have different definitions of project success and take into consideration different success criteria. For example, the information systems success model by Delone and McLean (1992) addresses the dimensions of user satisfaction, use, system quality, information quality as well as individual and organizational impact. As these dimensions are most likely relevant success factors still in today's project, they do not consider the communicational and managerial aspects of the project success. Similarly, a more recent study by Remus and Wiener (2009) defines "the critical success factors model for managing software projects" as internal and external suitability and managerial factors but does not discuss product and quality-related factors.

However, an extensive literature review by Sudhakar (2012) defines 80 critical success factors for software projects and categorizes those factors into seven different categories. These categories consider not only managerial and communicational levels of critical success factors but also technical and implementation-related factors of software development success. Sudhakar further continues to place the found success factors among the categories into arranged order based on the number of appearances of the success factor based on their studies. The categories and their corresponding success factors can be seen in the table below, Table 2, "Categorized critical success factors based on literature review by Sudhakar (2012)".

Category	Critical success factors
Communication factors	Communication, leadership, relationship between users and IS staff, reduce ambiguity, maximize stability, balance flexibility and rigidity, cooperation
Technical factors	Technical tasks, troubleshooting, technical uncertainty, technical implementation problems, integration of the system, technology support, system testing, removing legacy systems
Organizational factors	Top management support, realistic expectations, organizational politics financial support, power, market intelligence, personnel recruitment, business process reengineering, reducing cost base, increasing efficiency, attrition
Environmental factors	User involvement, customer involvement, vendor partnership, external environment events, client acceptance, user's confidence in the system, community involvement, legal problems, user training and education, opening up a new market
Product factors	Accuracy of output, reliability of output, timelines of output, quality control, documentation of systems and procedures, realization of user requirements, product management

Team factors	Team capability/competence, teamwork, select right team for the project, project team coordination, task orientation, team commitment, team empowerment
Project management factors	Project planning, project control mechanisms, project schedule, project manager's competence, clear project goal, availability of resources, project monitoring, project organization, progress meetings, project review and feedback, well-defined project requirements, risk management

Table 2: Categorized critical success factors based on literature review by Sudhakar (2012)

As we can see on the table above, there exists some level of overlapping on the success factors on the categories, such as in communicational and project management factors.

3.4 Critical success factors in Artificial Intelligence

Artificial intelligence has been studied for decades. However, the interest in artificial intelligence solutions has varied throughout the years based on a multitude of reasons, such as general interest in the public and even computational limitations in the past. Regardless of the interest in artificial intelligence, the critical success factors of artificial intelligence implementation or adoption have not yet been studied widely.

However, Brock and Von Wangenheim (2019) studied the successful implementations of artificial intelligence in the context of digital transformation and proposed some of the success factors needed for the successful implementation of artificial intelligence. Similarly to Sudhakar, Brock and Von Wangenheim organized success factor findings into "categories", or perspectives, with distinct definitions, including a set of success factors. However, it is noteworthy to state that in Brock and Von Wangenheim's study the success factors are bound to their proposed framework, DIGITAL, being an acronym of the suggested success factor categories based on empirical findings of their studies.

Perspective	Description
Data	Data is the fundamental basis of artificial intelligence implementation – without proper set of data, usage of artificial intelligence is impossible
Intelligent	Skilled staff is required to achieve results when implementing artificial intelligence. This expands further than data engineering knowledge, but also in skills such as strategic and security related knowledge.
Grounded	When implementing artificial intelligence, the recommended approach is to start small – for example, apply artificial intelligence into existing systems and improving existing business processes.
Integral	Successful wide implementations of artificial intelligence require holistic approach. This should include strategy, processes, data management, technology alignment employee management and culture.
Teaming	Implementing artificial intelligence alone does not likely lead into successful results. Teaming up – partnering with other organizations can lead to more prominent results.
Agile	Organizational agility can be either key success factor or key barrier into AI implementation – lacking agility means challenges in the artificial intelligence implementation process.
Leadership	The project should be actively endorsed and supported on the managerial and top managerial level to be accepted in the organization.

Table 3: Artificial intelligence implementation success factors by Brock and Von Wangenheim (2019)

As we can see from the table above (Table 3), the top-level approach on project success factors and success factors on software projects have a fair number of similarities with the critical success factors – but also differences. Software projects differentiate by nature greatly from traditional projects, but similarly, artificial intelligence projects and implementation differ from traditional software projects and need additional approaches to concepts such as critical success factors.

Similarities and conjunction points can also be observed from the Enholm et al (2022) study discussing artificial intelligence business value. Even though the study focuses on business value, Enholm et al also discuss enablers and inhibitors of artificial intelligence usage. Multiple similarities can be found; Enholm et al categorize enablers and inhibitors into technological (data, technology infrastructure), organizational (culture, top management support, organizational readiness, employee-AI trust, AI strategy, compatibility), and Environmental (ethical and moral aspects, regulations and environmental pressure).

4 BUSINESS VALUE

This chapter discusses business value in information technology and artificial intelligence. Chapter 4.1. defines business value, Chapter 4.2. discusses information technology value and Chapter 4.3. artificial intelligence business value and its impact on business functions.

4.1 Definition of business value

Business value is usually defined by the context of the use of the term, and it can refer to a myriad of different aspects of value. That being said, in literature, business value usually refers to the worth or significance that an organization receives from the activities, assets, products, or services – or in this thesis' scope, information technology and more specifically artificial intelligence implementation. Business value includes both tangible and intangible elements that contribute directly or indirectly to the value of the organization, for example directly in the means of increasing the organization's estimated valuation, reducing costs or bringing competitive advantage to the organization in opposition to their competitors. In more detail, business value extends the concept of economic value, including other forms of value – tangible or intangible.

4.2 Information technology business value

In the past, there were discussion within the scientific literature about whether information technology creates value – but now it is clear that information technology certainly creates value in one form or another (Kohli & Grover, 2008). Information technology implementations certainly bring business value to the organization, whether it is direct tangible financial value, intermediate or affective (Kohli & Devaraj, 2003). However, as Kohli and Grover (2008) note, information technology does not itself create value as an independent and isolated entity in the organization, but information technology creates value as a part of the business process creating business value along with other information systems and organizational functions or components. This means that other components of the ecosystem work synergistically creating business value, information technology and its tools being one part of the value-creating process (Melville et al, 2004). That being said, in simplicity, information technology can create value as a tool in a process that creates value.

4.3 Artificial intelligence business value

Enholm et al. (2022) composed a literature review about artificial intelligence business value, highlighting the key enablers and inhibitors of artificial intelligence adoption and use, the typologies of artificial intelligence use in the organizational setting, and the first- and second-order effects of artificial intelligence. On the impact of artificial intelligence, the study more specifically addresses the impact of artificial intelligence on business value – and for example, competitive advantage, and business processes. The authors divide these impacts into two separate categories, first-order and second-order impacts of artificial intelligence. First-order impacts and effects of artificial intelligence are the effects that cause changes at the process level of the organization. The overall impact of these factors can be measured for example, in KPIs (Key Performance Indicators), which on the process level commonly are concerned with e.g., effectiveness, productivity, or quality. Enholm et al. assess the impacts of artificial intelligence with three different effect categories: process efficiency, insight generation, and business process transformation. Second-order impacts, on the other hand, are artificial intelligence impacts that have a firm-level impact - for example, creating new products or services or enhancing the quality of existing ones. Enholm et al. categorize these effects into operational, financial, market-based, and sustainability performance and unintended consequences and negative impacts. Impact effects and categories are presented in Table 4 below, "Artificial intelligence impact on business value, Enholm et al. (2022)".

First-order effects

Category	**Effects**
Process efficiency	Improved productivity
	Reduce or eliminate human errors
	Greater precision
	Reduce risk to human operators
Insight generation	Decision quality
	Organizational agility
Business process transformation	Process reengineering
	Organizational structure redesign

Second-order effects

Category	**Effects**
Operational performance	New products or services Enhanced products or services
Financial performance	Growth Profitability
Market-based performance	Market effectiveness Customer satisfaction
Sustainability performance	Environmental Social
Unintended consequences and negative impacts	Distrust Corporate reputation deterioration

Table 4: Artificial intelligence impact on business value, Enholm et al. (2022)

On first-order impacts, business performance can be increased by increasing process efficiency by utilizing artificial intelligence - for example, using artificial intelligence to automate tasks or augmenting human intelligence (Coombs et al., 2020). Automating repetitive tasks can reduce business costs whether they require human interference or not, by replacing human process factors in tasks that do not require human interaction and improving productivity in those that do. Not only does it improve productivity, but for example, reduces human interaction. Through insight generation, artificial intelligence can be utilized to create new information by revealing hidden patterns and unlocking insights from large volumes of data (Mikalef & Gupta, 2021). Because artificial intelligence is capable of processing data at a superhuman level compared to human cognition, it opens up new possibilities in revealing new insights from data such as customer segmentations (Alsheibani et al., 2020) - which enables more efficient decision making for organizations. In business process transformation, like new technologies overall, artificial intelligence can impact and even transform business processes or even redesign organization structure as a tool for improving existing processes or even replacing them.

On second-order impacts, the impact of artificial intelligence can be observed at the organizational level. By introducing new products or services, artificial intelligence implementation can surpass existing solutions or even tap into untapped market opportunities. Financial performance can also be affected, not only by increased revenue but also by cutting costs by e.g., improving productivity, thus improving financial performance. Market-based performance can be improved by artificial intelligence either via marketing effectiveness or customer satisfaction. As aforementioned customer segmentation reveals new approaches and opportunities to marketing, it enables the improvement of marketing efforts. Customer satisfaction has also a variety of use cases and examples that artificial intelligence is capable of improving; by learning from past customer data, the company representatives have a better understanding of customer behaviour and possible customer service caveats, which brings opportunities for improved customer service and customer satisfaction. However, it is noteworthy to state that utilizing artificial intelligence can lead also to negative customer satisfaction, for example, frustrating and ineffective customer service by chatbot implementation (Castillo et al., 2021). Environmentally, artificial intelligence can impact sustainability by reducing energy costs and consumption, which also leads to social impact. As Enholm et al. (2022) state, artificial intelligence can also have negative, unintended impacts - for example, via biased data sets used in artificial intelligence implementation's learning phase, leading to biased outcomes.

Brock and Von Wangenheim (2019) reached somewhat similar findings in their studies of artificial intelligence with a more grounded viewpoint. Similarly to Enholm et al, Brock and von Wangenheim categorize artificial intelligence business value impact into several subcategories; in opposition to process and organizational level impact, Brock and von Wangenheim categorize artificial intelligence business impacts into business model transformation, operational efficiency, revenue increase, organizational agility, offering competitiveness and customer experience. Almost all of the aforementioned categories have interchangeable counterparts (or are defined at least as subcategories) in the study by Enholm et al. However, the definition of Enholm et al takes organizational level business value impact into more broad consideration.

5 LITERATURE REVIEW SUMMARY

Based on the literary review, artificial intelligence is an umbrella term for a variety of different kinds of applications that have no commonly agreed definition. However, artificial intelligence can be observed and described from a variety of viewpoints such as a subfield of computer science or on a more philosophical level, from the relation to human-like behaviour. From the viewpoint of computer science, artificial intelligence is seen as a multidisciplinary field utilizing computer science, mathematics, and statistics in solving complex problems usually requiring human-like behaviour.

Observed from a practical standpoint of artificial intelligence algorithms (and set of algorithms) artificial intelligence is a nested set of concepts developed to solve complex problems, including a variety of nested subfields; machine learning, neural networks, and deep learning. Machine learning, being a subfield of artificial intelligence, is a program that aims to provide preferred results and outcomes via learning from past data or experience (Alpaydin, 2020). Machine learning algorithms can be further divided into subcategories or classifications, which are usually classified by how they process data (Alpaydin 2020). However, traditional machine learning methods are not always sufficient to solve more complex problems requiring more advanced techniques.

In more complex problems, more advanced solutions can be created using multiple artificial intelligence and/or machine learning methods. For example, machine learning methods can be built into layers of machine learning algorithms called neurons, creating systems that are referred to as neural networks. These neural networks can be further combined into multiple-layer networks, creating methods for deep learning solutions to solve even more complex problems. Machine learning and its subcategories, neural networks, and deep learning implementations have become popular in applications like computer vision and natural language processing (Jordan & Mitchell, 2015). Artificial intelligence and machine learning have gained a growing interest in possible applications with recent developments of generative artificial intelligence and natural language processing in applications such as Chat-GPT, Dall-E, and Midjourney. The growing interest in artificial intelligence has led to a new wave of companies trying to implement it, however with little success; according to Enholm et al., (2022) and Mani et al., (2020), only a small percentage of companies have succeeded in implementing artificial intelligence beyond pilot projects. This study aims to find the critical success factors of implementing artificial intelligence to possibly improve the percentage of successful aforementioned implementations.

Findings in the literature review state that critical success factors can be approached from the viewpoint of success and/or failure on the individual, manager, or organizational level or strategic viewpoint of the organization. The term itself is quite broad but can be defined as a group of factors that are necessary for the project to ensure the success of the observed entity. The literature has many definitions of critical success factors depending on the viewpoint of project success, but Bullen & Rockart (1981) defined fairly descriptively critical success factors as "limited number of areas in which satisfactory results will ensure successful competitive performance for the individual, department or organization". In the scope of this thesis, the information system success is perceived as the business value success of the implementation project.

Critical success factors have been observed in literature not only by aforementioned viewpoints but also by certain fields and project settings. As there are no general principles in a global setting to define critical success factors, projects in fields and subfields on certain areas require a more sophisticated approach; in literary software projects critical success factors have been approached e.g., by Sudhakar (2012) defining a myriad of critical success factors including for example, project management, product, and team factors. These might be at some level suitable for artificial intelligence implementation projects (and there of course exists some level of overlap), but in a more defined scope, a more exact approach is needed in this study.

Critical success factors have not yet been studied widely in the context of artificial intelligence implementation. However, Brock and Von Wangenheim (2019) studied the successful implementation of artificial intelligence in the context of digital transformation and proposed a framework as a set of categories of critical success factors on artificial intelligence implementation projects. These categories or perspectives include critical success factors labelled by perspective forming the acronym DIGITAL, their proposed framework for artificial intelligence implementation.

Enholm et al. (2022) discuss artificial intelligence business value and the impact of artificial intelligence usage in an organization in their literary review. The study separates the artificial intelligence impact into two distinct categories based on the level of impact the artificial intelligence has on the organizational level: first-order impacts and second-order impacts. First-order impacts are effects that cause changes on the process level of the organization, impacting e.g., effectiveness, productivity, and quality of the organization's processes. Second-order impacts create changes on the organizational level; for example, impacting operational performance via new products and services, or financial or market-based performance.

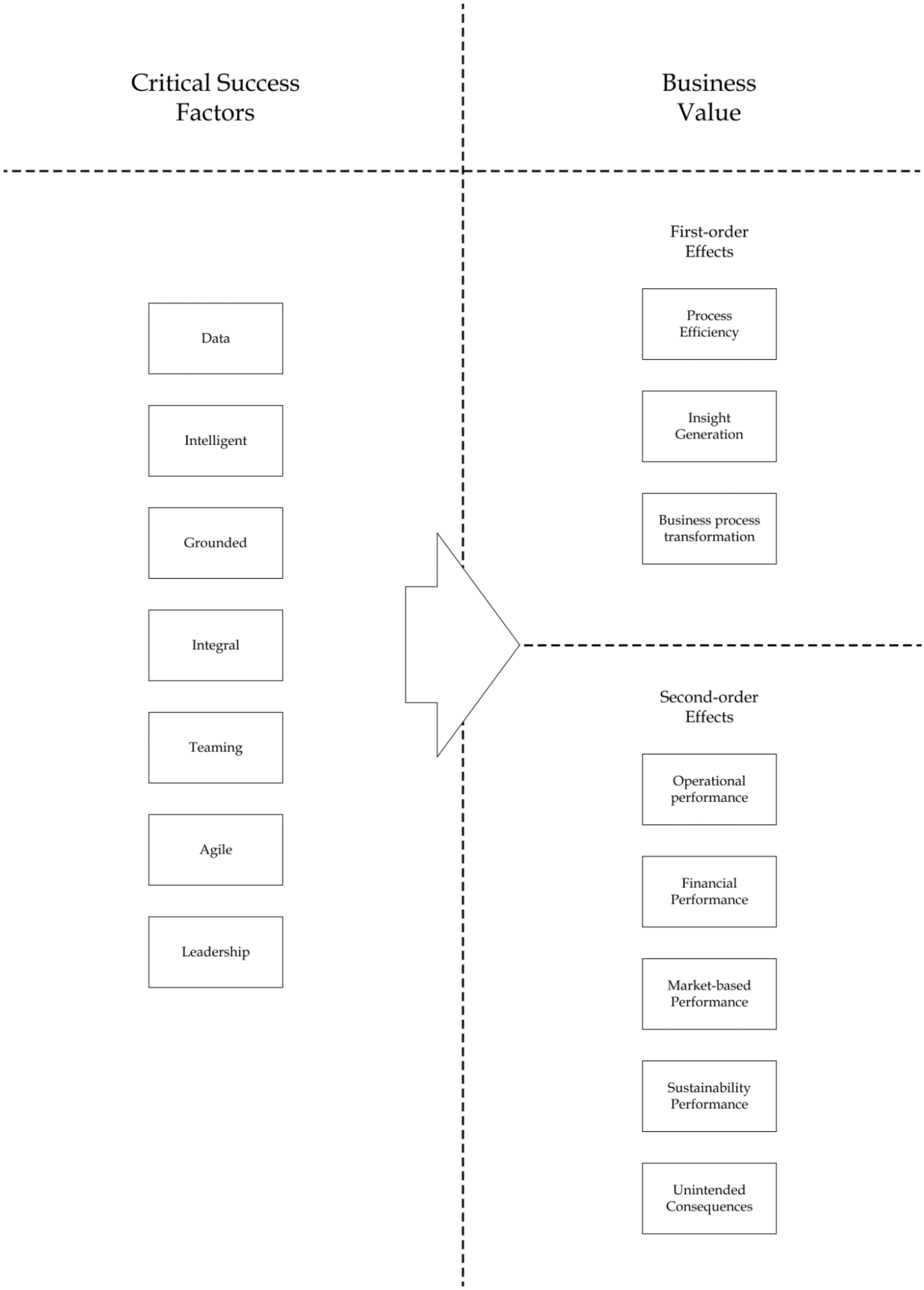

Figure 3: Theoretical Framework

The theoretical framework (illustrated in Figure 4) is formed by the findings of the literature review and the supporting research sub-questions, "What are the potential artificial intelligence critical success factors previously identified in the existing literature" and "What is the business value of artificial intelligence". The theoretical framework combines findings from two aforementioned studies from Brock and Von Wangenheim (2019) and Enholm et al. (2022), demonstrating the relationship between the two concepts; artificial intelligence critical success factors and business value impact. Brock and Von Wangenheim (2019) presented seven categories of critical success factors that are used in this theoretical framework as the baseline of critical success factors of artificial intelligence implementation. The business value of artificial intelligence is presented by the Enholm et al. (2022) classification of artificial intelligence business value impacts, containing a set of first-order effects (process impacts) and second-order effects (organizational impacts). The combination of two models from the aforementioned studies forms the theoretical basis for the empirical research in this study to answer the research questions.

6 METHODOLOGY

The empirical section of the study was conducted as a qualitative study, utilizing semi-structured, thematic interviews. According to Hirsjärvi and Hurme (2022) thematic interviews as a term specifying interview strategy is not widely used outside of Finnish literature, let it be clarified that in this context, the referenced thematic interview strategy is close to semi-structured research strategy with the discussion focusing on provided themes and not precisely set of questions. For example, this kind of interview strategy is referenced as "the general interview guide approach" by Patton (1990).

Previously in this study, the research questions were approached with literary review, forming the theoretical framework for the empirical section of the study. This chapter describes the empirical part of the study. First, the goal of the research is described in Chapter 6.1. The Chapter 6.2 describes the research method and the description of the chosen research strategy. Further, the means of data acquisition (selection of the interviewees and execution of the interviews) are described in Chapter 6.3, and finally, the analysis of the acquired data is described in Chapter 6.4.

6.1 Research goal

The scientific literature regarding artificial intelligence implementation presents multiple research gaps regarding artificial intelligence implementation and artificial intelligence business value. As more and more artificial intelligence project implementations are being carried out by organizations, the research, and the organizations need more information about artificial intelligence implementation success; what kind of success – in the scope of this thesis, success by business value – does artificial intelligence implementations produce? What are the factors leading to artificial intelligence project success?

The goal of this thesis is to create more information on the matter; by taking these aforementioned research gaps and real-life need for information, the following research questions were formed:

- What are the critical success factors in implementing artificial intelligence from the business value viewpoint?
- What is the relationship between the critical success factors of artificial intelligence implementation and artificial intelligence business value?

These research questions were approached by forming the following supporting sub-questions with the existing literature in the literature review, thus creating the theoretical framework of this study:

  - What are the potential artificial intelligence critical success factors previously identified in the existing literature?
  - What is the business value of artificial intelligence?

6.2 Research method

The research strategy for the empirical part of this study was chosen to be qualitative study. The qualitative study was conducted as a selection of individual expert interviews, with semi-structured, thematic manner (see start of Chapter 6, methodology). As Hirsjärvi and Hurme (2022) states, the method for the study itself should be chosen by the research problem in hand, and this study addresses concepts like observed critical success factors and business value, it is natural to choose a research method that fits for observing phenomena related to often subjective views of covered research subjects. As Hirsjärvi and Hurme further express the suitability of interview approach for research, they state that interview is a beneficial approach for example, when…

- The studied phenomena are unknown, so the direction of the study and the subjects are uncertain,
- There is a need for the answers of the interviewee to be placed into a wider context, and
- There is a need for deeper understanding of the available information.

As the focus of this study is to create a wider understanding of the underlying concepts and phenomena, such as artificial intelligence implementation critical success factors, created business value and their relations, the interview research strategy is highly suitable for the research problem in hand. As the theoretical concepts and required theoretical background were created in the literature review, the interviews were a suitable research strategy also by the criteria of Puusa, Juuti, and Aaltio (2020). Furthermore, based on the literature review conducted for this study, the underlying concepts and topics are not seen coherently in the literature and the research problem itself is subjective in its nature, the thematic approach was selected for conducting the structure of the expert interviews. As the topics themselves were defined and somewhat limited but the inexistence of unanimous views of the subjects were certain, the thematic approach enabled the researcher to form wider yet limited themes for the interview with a set of questions and possible subquestions. The questions and subquestions followed a "funnel structure" (Hirsjärvi & Hurme 2020), which allowed the interviewee to address broader themes of the interview and then proceed to the more specific subjects in hand. The themes for the interview were created based on the findings of the literature review. As per instructions of Hirsjärvi and Hurme (2022), some information (the definition of first-order and second-order effects in the context of artificial intelligence business value) was presented for the interviewees about the themes in hand to create a clearer and mutual understanding of the themes and the related questions.

6.3 Data acquisition

The meaning of data acquisition is to gather relevant information about the researched phenomena (Hirsjärvi & Hurme, 2022). The data acquisition was executed as individual interviews to extract individual insights about the research subject. This chapter presents the interviewee selection and interview execution. The background information of the interviewees is presented in Table 5.

6.3.1 Selection of the interviewees

The group of interviewees were chosen following the principles stated by Hirsjärvi and Hurme (2022) which state that the sample subjects of the research should be chosen based on the chosen research subject and following adequacy principles. As the research subject was closely related to the technical implementation of artificial intelligence and the business value of the success of the project, the goal was to find information technology experts who have experience in providing artificial intelligence implementation projects and understand the business value creation of artificial intelligence. As all the interview participants had some level of experience in artificial intelligence implementation and had close business practicality viewpoint of project success on their previous contract assignments, we can conclude that the sample can be addressed as an "adequate and discretionary sample" by the standards of Puusa, Juuti and Aaltio (2020).

As stated previously, the criteria for research subjects were to have experience in artificial intelligence project implementation and to understand the business aspect of provided artificial intelligence implementation. The interviewees were acquired and approached for the research via various channels; an initial list of potential interviewees was acquired via LinkedIn search and screening with the aforementioned criteria, followed by contact via LinkedIn messages or direct email contact. This was followed with "sample snowballing", the method for acquiring more interviewees by the contacts of previous interviewees. This led to a sample size of nine participants with a variety of backgrounds, variety of expertise, and experience years; to avoid "elite bias" (Myers & Newman, 2006), the failure to gain an understanding of the broader situation by interviewing only high-profile interviewees, the aspiration was to acquire interviewees with various levels of expertise, professional background, and titles. The sample size was limited by the common qualitative research approach, sample saturation principle, which states that there exists no need for additional interviews when the interview content begins to repeat itself (Hirsjärvi & Hurme 2022; Puusa, Juuti & Aaltio 2020; Tuomi & Sarajärvi, 2018). The additional information on the background of the interviewees is assembled in Table 5 below.

Interviewee	Organization	Title	Experience with AI in years
I1	Solita	Data Business Designer	3
I2	Pinja	Data Architect	1
I3	Accenture	Managing Director, Data & AI	7
I4	Accenture	Principal Director	23
I5	Multiple organizations	Multiple titles	8
I6	Digia	Lead Data Scientist	20
I7	Digia	Head of Data Insight	20
I8	Digia	CTO	36
I9	CGI	Senior Consultant	1

Table 5: Background information of the interviewees

6.3.2 Execution of the interviews

As described previously, the interviews were established in a semi-structured manner in thematic sections defined by the theoretical background from the literature review. The themes were organized logically, approaching from defining background information and most fundamental concepts, to the more complex topics. The thematic structure provided the limitation and the scope for the main questions, which were in some interviews further discussed more deeply with additional questions based on themes of ongoing interview. Additional questions were either predefined subquestions or otherwise related to a subject in hand, thus following the "funnel technique" (Hirsjärvi & Hurme, 2022) and going deeper into the research themes. The interviews themselves were conducted in the following manner: data processing and ethics of the study, background information, and the thematic interview itself. The themes for the interviews were artificial intelligence and artificial intelligence projects, artificial intelligence critical success factors and business value in general, first-order/process level impacts, and second-order/organizational level impacts.

As the goal was to acquire interviewees from various backgrounds and various levels of expertise, the sample included experts from various locations. As the locations of the interviewed experts were scattered and the interview strategy required transcription precision and therefore recording of the interviews, the remote interviewing with a digital platform was a natural choice for interview execution. The interviews were held via Microsoft Teams and recorded with the platform-provided tools. As the interview participation of the researcher is imperative for the research's success (Hirsjärvi & Hurme, 2022), the interviews were held solely by the researcher himself.

6.4 Data analysis

Before the data analysis itself, some preceding tasks were performed after the suggestions by Hirsjärvi & Hurme (2022). Hirsjärvi & Hurme state that before creating conclusions from the empirical data, the following tasks should be performed:

- Verification of information
- Completion of information
- Organization of information.

As the interviews were held, the interviews were transcribed into text format as soon as possible. After the transcription, the transcribed interviews were read multiple times and observed as individual entities from multiple viewpoints as per instructions by Puusa, Juuti, and Aaltio (2020). After the transcription and thorough inspection, the process of data analysis itself was conducted by following widely accepted principles of qualitative study data analysis with the procedure of proceeding from the whole interviews to separated and analysed subparts and quotes, and then again to the synthesized and structured entities. Hirsjärvi and Hurme (2022) as well as Puusa, Juuti, and Aaltio (2020) describe this process as inductive reasoning from entities to secluded parts to a deductive assembly of data grouping and creating of entities. By following these guidelines, the parts and quotes of the interviews were compared to the literature review findings. The comparison included searching similarities and differences between the existing literature and empirical findings, which is recognized as one of the recommended methods of qualitative research data analysis (Rissanen, 2006), with the goal of creating a coherent, meaningful, and rich observation of the researched phenomena. This resulted in a set of themes and subgroups formed from the transcribed interviews, not only including the existing themes acknowledged from the existing literature but also additional grouped findings. The most fundamental findings based on the data analysis are presented in the following chapter.

7 RESULTS

The analysis of the empirical material is mainly implemented based on material obtained from the interviews. During the interviews, some basics of the underlying concepts (the theoretical meaning of first-order and second-order effects) were presented to the interviewees during the interviews, which reflects on how some of the theoretical basis themselves can be seen in the analysis. The analysis utilizes theming as a means of structuring the interview findings, and the analysis process is described in more detail in Chapter 6, Methodology. The themes presented in the results have been created based on the recurring topics found in the interviews. The analysis presents similarities and differences between the empirical findings and the theoretical background; the artificial intelligence implementation critical success factors and business value have been identified from the interviewee recitations. Artificial intelligence implementation critical success factors were found to occur with some weighing differences regarding the observed project success scope, in this context, either the first-order effects or second-order effects. Additionally, a new theme and its categories were identified from the observed data, creating additional perspectives about the addressed subjects. This chapter reports the findings of the study, and each theme is addressed in their chapters. The synthesis is presented at the end of the chapter.

7.1 Background and views

7.1.1 On artificial intelligence and artificial intelligence projects

As part of the background questions presented at the beginning of the interview, the interviewees were asked about their views of artificial intelligence; as this study's research subject is deeply intertwined with the concepts addressed by the research, artificial intelligence, it is meaningful to determine the interviewee's views on the matter to find out possible distinctions between the experts' views and literature - to more precisely describe, what kind of phenomena are we dealing with when we are researching the subject.

Russel and Norvig (2016) attempted to define artificial intelligence from a philosophical standpoint by dividing the gathered definitions in the set of categories based on the view of how artificial intelligence is seen to think or act; rationally or humanly. The answers on the subject followed a similar pattern with a wide range of definitions with a slight emphasis on the answers that can be perceived as belonging to the category "Thinking rationally".

> ... When it is required to deduct something bigger from the starting point, something surprising, and there are multiple different options and not a plain simple, single solution... We're pretty close to artificial intelligence when we're talking about probabilistic deduction. (I8)

From the viewpoint of underlying technologies, the interviewees viewed artificial intelligence as a wide concept, acknowledging the depth of different technologies, but with an emphasis on machine learning and machine learning related technologies, such as deep learning and neural networks. Multiple interviewees stated that they realize that the concept itself withholds a lot of different subconcepts but viewed artificial intelligence in terms of machine learning partly due to the latest advances on the field and ongoing hype, impacting also the ongoing and incoming commercial projects in the organizations. In some interviews, the machine learning perspective was taken as a basis for approaching artificial intelligence as a concept.

> I'll define it as an ability to produce... Actually, I'd define this by taking machine learning on the base, that we have the ability to teach a machine to do things that we've taught it to do. And then these generative artificial intelligence implementations which sample parameter distributions into something that is seen based on the learning data, but still, the base is in the learning data. (I4)

However, additionally to technical specifications, it is noteworthy to state that the mathematical background was a recurring subject when discussing the background and the meaning of artificial intelligence. The mathematical algorithms and the statistical means for achieving results in artificial intelligence implementations were seen as one of the underlying key concepts in the domain of artificial intelligence. Also, when talking about artificial intelligence implementations, the interviewees usually limited the definition of artificial intelligence projects to larger projects and concepts, not including more simple implementations of for example, implementing small functions including statistical analysis or similar mathematical models.

7.1.2 On artificial intelligence business value consideration

One of the most fundamental things about creating business value is the intention to do so; not many technological implementations create business value accidentally. As it was shown later in answers in the interviews in discussions about critical success factors, sometimes technical implementations are prototypes and experiments with no greater context. As Alsheibani et al., (2020) stated that many companies face challenges in artificial intelligence adoption and deployment, it was relevant to ask the interviewees, is business value considered when planning the implementation process, and if it is, how?

In short, the answers were surprisingly coherent throughout the interviews, and were dividable into two sections; the experts who view that the age of proof of concepts is still ongoing and business value is not considered enough, and the experts who view that age of POC's is over and the world is ready for business-oriented implementations. However, the answers withheld recurring statements; it would be stupid not to take business value into consideration during the implementation process, yet again right now, it is not being taken into consideration well enough.

> Still a bit too little... It is like I said before, it is often that they want to have the text that they use artificial intelligence (on their website). Then again, there are a lot of POCs, experimenting the artificial intelligence without a greater plan of how to go forward with it. (I6)
>
> ... There was a time, when artificial intelligence was taken as, well, we've got this data and we experiment with it, like this kind of explorative side, but in my opinion that hasn't existed in a long time. (I7)

Also, as was seen in discussions about critical success factors, the viewpoints of both technical and businesspeople are not visible to one another; when technical people in the organizations talk about technical possibilities that could be implemented, business value factors may not be considered as much as they should be.

> Well at this moment my experience is that there are a lot of experimental POCs, and the client's IT people talk with the vendor side's IT people about what things are technically possible, but this is something that advances all the time as tools advance, but at this moment more like technical POCs... (I9)

7.2 Critical success factors of artificial intelligence implementation

The critical success factors of artificial intelligence implementation identified in the literature review and the theoretical framework of this study were also mostly found within the interview data. However, there were some distinctions between the study's theoretical framework's model of critical success factors and the research findings; some of the identified factors had a lot more correlation than others, with only a few or one mention in the whole interview data. As well as previously identified implementation critical success factors, some new were found which were presented in a significant amount of the interviews.

Organizational factors

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	Total
Data		X			X		X	X	X	5
Intelligent		X	X		X	X		X		5
Grounded	X	X					X		X	4
Integral			X	X	X	X	X	X	X	7
Teaming								X		1
Agile				X	X				X	3
Leadership				X	X			X		3

Implementation factors

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	Total
Problem-solution fit	X	X	X	X	X	X		X		7
Domain understanding	X	X		X	X	X				5
Tech & Business cooperation			X		X	X	X			4

Table 6: Interview mentions of general artificial intelligence implementation critical success factors.

As we can see from Table 6 “Interview mentions of general artificial intelligence implementation critical success factors” above, a lot of mentions in the interviews about general critical success factors of artificial intelligence had characteristics that can be categorized in the Brock and Von Wangenheim (2019) model. It is noteworthy to state that not nearly all of the categories have mentions that could be interpreted as a strong correlation between the findings on the data and the theoretical framework. For example, the category "Teaming" had the fewest mentions with only a single interview mention. However, it seems that there are some correlations in the interviews and the answers as to what factors are seen as important based on the interviewee’s position on the organization. Therefore, the organizational position may affect the perceived critical success factors.

The findings withhold not only similarities and minor differences in the categorizations presented in the theoretical framework; some groups and themes that had a significant amount of mentions in the data were not interpretable as a member of the theoretical framework's categorizations. The previously identified categories and their critical success factors seem not to fully suffice, and the factors themselves need additional observations. It seems that the distinction is seen in the data between the factors that are present in the organization, and also the factors that affect the project success during the implementation. This led to two distinct themes of critical success factors depending on their position in the implementation process. The distinction between the themes was whether they are a characteristic of the implementation organization or the actions taken into consideration during the implementation process. The identified factors, affecting the project's success during the implementation, are labelled under the theme "Implementation factors" in this study.

The general findings of the critical success factors of artificial intelligence implementation are thus divided into two sections; "organizational factors", paralleled to the critical success factors by Brock and Von Wangenheim (2019), and "implementation factors", identified in the study, being related to the artificial intelligence implementation process itself. The organizational factors are presented more in-depth in Chapter 7.2.1, "Organizational factors", and implementation factors in Chapter 7.2.2, "Implementation factors."

7.2.1 Organizational factors

As stated above, the mere classification of categories under the critical success factors proved to be insufficient and needed deeper observations; therefore, the distinction was made between the critical success factors presented in the theoretical framework and additional factors identified from the research data. Categories presented by Brock and Von Wangenheim (2019) and utilized in the theoretical framework of this study, were labelled under the theme called "organizational factors".

Organizational factors

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	Total
Data		X			X		X	X	X	5
Intelligent		X	X		X	X		X		5
Grounded	X	X					X		X	4
Integral			X	X	X	X	X	X	X	7
Teaming								X		1
Agile				X	X				X	3
Leadership				X	X			X		3

Table 7: Interview mentions of critical success factors under organizational factors.

As we can see from the table above, the frequency of the mentions in the interview data varies greatly. As the total number of interviews was 9, it is possible to form an indicative ratio that determines the correlation between the research data and the theoretical background. Based on the frequencies of the mentions, the categories "agile" and "leadership" focus on the weak end of the correlation spectrum, "data", "intelligent" and "grounded" forming the middle ground, "integral" with the strongest correlation with seven participants mentioning the subject, and the "teaming" having the weakest, with only one mention in the whole research data set.

Data. Data is seen as the number one critical success factor in artificial intelligence implementations by Brock and Von Wangenheim (2019) and is justified by the following statement: "Data is the fundamental basis of artificial intelligence implementation – without proper set of data, usage of artificial intelligence is impossible". The same paramount impact of data was recognized by a lot of interview participants who mentioned data as a critical success factor, and for example, the importance of data was emphasized as being the "success factor number one".

> Everything comes back to the data; still the quality of the data, the mathematics do not change anything if the basis is not in order. The quality of the data, this repeats that for example, generative artificial intelligence can't create anything from thin air. (I4)

As we can interpret from the quote above, artificial intelligence implementations, how great they ever would be, would not work without the proper amount of available data. Not only was it seen as important to have just any available data, but the interviewees also mentioned data-related factors such as data volume, data quality, and what period the data was gathered from as being important to the artificial intelligence implementation. As data is the very basis of how modern artificial intelligence applications (or at least, machine learning implementations) work, it is natural to emphasize the meaning of it. However, it is noteworthy to state that the previous discussions of the views of the artificial intelligence meaning can be seen in the answers related to data. Based on the literature, not all artificial intelligence implementations require massive amounts of data to operate, however, the latest machine learning applications such as generative models would not function without massive amounts of available learning material.

Intelligent. Brock and Von Wangenheim (2019) determine that "skilled staff is required to achieve results when implementing artificial intelligence". The skills and understanding of underlying subjects and technologies as well as surrounding domain were seen as of great importance among the interviewees. However, in this study, the domain understanding was seen as a strong, separate concept, and thus was separately presented under "implementation factors". The sole concept of artificial intelligence utilization was seen as a complex entity, and the understanding of the underlying concepts was seen as something that requires certain skill, knowledge, or experience on the subject. As data was seen as the basis of the artificial intelligence implementation, the next natural step would be the ability and the know-how to utilize the data.

> OK, let's start with people. We're talking about artificial intelligence, but people impact it how, and dividing further the people… Firstly, the expert used in the project, experience, things like that, but then also stakeholders. (I8)

Grounded. Brock and Von Wangenheim describe "grounded" as a way of starting small, meaning the implementation projects to be focused for example on existing systems and improving existing business processes. The grounded category appeared throughout the research data as mentions of starting small, as the Brock and Von Wangenheim description states. The proof-of-concept, or POC approach was seen as the initial method of trying out artificial intelligence implementations. However, the proof of concepts as a term was not solely mentioned as a critical success factor; it was also seen as an old way of doing things, the way artificial intelligence implementations were some years ago. In multiple interviews, the experts described the evolution of artificial intelligence implementation projects and described how it has evolved from the initial proof of concept try-outs to more holistic and controlled, more project-like approaches. This may be due to the increased understanding of artificial intelligence capabilities and how they can be utilized, leading to more coherent artificial intelligence implementations and therefore more structured project approaches. Still, the grounded approach was identifiable when discussing how to start with artificial intelligence implementations, however, with clearer use cases, grounded may not be seen as critical as it would be in more experimental cases.

> … Like with the structured approach, the project-like progression, and with that, like the researcher approach may produce results yes, but not as fast as business side has patience for. Like more project-like approach and bringing small victories along the way into attention. (I7)

Integral; wide implementations require a holistic approach, including strategy, processes, data management, technology alignment, employee management, and culture (Brock and Von Wangenheim, 2019). Answers related to the integral category reached seven mentions in the data, which is the highest achieved ratio of interview mentions of the observed categories under the organizational factors. The interviewees mentioned multiple characteristics of the organization and its human resource capabilities that can be categorized under integral. The understanding of the impacts and the possibilities of artificial intelligence implementations should not be limited to the people implementing artificial intelligence, and not even the parts of the organization beneficing it; succeeded implementation requires understanding, knowledge, and trust throughout the whole organization to reach the full potential of possible implementation benefits. For wider implementation and therefore wider success, the implementation requires more holistic cultural change towards artificial intelligence and understanding it.

> The most important factor is cultural, comprehensive cultural change, which requires the support of the very top of the management and understanding of what artificial intelligence, artificial intelligence solutions, the operational environment change require from practical leadership and execution. (I4)

> ... In a way, the critical factor for success is to get the solutions embedded in the whole operational environment and also to get the people to work according to the new operational model. (I9)

The people, business, and technology impacts are not only factors in integral which matter for the success of the artificial intelligence implementation project; communication is the key. The impacts of the artificial intelligence implementation process should not only be the concern of the people strictly related to the project, and the impacts should be clear and visible for the whole organization. The communication of the impacts and possible changes in the organization should be clear for the employees and the stakeholders of the organization.

Teaming. Brock and Von Wangenheim hypothesize that implementing artificial intelligence alone would not be likely to lead to successful results, and partnering with other organizations would lead to increased chances of success. This category had the lowest rate of mentions, with only one reference that could be labelled under teaming; partnering with other organizations was not mentioned in the vast majority of the interviews. The only reference was when artificial intelligence implementation was discussed with high-level functions of the organization, such as large service providers, where artificial intelligence service providers would be useful for the future implementations of the organization. Therefore, it would be possible that teaming would be a relevant factor for implementation success only when reaching for massive organizational impacts.

Agile. "Organizational agility can be either key success factor or key barrier into AI implementation" (Brock and Von Wangenheim, 2019). Agility - or organizational agility - manifested in the interviewee responses as descriptions of the transformational capabilities of the organization. The organization implementing artificial intelligence is more likely to succeed if the organization has the abilities and capabilities to adapt to the changes regarding artificial intelligence, and it is not limited only to the implementation process itself, but also the impacts of the artificial intelligence implementation. Artificial intelligence can create organization-wide impacts, and the organization should be ready for the possible implementation disruptions. The contextual changes should be understood and organized correctly.

> ... And then, are there like, contextual understanding of what we are utilizing? What are we getting from this data? How do we analyse it, and this also has to be organized. (I5)

Leadership. Brock and Von Wangenheim defined that "the project should be actively endorsed and supported on the managerial level to be accepted in the organization". The thoughts derived from interview data can be culminated in a similar manner; the required culture and change for successful implementation come from the top of the organization. As the people implementing artificial intelligence in the organization and the people that are being affected by the artificial intelligence implementation, the leadership has to see the impacts and the benefits to positively impact the implementation. When utilizing artificial intelligence generated information to support decision-making processes, the leadership should take that information into consideration - otherwise, the implementation work has no value.

> And another great challenge is how we get the leadership to actually utilize the analytics and information the artificial intelligence produces, the status quo sits pretty tight there in the management. The management does not easily change their behavioural patterns. So, if the management wants to make decisions based on intuition... It sits pretty tight there. (I5)

7.2.2 Implementation factors

As the interviews proceeded with the discussion about critical success factors, it became imminent that the existing categories would not suffice to contain everything that was presented by the experts during the interviews. As stated previously, the distinction was made between the critical success factors presented in the theoretical framework and the additional categorizations labelled under the additional, identified theme. These additional factors were identified in the research data and were found to be present especially during the implementation process. These factors are labelled under the theme "implementation factors."

Implementation factors

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	Total
Problem-solution fit	X	X	X	X	X	X		X		7
Domain understanding	X	X		X	X	X				5
Tech & Business cooperation			X		X	X	X			4

Table 8: Interview mentions of critical success factors under implementation factors.

As we can see from the table above, of the nine interviews held, the identified implementation factors were presented in significant numbers. Most mentions and descriptions were under the category “problem-solution fit”, with a total of seven mentions, providing a notifiable presentation in the study. The other categories, “domain understanding” and “tech and business cooperation” were also presented significantly with a total of 5 and 4 mentions.

Problem-solution fit. Problem-solution fit is a category that repeatedly found its way into discussion one way or another during the interviews. Problem-solution fit (or PSF) means the stage of completion of the implementation, where the implementation firstly, solves the right problem, and secondly, has the right solution for it. The very problems that lead to artificial intelligence implementations not reaching levels after the pilot stages that Enholm et al., (2022) and Mani et al., (2020) described, derive from the very definition of the problem in hand the artificial intelligence implementation is being used to solve. In the hype, it is easy to look for problems that do not exist and start implementing technologies for all the wrong reasons, which evidently leads to an unsuccessful project - if there is no problem to be solved, there are no solutions to be created, and therefore no business value to be acquired. Artificial intelligence business value is discussed in Chapter 7.3.

> Well, it begins with the available data and the problem should be defined pretty precisely, pretty often we come across situations where they want to utilize something but not quite yet understand where it could be utilized and what do we want from it, like let's just drive some data through it and see if we can do something with it. It does not work like that, and then we have to discuss with the client and ideate about what we even want to achieve with it. (I2)

As stated previously, not only is it a problem that there is no problem – it is a problem if the solution is not suitable for the problem at hand. In artificial intelligence implementation projects, it is way too usual scenario for organizations to find themselves in a situation, where they have over-engineered solution for a simple problem - and the root cause seems to come from the way things are done from the very beginning, defining the project and the scope of the implementation. As artificial intelligence and machine learning have a lot of different kinds of approaches, it can be difficult to find suitable solutions for the problems, and sometimes more simple approaches bring better results. For example, Kärkkäinen and Hänninen (2023) argue, that even with the problems that can be solved with deep or shallow computing, shallow networks can endure as well as (or even better than) deep networks. To put it simply, one does not need a sledgehammer to pound down a couple of nails.

> The greatest challenge is the deeper understanding of the context. That some may too easily start to code artificial intelligence into things, that they don't quite understand and then it leads to inaccurate decisions... (I5)

> ... Then it comes to that, have we chosen the right technologies, meaning have made intelligent choices there. Then after technologies, we have the architectural questions. (I8)

Domain understanding. The wider the area of impact of the artificial intelligence implementation, the bigger the number of things needed to be taken into consideration during (and after) the implementation process. Even though some artificial intelligence implementations are data-heavy, some use (and require) tremendous amounts of data, which leads to a myriad of problems and challenges. For example, depending on the context and domain of the implementation and what kind of data is utilized by the implementation, various ethical and legal aspects should be considered. In terms of legal challenges, e.g., a lot of certain aspects have been on public discussion related to training data of the machine learning algorithms; who owns the data that these algorithms are trained with, is it legal to do so, and who has the intellectual property rights of the outcome of the machine learning algorithm trained with data owned by others? As well as data related to individual human beings, at what level is it ethical (or is it at all) to utilize the data on the machine learning algorithms? Not only is domain success a question of ethical or legal aspects, but a question of understanding the environment of the problem to be solved. Relating to the challenge of problem-solution fit, it is imperative to understand the context of the implementation to actually produce meaningful solutions.

> But when we want to get past the POC phase it is good to understand the surrounding processes and surrounding world, where it is implemented, who is it done for and, who uses it. So, the organization's structure and the client's operations should be understood. (I1)

> But in practice, it is not at all common, that the organization understands what it requires to implement artificial intelligence in their functions. It usually is practically about this kind of change of operational actions, which begins from the very core of the company's or faculty's or organization's substance functions. (I4)

As implementations may impact the organization and its stakeholders, the people should be aware of the incoming changes they may have e.g. on processes related to their tasks. These are things that very much need to be taken into consideration during the implementation process. To put it simply, people involved with the artificial intelligence implementation should be aware of the implementation impact and the domain - who does the implementation affect and how.

Tech and business cooperation. To achieve success from a business value viewpoint, in technical implementations, technical executors must work hand in hand with people who understand surrounding business functions, and where the implementation brings actual value. From the technical viewpoint, implementation can be successful and work perfectly, but that does not necessarily mean that it would bring business value. Therefore, by linking tech and business cooperation to other implementation factors, the implementation should solve the right problem. The people executing the implementation should understand the surrounding environment - and from the business value viewpoint, especially understand how the implementation brings value to the organization. It requires cooperation, for technical implementors to understand business value, and business functions to understand where artificial intelligence can be utilized and where it can't.

> ... As with the things you can do with artificial intelligence solutions, they are not intuitive to many, so they're not something that business specialists necessarily come to think about, and then again, the technical people who knows very well the technical capabilities do not necessarily know what the pain points there are, and how the business benefits the most. It's maybe, in my opinion, one big theme, that how we could combine business and

> technology so close to each other, that it would actually be possible to utilize these capabilities in the best way possible. (I3)

> Maybe in this context is that there is the horse whisperer who is between the business and the technology, like what we've done a lot during this digital time like just implementing POCs, there's a lot of interested technical people, and then it does not necessarily produce value for the top-level management... (I6)

The business value of artificial intelligence and factors leading to business value impact are further discussed in Chapter 7.3.

7.3 Business value of artificial intelligence

Interview data of expert views about artificial intelligence business data reached a strong correlation with the proposed theoretical framework and the basis of artificial intelligence business value definitions by Enholm et al. (2022). With results and total mentions mostly ranging from 6 to 9 mentions (sustainability performance being an exception with only 3 mentions), it is acceptable to state that research data corresponds greatly with the proposed artificial intelligence business value categorizations.

The business value of artificial intelligence observed from research data is being presented in this chapter in parallel to the theoretical framework and Enholm et al. (2020) proposed artificial intelligence business value categorizations. The categorizations are divided as presented by the authors, into first-order (process level) and second-order (organizational level) business impacts. The business value categorizations are further discussed in Chapter 7.3.1. Finally, the critical success factors regarding business value are further discussed for first-order effects in Chapter 7.3.2. and second-order effects in Chapter 7.3.3.

First-order effects

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	To-tal
Process efficiency	X	X	X	X	X	X	X	X	X	9
Insight generation		X	X	X	X	X	X	X		7
Business process transfor-mation		X	X	X	X			X	X	6

Second-order effects

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	To-tal
Operational performance	X		X	X	X	X	X	X	X	8
Financial performance		X	X	X	X	X	X	X	X	8
Market based performance		X	X		X	X	X	X		6
Sustainability performance	X	X	X							3
Unintended consequences	X	X	X	X	X	X	X	X	X	9

Table 9: The business value of artificial intelligence

7.3.1 The business value of artificial intelligence, first-order impacts

First-order effects

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	To-tal
Process efficiency	X	X	X	X	X	X	X	X	X	9
Insight generation		X	X	X	X	X	X	X		7
Business process transfor-mation		X	X	X	X			X	X	6

Table 10: Business value of artificial intelligence, first-order effects

Process efficiency. Enholm et al (2022) categorize effects such as improved productivity, reducing or eliminating human errors, or increasing precision under process efficiency. The interviewees seemed to have similar thoughts on artificial intelligence creating business value via process efficiency, with an astonishing ratio of nine out of nine interviewees mentioning said impacts one way or another. A lot of the interviews included mentions and further discussions about improving productivity in existing processes, but also human error elimination and precision increase were mentioned.

Improving productivity included mentions from a myriad of business functions that can be (and have been) improved with artificial intelligence. For example, mentions include finance functions such as billing processes, HR functions such as recruitment processes, production function enhancement, etc. On a higher level, interviewees mentioned improved productivity via process enhancement; whether it is a core function of the business or a business function supporting core functions of the organization, almost everything with existing automation or a sufficient amount of data and predictability can be enhanced or automated.

> Practically the sky is the limit where it can be utilized, but basically, process productivity improvement. (I1)

> Well, what I was working with just now included forecasting of demand, which aimed at steering production to decrease deficit etc. (I2)

> Well, I talk mostly about the hyperautomation side, like I connect this pretty much with robotics and such automation, so let's say with HR functions, there exists a huge pile of things that can be done. (I7)

Not only can artificial intelligence improve process efficiency in a quantitative manner by enhancing productivity in ways of e.g., reducing time of completion, but artificial intelligence can also improve qualitative factors of processes. Some interviews mentioned generative models, which can be used in various expert tasks supporting experts in their activities, such as marketing material production and software code writing.

> It comes to the very core of our business, like how we change the software engineering, how we enhance it? How do we produce better code and consider the whole solution better, like how the integrations work? (I9)

Insight generation. According to Enholm et al. (2022), insight generation effects include effects aiming to improve decision quality or organizational agility. As process efficiency reached nine out of nine interviews mentioning the category, insight generation also reached a significant correlation between the theoretical framework and the research data with a total of seven mentions. Regardless of the line of business of the organization, the interviewees mentioned a lot of general business activities that artificial intelligence could be utilized in the decision-making process. For example, in marketing, artificial intelligence was seen as useful in analysing clientele and creating customer segments, as well as predicting effectiveness and marketing trends. However, depending on the field, the data, and the process involving artificial intelligence, artificial intelligence in the decision-making process was not always seen as unproblematic. For example, in insurance decisions and similar decisions regarding to personal data of individuals, artificial intelligence usage raises questions regarding ethical issues.

Scenario analysis was mentioned multiple times regarding decision-making, especially at the higher levels of the organization. Scenario analysis can be utilized practically anywhere in the business functions of the organization that can make use of future scenarios, including marketing, and finance functions such as budgeting and production volume control. Artificial intelligence was best seen as a supporting function in expert work, in a way where humans and algorithms work together, in a "human plus machine" way of working. Not only was artificial intelligence’s impact on decision-making seen as related to the decision-making process itself, but also as a tool for understanding the decision-making impact and measuring the made decisions on the selected metrics.

> Then there are a lot of these decision-making support tools, with different ways of producing probabilities and suggestions on how these kinds of situations have been solved previously, that all these... Human plus machine has been used as a term for these, where basically human and some kind of algorithmic solution works together. (I3)

> As well as certain decision-making impacts on results, meaning that it is possible to better understand made decisions and what the impact is on the selected metrics. (I4)

> Finance functions, like what I've been talking about scenarios, and budgeting. For example, budgeting could be done supported by artificial intelligence with business functions that have continuity [...] Prediction models, marketing trends could be utilized for strategic planning, that one could a little better see and create a basis from data for where the market is going by using information from different sources... (I7)

Business process transformation. Process reengineering and organizational structure redesign are effects mentioned by Enholm et al. (2022). As business process transformation is directly related to process efficiency, there is a fine line between the separation of impacts on process efficiency and the whole business process transformation. In the research data, in some interviews, the interviewees first addressed the impacts on process efficiency and on further discussion, moved on to talking about business process transformation in the same domain. Within these discussions, it can be concluded that with significant process efficiency improvements and changes, the whole business process can be transformed. For example, a significant improvement in certain process functions can eliminate some details of the process, and even remove the human labour from the process entirely. At this point, it is justifiable to address the impact as business process transformation.

Otherwise mentions on business process transformation included for example HR function remodelling to identify potential risk factors on the available workforce for example in terms of work fatigue or utilizing generative models in "creative" functions such as programming.

> I'll use a new example about this, that can be changed... Meaning really changes the execution process, but then we can impact especially nowadays with these different GPT models, it is possible to modify basic processes like programming, it can be done really differently. You have a friend, and by a friend, I mean this artificial intelligence, giving you the basis and giving you examples, but you can even have a set of AIs... (I8)

7.3.2 The business value of artificial intelligence, second-order impacts

As with first-order effects, second-order effects also reached a high correlation between the theoretical background and research data. As theory implies first-order effects (process level effects) lead to second-order effects (organization level effects), the interviewees also saw the waterfall effect of process level impacts leading to organizational level impacts. A lot of conversations including first-order effects of artificial intelligence implementations lead to mentions of wider impacts - organizational impacts.

Second-order effects

Interviewee	I1	I2	I3	I4	I5	I6	I7	I8	I9	To-tal
Operational performance	X		X	X	X	X	X	X	X	8
Financial performance		X	X	X	X	X	X	X	X	8
Market based performance		X	X		X	X	X	X		6
Sustainability performance	X	X	X							3
Unintended consequences	X	X	X	X	X	X	X	X	X	9

Table 11: Business value of artificial intelligence, second-order effects

Operational performance. Effects regarding operational performance are the organization's new products or services, or enhanced products or services (Enholm et al, 2022). Mentions of operational performance impacts reached a total of 8 mentions. As improved processes (see Chapter 7.2.1, critical success factors, first-order effects, the section of process efficiency) are related to better operational performance especially when processes are related to the organization's products or services, the interviewees also connected these two phenomena. The greater the impact on process, the greater the impact on an organizational level.

> There are endless examples for different industries, so especially inside the company. Like these operational factors, but then product development and their own business, own business reorganization. (I3)

> What have already been for some, like products made with artificial intelligence, like creating new flavour combinations inspired by artificial intelligence... (I6)

Financial performance. Financial performance means effects on either growth or profitability (Enholm et al, 2022). These effects were seen to realise with a lot of different kinds of scenarios of implementations, not only cutting costs of processes but also via other first-order effects such as insight generation. Interviews mentioned for example optimization of trade of products regarding what is sold, how much, and on what season to cut costs and improve sales on different periods. As savings can be gained from reducing the human workforce from processes, they can also be gained via HR functions when predicting human resource needs and e.g., sicknesses. Optimization and prediction were also mentioned in creating growth and savings through sales.

> Well, what we discussed with one client was that they do this kind of bulk product with relatively low volume, and sometimes a shipment of the same kind of stuff comes from India which is significantly cheaper. So, they thought that they could play this kind of scenario, how and at what price should they market their own product in a way that they won't dump prices altogether, like after the market disruption they would be able to return to relatively normal state. (I6)

Market-based performance. Market-based performance includes effects such as market effectiveness and user satisfaction (Enholm et al., 2022). As discussed with previous effects, according to interviewees, market-based performance can be improved by enhancing and optimizing sales and production processes and anticipating demand. Marketing trends and vision prediction were also seen as an effect that artificial intelligence implementation can produce. Customer communication and customer service were seen as probable targets for artificial intelligence usage; responsiveness in customer service can be easily improved by scaling artificial intelligence systems, which can be set to work 24 hours a day. The qualitative factors were also brought to discussion; artificial intelligence can also improve the quality of customer communications, by means of language correction.

> Communication can be improved, and the communicational processes can be transformed into AI-based, face the customer with AI, we can enhance the day-to-day activities of how we communicate live, simultaneously with AI. (I8)

Sustainability performance. Sustainability performance includes effects on environmental or social factors (Enholm et al. 2022). It is noteworthy to state that sustainability performance had the least mentions among all of the other categories in second-order effects. However, this may be due to the views on sustainability factors; sustainability factors may not be usually directly linked or discussed with anticipated business value.

As discussed previously, processes can be changed and optimized with artificial intelligence, and this applies also to e.g., industrial systems. In industrial systems (or other production systems that use volumes of production materials) the production processes themselves can be optimized to minimize deficit and emissions, but the products themselves can be improved to be more sustainable. The same applies to organizations' resources, such as IT resources that can be optimized with artificial intelligence to be more sustainable. Within social factors, artificial intelligence can be used for predicting possible personnel sicknesses and within possibilities, intervene and reduce them.

> This environmental side is pretty clear for example on the industrial side. The processes can be changed, optimized with artificial intelligence so that for example sulphur or CO_2 emissions can be reduced. (I1)

> ... Then there are these smaller parameters we can direct, like, for example, these IT resources, data centre capacity, and cloud resources as efficiently as possible. (I3)

Unintended consequences. Unintended consequences are effects leading to distrust or corporate reputation deterioration (Enholm et al., 2022). According to research data, a lot of unintended consequences can occur during or after the artificial intelligence implementation. As the software usually does, so does artificial intelligence implementation requires maintaining and surveillance for possible unwanted scenarios. With data-driven machine learning solutions, a simple shift in data volume, quality, or orientation can change results drastically, leading to biased and delusional results. Bias was seen as a common unwanted consequence among artificial intelligence implementations, as (at least in machine learning implementations) rely heavily on data; bias and unwanted results can occur with simply poorly chosen data sets or one way or another corrupt or polluted data. Unwanted results can occur also simply from using the model or the learning data incorrectly due to not understanding well enough the surrounding processes and environment.

> Well in the negative spectrum... These different kinds of biases might come, that the model is thought for something or learning process have been limited. Learning material is not sufficient enough, it learns some characteristics... And then comes some other kind of need for prediction, and there's no learning material for it, and thus it produces a bit delusional, biased predictions. Favouring something, leaving something without attention. (I4)

> It does not even need someone from the outside to affect it, by just choosing the data material poorly, one can cause this kind of interpretation distortion. (I8)

These unwanted, unintended consequences manifest in many ways depending on the business functions they are implemented into. In recruitment and HR functions that handle data about individual people, the results can be biased if the training data of the model is biased for some reason - for example, a model trained with mostly Anglo-Saxon people can be discriminating against people with African or Asian ethnicity. As artificial intelligence may change processes drastically, it may result in certain jobs changing or disappearing completely - leading to changes among personnel. Among other things, in insight generation, minor faults in the artificial intelligence systems can multiply into tens of millions worth of errors in the results. As these effects mostly cover negative consequences, the interviewees also found possibilities for positive effects that could occur after implementation. For example, as a positive surprise, some stated that in some cases the LLM machines reached multimodality, meaning the ability to interpret not only text input but also audio or video.

7.4 Critical success factors of creating business value impact

As critical success factors regarding project success from a business value viewpoint have been defined, and potential business value observed, natural continuum to the next question would be as follows; what critical success factors affect the creation of business value? What are the factors that lead to the manifestation of desired business value?

	Implementation factors			Organizational factors						
	PSF	DU	TBC	D	I	G	I	T	A	L
First-order impacts	7	7	6	3	4	2	7		3	
Second-order impacts	5	8	4	3	4		7	1	5	3

Table 12: Quantity of interviews mentioning critical success factors on observed business value creation.

Table 12 presents the number of interviews mentioning certain critical success factors regarding observed business value creation. The total amount of interviews is presented on the cells intertwining the business value category by Enholm et al (2022) and the critical success factor category previously identified in this study or presented by Brock and Von Wangenheim (2019). As we can see, the mentions possess a lot of similarities between first-order and second-order impacts - however, the distinction is observable between the two, at first glance and unsurprisingly, between factors related to the level of implementation in the organization. As fundamental critical success factors are relevant regardless of the level of the implementation, it is natural to identify them from both first and second-order effects, however, second-order effects related to success on the organizational level may not be critical or even needed when operating on the process level of the organization.

Critical success factors are discussed in more detail in Chapter 7.2. The characteristics and key takeaways of success at the process level, first-order effects, are further discussed in Chapter 7.4.1, and on the organizational level, second-order effects, in Chapter 7.4.2.

7.4.1 Critical success factors of creating first-order effects

Creating process level impacts requires process level consideration of factors related to implementation. When reaching for impacts manifesting on a process level, the most fundamental things raised into discussion; earlier defined implementation factors (problem-solution fit and domain understanding reaching seven interviews out of nine interviews, and tech and business cooperation six) and paramount factors on the organizational level, such as data and intelligent. This comes naturally since when implementing artificial intelligence solutions requiring data to operate, it is impossible to reach successful solutions without relevant data, as well as it is impossible to build implementations leading to sufficient results without personnel with the necessary knowledge.

> Well, the same as I replied previously, that in any artificial intelligence project, it is important that there is an understanding of how the process works. What operators are there in the environment? This, like participating in development, taking in the people working on those processes so it is possible to understand, what are the real bottlenecks, so this kind of planning in advance enables it a lot. (I1)

> Describing the present state of the process as accurately as possible. Process, the ability to dismantle the process into pieces... In our process, where automation or artificial intelligence handles some of the tasks or some parts of the process, the success factor from the reforming point of view is that we can rethink the human's responsibility and job in the process what artificial intelligence cannot do, or it cannot be used for. (I4)

> Still, all that artificial intelligence implementation requires that there is a person, an expert, alongside who actually knows the practical process. (I7)

As we can see from the data and Table 12, not all of the success factors previously identified in general discussion about critical success factors are present in the critical success factors creating first-order impacts. This may be because when operating on the process level of the organization, the organization level observation and consideration are not needed - unless the aim is (later) on the organizational level impact. However, one critical success factor is noticeably presented in both first-order and second-order impact critical success factors; integral. Whether the implementation is on the process level or organizational level, the integral approach is needed, and the holistic approach to the implementation process increases the chances of success. When bringing implementations and their results to a wider context, it is required to understand the big picture and the impact it may have – a strategical approach with culture changes and employee management not only increases chances of success, but also mitigates future risks of implementation.

> If we go there and say that we'll automate their work, then they don't want to do it. So, the surrounding communication and the culture are important to understand from the softer side, of course. (I1)

> From my own experience, I'd say that there are multidisciplinary teams involved so that it doesn't stay as a technical team's or even the business people's practice, but with nowadays when we have AI act and GDPR et cetera, and other legal things... (I6)

7.4.2 Critical success factors of creating second-order effects

As process level implementations require a process level approach, so does pursuing organizational level business impacts require organizational critical success factors. As stated previously, it seems that some fundamental things regarding artificial intelligence implementations are also included in critical success factors when discussing second-order impacts due to their paramount nature on the implementation. In addition to these factors, some factors identified by Brock and Von Wangenheim (2019) are emphasized more on the second-order impacts.

First, of the implementation factors identified previously in this study, domain understanding stands out from the other implementation factors with eight mentions of the nine interviews; with closer inspection of the research data, domain understanding is seen as a major success factor regarding organizational level artificial intelligence implementations. As the aim is to achieve impacts on the organizational levels, it is required to understand where and how the impacts are going to take place in the organization.

> But in a way should define what the success looks like? That there would be a clear vision of what to do. (I3)

> Well that it has been beforehand identified that organizational level impacts may occur. So that's first. Meaning that it is understood what is being done if it hadn't been thought at all. So, there are some point-like solutions without thinking whether it has some organizational level impacts, and one may shoot themselves in the leg with it. But that's the first success factor when wanting to affect in the organizational level. (I8)

In addition to the other factors, the integral category reached the same amount of mentions as in first-order effects, but agility and leadership stand out with five and three mentions. Also, teaming was only mentioned in the second-order effects. As discussed previously, we can hypothesize from the data that these factors stand out in the mentioned quantities for their nature of impact level of the organization. As organizational agility and leadership naturally apply on the organizational level, they are visible in the number of mentions. Further inspection of the interviews confirms the relevance of the subject; interviewees find that when creating organizational changes, agility increases chances of success, and managerial support throughout the implementation process strengthens the impact of the change, reducing the resistance it might generate.

However, one critical success factor identified by Brock and Von Wangenheim stood up as an oddity among others, with an almost non-existent amount of interview mentions in the research data: teaming. Teaming, meaning teaming up with other organizations to achieve better results, is not understandably the first thing to consider in a fast-paced and heavily competitive environment, at least not on the process level implementations. However, when the volume of changes increases or the size of the implementation or the change itself escalates, teaming up with other operators may be useful, whether it be in terms of strategic partnership, consultancy, or acquired software.

Change management was also viewed as vital when creating organizational level impacts; it is of great importance to provide appropriate leadership and change management in order to provide controlled changes in the organization.

> Well, committing to the deployment. And then the organization the implementation is brought to, and the education into that, once again we return to the competent personnel and cultural change. (I4)

> The organization’s ability to change. Let's say that the organization invests and makes some new product, product development, or some digital, or artificial intelligence implementation so it matters how the organization receives the change, does it eagerly implement it or resist it? So that's crucial. (I5)

7.5 Summary of results

This chapter observes the results based on the research data. Utilizing the theoretical framework in building the research interview questions was observable from the data. The interviewees answered extensively on most cases, reflecting on their professional work, which created theory-based thematic results according to the objectives of this study. The themes and categories identified in the theoretical background related to artificial intelligence implementation critical success factors and business value were all discovered from the research data; however, additional theme and categories were identified.

The results state that for the most part, the critical success factors of artificial intelligence implementation comply with the Brock and Von Wangenheim (2019) DIGITAL model, and critical success factors form according to the categorizations of the model. However, it is noteworthy to state that some of the critical success factors were significantly more emphasized than others, and one factor category (teaming), was mentioned only once. Furthermore, an additional theme was identified from the research data with additional categories not fit into the DIGITAL model. This theme was strictly related to the implementation process itself and named "implementation factors", whereas categories under DIGITAL were in opposition named "organizational factors". The categories identified under implementation factors were problem-solution fit, domain understanding, and tech and business cooperation.

Regarding business value, the identified themes and categories followed the structure presented by Enholm et al. (2022). All of the categories described by Enholm et al. were identified from the research data. Nearly all categories on both process and organizational level impacts reached strong presentation on the research data with six to nine interviews out of nine, with the exception of three mentions of sustainability performances.

As artificial intelligence implementation project success was observed from the success viewpoint of business value creation, the critical success factors varied depending on the level of pursued impact. As process level implementation factors were mostly present also when discussing organizational level impacts (due to being relevant in any implementation), some categories were emphasized in the research data. Domain understanding, agility, and leadership acquired distinctive results compared to process level impacts, due to their direct relationship to the level the implementation is executed at. Therefore, artificial intelligence implementation's critical success factors are related to the level of desired impact.

8 DISCUSSION

The goal of this study was to identify critical success factors of artificial intelligence implementation from the business value viewpoint and observe the relationship between the identified critical success factors and pursued business value. The study identified critical success factors and artificial intelligence business value first with the means of a literature review, and later thematic expert interviews. The literature review created the theoretical background which formed the basis for the interview study. With the data gathered and further analysed from the expert interviews, this study answers the following research questions:

- What are the critical success factors in implementing artificial intelligence from the business value viewpoint?
- What is the relationship between the critical success factors of artificial intelligence implementation and artificial intelligence business value?

These research questions were approached with existing literature and the following sub-questions:

- o What are the potential artificial intelligence critical success factors previously identified in the existing literature?
- o What is the business value of artificial intelligence?

This chapter answers the research questions of this study and presents the essential findings conducted from the research findings. The results are observed critically and compared to the previous studies about the subjects. The first subchapter presents the essential findings. The essential findings include the answers to the research questions along with the artificial intelligence critical success framework for business value creation derived from the theoretical background and the research findings. The second subchapter addresses the theoretical contributions, and the third one the managerial implications of this study. The last subchapter discusses the limitations of this study and possible further research directions of the studied subjects.

8.1 Essential findings

Information technology implementation critical success factors have been studied widely in the past. However, despite the latest advancements in the field of artificial intelligence technologies, artificial intelligence implementation critical success factors have not yet been studied widely. As project success can be defined e.g., as managerial success or business value success, it is conductible that the critical success factors themselves rely on the very definition of the project success; the different outcomes may need different settings. Previous literature does not exist to a great extent about artificial intelligence critical success factors. As artificial intelligence implementations face many problems in adoption and deployment (Alsheibani et al., 2020), it is relevant to study artificial intelligence implementation critical success factors, especially from the viewpoint of business value creation.

As artificial intelligence implementation success relies on various number of factors, the success is not solely based on organizational characteristics of the organization implementing artificial intelligence (and if different, the organization that the artificial intelligence is implemented to). As implementation projects have their own characteristics, the factors affecting the implementation process itself should also be taken into consideration. The artificial intelligence critical success factor framework for business value creation derived from the theoretical background and the research findings is presented in Figure 4.

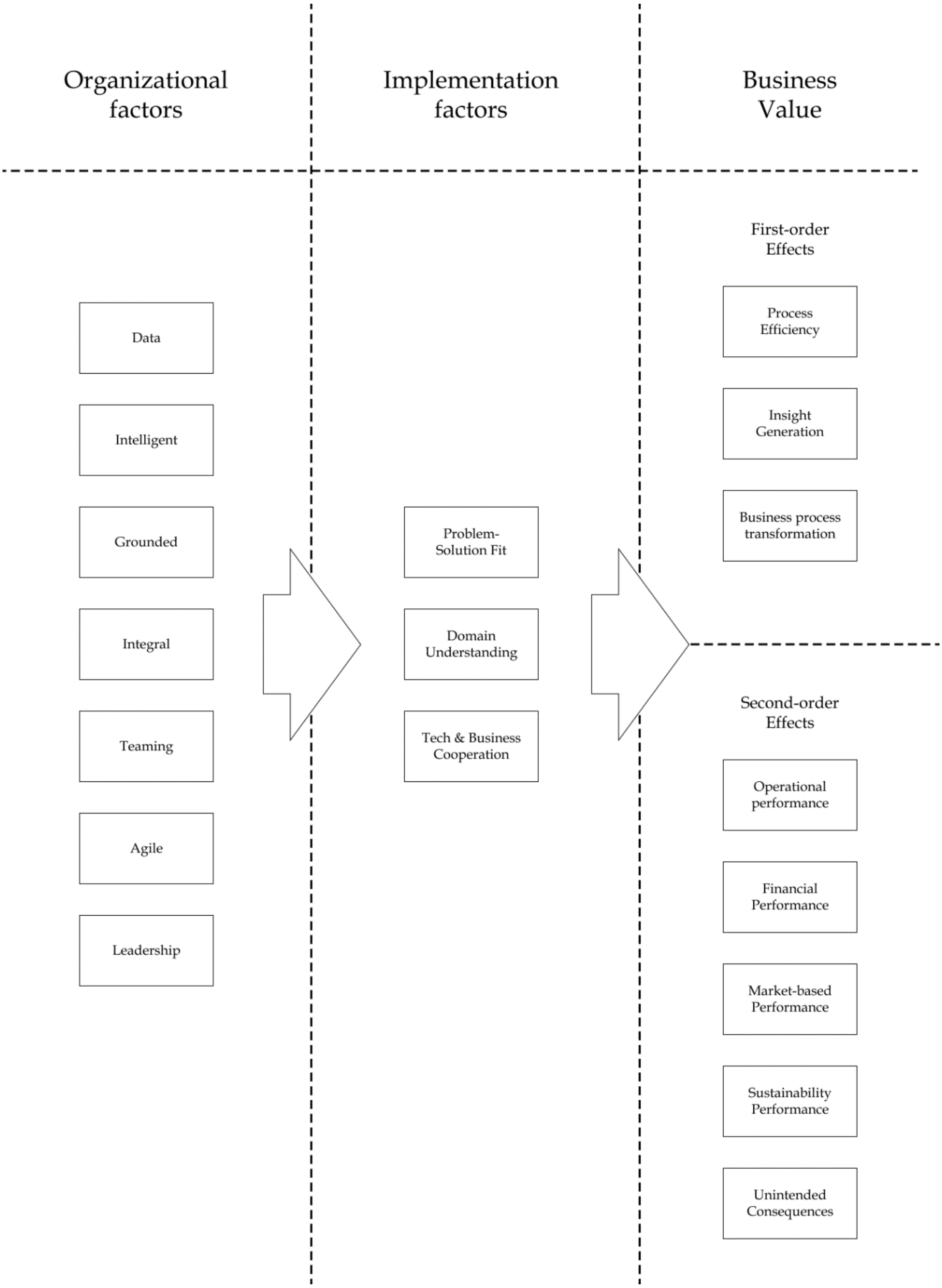

Figure 4: The framework of artificial intelligence critical success factors for business value creation

The organizational factors presented in Figure 4 are factors presented by Brock and Von Wangenheim (2019). Data is the basis of artificial intelligence projects, as it is especially in machine learning implementations a necessity for success. Intelligent contains factors related to personnel competence, and any implementation requires a capable implementer to succeed. Grounded is the view of approaching implementations iteratively, starting small. This is especially relevant for process level implementations. Integral means holistic approach, including strategy, processes, and technology, a capability of a comprehensive approach. Teaming suggests that partnering with other organizations would be beneficial to the results, however, teaming had a very weak response on the research data and was mentioned by only one interviewee regarding organizational level implementations. Agility and leadership were also especially important for implementations with the pursue for greater impact, agile meaning organizational agility and leadership the managerial support of the implementation process.

However, according to the research data and the analysis, the categories presented in the theoretical framework proved not to be solely sufficient in presenting critical success factors in artificial intelligence implementations. In opposition to the theoretical framework of this study, it was identified that a significant amount of consideration of the critical success factors was concentrated on the factors outside the scope of categories present in the theoretical framework. Therefore, the categories were split according to the themes identified during the process of the analysis. As Brock and Von Wangenheim's model was identified thematically as "organizational factors", the additional theme was identified as "implementation factors." As the organizational factors provide the backbone and the starting point of the implementation, the implementation factors include factors that should be taken into consideration in the implementation process itself.

Problem-solution fit means that in the scope of the project, and in this case, an artificial implementation project, the appropriate solution can be defined based on the problem it is meant to solve. This also means the scope of the implementation, where and on what scale it should be implemented, and also the technologies related to it. As in artificial intelligence, there exists a myriad of technologies to choose from to use in the implementation, and often the most technologically advanced option might not be the most suitable for the solution. As Kärkkäinen and Hänninen (2023) identified, machine learning implementations utilizing shallow networks sometimes provide outcomes perceived as good or even better than deep learning solutions. To provide an implementation that creates business value and actually benefits the organization, sufficient domain understanding is paramount. As artificial intelligence implementations can impact the surrounding processes heavily, it is essential to understand the environment of the implementation and the scope of the effects of the implementation. This includes the organization itself and the stakeholders that the implementation will affect. The needed understanding is not limited to a technical domain, but a multidisciplinary approach is often necessary. For example, artificial intelligence implementations requiring vast amounts of data requires also legal understanding of the data process regulations. The processes need to be understood not only on the pragmatic level but also on the level of their business and production value. As the goal is to create business value, it is of great importance to understand where and how the value is pursued to be created, and how the implementation actually creates business value. As stated in multiple interviews, the technical team does not necessarily understand enough of the business functions of the organization and the business function does not understand the technical implementation and its capabilities. Therefore, discourse is absolutely necessary, preferably with a mediator with enough understanding of both domains.

As stated previously, for the most part, the results of this study confirm the success factors categories by Brock and Von Wangenheim. However, on closer inspection when observing the pursued business impact, it was clear that the critical success factors are not universal regarding to the scale of the implementation project. The definition of business value in the theoretical framework is first presented by Enholm et al. (2022) where artificial intelligence business value is divided by first-order (process level) effects and second-order (organizational level) effects. These effects are further categorized based on the effects they create. This study validated these effects with a strong correlation between the interview mentions of said effects and the effects mentioned by Enholm et al. - however, the sustainability effects did not reach as high a correlation as other categories. Further in the study, the critical success factors of artificial intelligence implementation were observed based on the pursued business value impact as presented by Enholm et al. and validated in this study.

The research identified that first-order and second-order effect critical success factors differentiate from each other. Naturally, critical success factors were emphasized based on the level they impact the implementation process - whether they naturally occur on the process, or the organizational level implementations. For example, critical success factors such as problem-solution fit and grounded were more present in the results regarding first-order impacts. Similarly, critical success factors such as domain understanding, agility, and leadership were emphasized in answers regarding second-order impacts. By these findings, it is reasonable to deduct that the critical success of artificial intelligence implementations depends on the scope of the project and the pursued business value impact.

8.2 Theoretical contributions

This study provides several scientific contributions. Firstly, the study contributes yet limited existing research on artificial intelligence critical success factors and business value. The study expands the current understanding and scope of critical success factors regarding artificial intelligence, e.g., as presented by Brock and Von Wangenheim (2019). As there is no existing research perceiving artificial intelligence implementations strictly from the viewpoint of business success, this study contributes by defining both artificial intelligence critical success factors and business value, and observing their relationship. Similar to the existing research on critical success factors, the study strengthens the understanding of artificial intelligence project success from the business value viewpoint. The study expands on the artificial intelligence business value presented by Enholm et al. (2020).

Second, the study contributes to the artificial intelligence project success understanding by thematic approach of critical success factors and the business value they create by categorizing observed critical success factors by their position on the implementation, whether the factors are related to the organizational capabilities or factors related to the implementation process itself. The provided themes and categories are conducted into a framework for artificial intelligence critical success factors for business value creation, as presented in Chapter 8.1, "Essential findings". Further analysis of the observed themes is discussed in the Chapter 7, "Results".

Third, the study provides theoretical insight into the relationship between the artificial intelligence implementation critical success factors and business value. As briefly discussed previously, the existing research (at least known to the researcher) does not observe critical success factors strictly from the viewpoint of business value success, the study contributes by providing a unique view of the critical success factors definition. The study expands the understanding of how pursued business value on the project affects the project's critical success factors, and how the emphasis on the factors changes by the scope of the project.

8.3 Managerial implications

As artificial intelligence implementations rarely get beyond pilot projects (Enholm et al., 2022; Mani et al., 2020), the pursued business value does not manifest in the desired way via the implementations. This study's goal was to observe the underlying phenomena and conditions of artificial intelligence implementation project success, especially from the viewpoint of business value impact. As the underlying technologies have not yet been commercially utilized widely in the past, the implementations face several different challenges to successfully utilize artificial intelligence. And as it undeniably exists, business value in artificial intelligence makes it intriguing for managers to implement it within the organizations. However, the critical success factors, the business value, and the potential are not yet understood entirely and artificial intelligence productivity impact is often exaggerated and misunderstood (Kauhanen & Pajarinen, 2023).

By observing the direct relationship between critical success factors and pursued business value, this study provides managers additional tools for evaluating the artificial intelligence project success outcome and what is needed for success to reach the defined goals. In practice, the business value impact can be created, and the implementation success can be reached by understanding the preferred outcome and the pursued business value impact. Understanding the implementation itself and what characteristics the implementation success requires from the organization and the implementation process improves the chances for project success.

The aforementioned implications are presented as the framework of artificial intelligence implementation critical success factors for business value creation, providing a tool for managerial evaluation and execution of artificial intelligence projects.

8.4 Limitations and further research

The study has certain limitations regarding the novel nature of the subject and the complexity of the observed phenomena. As technologies related to artificial intelligence are relatively new in wider, commercial use, the existing literature does not extensively exist regarding artificial intelligence critical success factors or business value. This proved to be a challenging factor during the research, and of course, especially with the literature review. As the nonexistence narrowed the literature review, it also revealed the research gap observed in this study. The research and the research scope were narrowed down to a business value viewpoint due to the wide nature of critical success factors; as critical success factors and business value itself can be observed in simple manners, the combination and the observation of their relationship proved to be more complex phenomena. As the number of interviewees was defined by the saturation principle (Hirsjärvi & Hurme 2022; Puusa, Juuti, & Aaltio 2020; Tuomi & Sarajärvi, 2018), and was observed to be sufficient in critical success factor and business value definition separately, in a broader context more data is needed. When analysing data from the perspective of impact width, it was identifiable that second-order impact critical success factors require more in-depth research. As some of the success factors were emphasized regarding organizational impacts, they did not have a strong presentation regarding the interview quantity. However, it is notable to state that this can also be due to the selected interviewees; the interviewees were selected from various organizational positions to avoid elite bias (Myers & Newman, 2006) which may affect the observation of critical success factors. It would be natural for interviewees closer to the implementation process themselves to understand more clearly the critical success factors related to the strict implementation itself, and vice versa. With more interviewees from the higher level of the organization with experience in larger implementations, the observed critical success factors could be emphasized more in the data. Therefore, additional research is needed for both first-order and second-order distinctive critical success factors. As all of the interviewees were from Finland and worked in Finland, there may be some cultural influence on the research data. It is an identified challenge that the researcher has no prior experience in conducting interview studies, which was addressed by familiarizing of literature regarding the matter.

As artificial intelligence critical success factors have not been previously studied from the business value impact perspective, further research on the subject itself is needed. As this study identified that the critical success factors depend on the pursued business value impact, more insight is needed about the distinctive characteristics between implementations aiming for first-order effects and second-order effects. As the distinction was identified in the data and the scope of the pursued impact often correlates to the scope of the implementation itself, it would be useful to research whether critical success factors correlate also to the project scope itself. As these are characteristics not only limited to artificial intelligence projects, these research angles should be considered also in researching information technology implementations in general.

The division between the organizational factors and implementation factors should also be further researched. As the organizational characteristics and project execution both can be considered to always have an impact on the project's success, it is conductible that these themes would also be relevant generally on IT implementations. As problem-solution fit, domain understanding and tech and business cooperation are all factors identified in one way or another in startup organizations, it would be beneficial to study more extensively the possibility of generalization of these factors on the wider spectrum in information technology. As the framework of artificial intelligence critical success factors for business value creation forms the basis of understanding business value creation, more research is needed in order to further develop the framework into a pragmatic tool for managers to use and evaluate artificial intelligence implementations.

9 CONCLUSION

As recent developments in artificial intelligence have brought artificial intelligence the status of a current megatrend on the information technology industry, organizations throughout the world are trying to utilize artificial intelligence and gather the business potential that exists in the potential implementations. However, many implementations do not reach beyond the pilot stage of the software lifecycle (Enholm et al., 2022; Mani et al., 2020), and the impact of artificial intelligence implementation is often exaggerated or misunderstood (Kauhanen & Pajarinen, 2023), it is undeniable that more knowledge is needed to produce more successful artificial intelligence implementations. This study aims to contribute to that knowledge and create an understanding of which critical success factors lead to a successful implementation creating business value, and what's the relationship between the critical success factors and business value on the implementation. The study was conducted in two parts, a literature review conducting the theoretical basis of the study, and an empirical expert interview study.

A literature review produced the theoretical basis for this study, defining artificial intelligence critical success factors and business value. The literature review also defines the fundamental concepts in this study, such as artificial intelligence and project success. The literature review produced a theoretical framework that further directed the structure of the interviews. The framework is based on the artificial intelligence critical success factors by Brock and Von Wangenheim (2019) and artificial intelligence business value by Enholm et al. (2022). The results of the literature review and the theoretical framework are further described in Chapter 5.

The empirical section of this study was conducted as a series of semi-structured, thematic expert interviews. The interview structure and basis were created by the theoretical framework. The interviewees were experts who have been working with artificial intelligence implementations, and the selection was made from various organizational levels and expert backgrounds to avoid elite bias (Myers & Newman, 2006). The sample consists of 9 expert interviews, which were further thematically analysed into themes and relevant categories; as the interviews were based on the theoretical background, the themes and categorizations were further utilized in the analysis and are identifiable in the results. The empirical study found strong similarities but also differences in the theoretical framework and identified additional theme regarding critical success factors. The analysis further conducted the framework of artificial intelligence critical success factors for business value creation and identified critical success factors for both process level and organizational level impacts.

This study answers the identified research gap on the critical success factors of artificial intelligence from the business value perspective. It contributes to the research by providing additional information about the artificial intelligence critical success factors and business value themselves and expanding the existing perception of artificial intelligence critical success factors. It also expands the angles of critical success factor research regarding IT implementations generally by identifying critical success factors from the viewpoint of pursued business value impact. The results also conduct a framework of artificial intelligence critical success factors for business value creation, providing a managerial tool for artificial intelligence implementation evaluation. The study identified the distinction between the critical success factors regarding process level impacts and organizational level impacts, which provide managerial direction for factors to take into consideration when planning and executing artificial intelligence implementations.

The identified limitations were aimed to be managed as thoroughly as possible. Most of the identified limitations were due to the inexperience of the researcher and lack of existing literature on the subject. The phenomena regarding the distinction between process level and organizational level impacts' critical success factors proved to be complex and require additional information about the subject, which also opens up various interesting research possibilities. The identified critical success factors possess characteristics that could be utilized on a more general level in the field of information technology. Also, the conducted framework withholds a multitude of possible research directions, for example, further developing the framework to a more pragmatic managerial tool for artificial intelligence implementations.

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APPENDIX 1: INTERVIEW FORM AND QUESTIONS IN ENGLISH

The study and it's purpose along with the information processing during the study is described to the interviewee. The process of the interview is told and the consent for using the interview recording for the study is confirmed before starting the official interview procedure.

Background Information

- Profession and/or work description
- Level of education
- Past experience on working with artificial intelligence projects (general experience and length in years)

Artificial intelligence and artificial intelligence projects

- How would you define artificial intelligence as a concept?
- What do you think artificial intelligence project includes? What kind of project meets the definition of artificial intelligence project?

Critical success factors on business value viewpoint

- Is business value generation being considered when planning and developing an artificial intelligence project? If yes, how?
- What factors impact the most in artificial intelligence project success?
- What of these factors have impact specifically from the viewpoint of business value generation?

Process level impacts

- In what ways can artificial intelligence implementations affect business processes?
- What kind of business value can artificial intelligence implementations generate by affecting these processes?
- What are the most important factors in the implementation regarding these processes, and succeeding in it?
- Is there something you would like to add?

Organization level impacts

- In what ways can artificial intelligence implementation affect organization on an organizational level?

- What kind of business value can artificial intelligence implementation create with an impact on organizational level?
- What are the most important factors in the implementation regarding organizational level impact, and succeeding in it?
- Is there something you would like to add?

Possible specifying questions:

As the conversation and the interview proceeds, the interviewee is addressed with specifying questions if seen needed for achieving satisfactory results for the interview and the answers. Additional questions can be asked also based on the themes risen on the interview process.

Process level impact

- In what ways can artificial intelligence implementation affect the customer's process efficiency?
    - What factors are important in developing these processes and succeeding in it?
- In what ways can artificial intelligence implementation affect insight generation (creating new information, processing old)?
    - What factors are important in insight generation, and succeeding in it?
- In what ways can artificial intelligence implementation affect business process transformation?
    - What factors are important in business process transformation, and succeeding in it?

Organizational level impact

- In what ways can artificial intelligence implementation affect the organization's operational performance?
    - What factors are important in organizational performance development, and succeeding in it?
- In what ways can artificial intelligence implementation affect the organization's financial performance?
    - What factors are important in financial performance development, and succeeding in it?
- In what ways can artificial intelligence implementation affect the organization's market-based performance?
    - What factors are important in market-based performance development, and succeeding in it?
- In what ways can artificial intelligence implementation affect the organization's sustainability performance?

    - What factors are important in sustainability performance development, and succeeding in it?
- In what ways can artificial intelligence create unplanned or unintended consequences and/or negative impacts from business value viewpoint?
    - What factors can affect the formation of these impacts?

APPENDIX 2: INTERVIEW FORM AND QUESTIONS IN FINNISH

Kuvataan haastateltavalle tutkimus ja sen tarkoitus sekä tietojen käsittely tutkimuksen aikana. Haastateltavalle kuvataan haastattelun kulku ja varmistetaan suostumus nauhoitukseen ja sen käyttöön tutkimuksessa.

Taustakysymykset

- Ammatti ja/tai työnkuva
- Koulutustaso
- Kokemus tekoälytoteutuksien kanssa työskentelystä (yleinen kokemustaso ja kokemusvuodet)

Tekoäly ja tekoälyprojektit

- Miten määrittelisit tekoälyn käsitteenä?
- Mitä tekoälyprojekti mielestäsi käsittää? Minkälainen projekti täyttää mielestäsi tekoälyprojektin määritelmän?

Kriittiset menestystekijät liiketoiminnallisen arvon suhteen

- Otetaanko tekoälyn liiketoiminnallisen arvon tuottoa huomioon tekoälyprojektin suunnittelemisessa ja toteuttamisessa? Jos otetaan, niin miten?
- Mitkä tekijät vaikuttavat eniten tekoälytoteutuksen onnistumiseen?
- Millä näistä tekijöistä on erityisesti merkitystä liiketoiminnallisen arvon tuottamisen näkökannalta?

Prosessitason vaikutukset

- Millä tavoin tekoälytoteutuksilla voi vaikuttaa liiketoiminnan prosesseihin?
- Minkälaista liiketoiminnallista arvoa tekoälytoteutus voi tuottaa vaikuttamalla näihin prosesseihin?
- Mitkä tekijät toteutuksessa ovat tärkeitä prosessien kehittämisen suhteen ja siinä onnistumiseen?
- Onko jotain, mitä haluaisit vielä lisätä?

Organisaatiotason vaikutukset

- Millä tavoin tekoälytoteutuksilla voi vaikuttaa organisaatiotasolla organisaation toimintaan?
- Minkälaista liiketoiminnallista arvoa tekoälytoteutus voi tuottaa vaikuttamalla organisaatiotasolla?

- Mitkä tekijät toteutuksessa ovat tärkeitä organisaatiotason vaikutusten muodostamisen suhteen ja siinä onnistumiseen?
- Onko jotain, mitä haluaisit vielä lisätä?

Mahdolliset tarkentavat kysymykset

Keskustelun lomassa ja haastattelun edetessä haastateltavalle esitetään tarkentavia kysymyksiä, jos se koetaan haastattelun suhteen tarpeelliseksi riittävän kattavien vastauksien saavuttamiseksi. Lisäkysymyksiä voidaan esittää myös haastattelutilanteessa nousseiden teemojen perusteella.

Prosessitason vaikutukset

- Millä tavoin tekoälytoteutus voi vaikuttaa asiakkaan prosessien tehokkuuteen?
    - Mitkä tekijät toteutuksessa ovat tärkeitä prosessien tehokkuuden kehittymisen suhteen ja siinä onnistumiseen?
- Millä tavoin tekoälytoteutus voi vaikuttaa organisaation uuden tiedon tuottamiseen tai vanhan käsittelyyn?
    - Mitkä tekijät toteutuksessa ovat tärkeitä uuden tiedon tuottamisen ja vanhan tiedon käsittelyn suhteen ja siinä onnistumiseen?
- Millä tavoin tekoälytoteutus voi vaikuttaa asiakkaan sisäisiin liiketoiminnan prosesseihin ja niiden muutokseen?
    - Mitkä tekijät toteutuksessa ovat tärkeitä asiakkaan sisäisten prosessien muutosten suhteen ja siinä onnistumiseen?

Organisaatiotason vaikutukset

- Millä tavoin tekoäly voi vaikuttaa organisaation operatiiviseen toimintaan?
    - Mitkä tekijät toteutuksessa ovat tärkeitä operatiivisen toiminnan suhteen ja siinä onnistumiseen?
- Millä tavoin tekoäly voi vaikuttaa organisaation taloudelliseen suorituskykyyn?
    - Mitkä tekijät toteutuksessa ovat tärkeitä taloudellisen suorituskyvyn kehittämisen suhteen ja siinä onnistumiseen?
- Millä tavoin tekoäly voi vaikuttaa organisaation markkinapohjaiseen suorituskykyyn (myynnin edistäminen)?
    - Mitkä tekijät toteutuksessa ovat tärkeitä markkinapohjaisen suorituskyvyn edistämisen suhteen ja siinä onnistumiseen?
- Millä tavoin tekoäly voi vaikuttaa organisaation kestävän kehityksen suorituskykyyn?
    - Mitkä tekijät toteutuksessa ovat tärkeitä kestävän kehityksen suhteen ja siinä onnistumiseen?

- Millä tavoin tekoälytoteutukset voivat tuottaa tahattomia ja suunnittelemattomia vaikutuksia liiketoiminnan kannalta?
    - Mitkä tekijät voivat vaikuttaa tahattomien ja suunnittelemattomien vaikutuksien syntymiseen?