Oliver Ahti

SYSTEMATIC PRIORITIZATION OF AI INITIATIVES: IMPLEMENTATION FACTORS AND ACHIEVABLE VALUE

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ABSTRACT

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Artificial intelligence has yet again surged in popularity, especially after recent breakthroughs in generative artificial intelligence technology. As organizations rush to implement artificial intelligence in their processes, the question of how and why to prioritize use cases over another is raised. To answer this, this thesis explores both the factors affecting the organizational implementation of artificial intelligence, as well as what types of value and how that value is achievable with the utilization of artificial intelligence. Researching these aspects of artificial intelligence initiatives allows for the development of a value-feasibility matrix, which can provide additional guidance to organizational decision-makers facing the issue. This study was conducted in two parts. First, a literature review on both the factors and enablers affecting the implementation of artificial intelligence, and the types of value achievable and the mechanisms used to create that value with artificial intelligence. This literature review provided the theoretical basis for the development of the value-feasibility matrix. Then, an empirical qualitative study was carried out to validate the model. 11 semi-structured interviews were conducted, with interviewees representing both industrial companies as well as technology providers. The findings from the interviews aligned strongly with existing research and the proposed value-feasibility matrix. This thesis was able to address the research gap on the systematic prioritization of artificial intelligence initiatives, and also contribute to existing research by providing new empirical findings. The developed and validated value-feasibility matrix can serve as a guiding tool for organizational leaders struggling with the prioritization of artificial intelligence initiatives.

Keywords: artificial intelligence, technology adoption, business value, prioritization, industry

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Tekoäly on jälleen noussut pinnalle, etenkin generatiivisen tekoälyn tuomien uusien mahdollisuuksien kautta. Organisaatiot pyrkivät ottamaan tekoälyä käyttöön eri liiketoimintaprosesseissaan nopealla tahdilla. Nopea käyttöönottotahti kuitenkin herättää kysymyksen siitä, voisiko eri hankkeiden priorisointiin olla systemaattinen ratkaisu. Vastatakseen tähän kysymykseen, tämä tutkielma käsittelee tekoälyhankkeiden käyttöönottoon vaikuttavia tekijöitä, yritystason arvoa jota tekoälysovellukset voivat luoda organisaatiossa, sekä prosessitason vaikutuksia, joilla arvoa luodaan. Näiden näkökulmien tutkiminen mahdollistaa arvo-toteutettavuus-matriisin kehittämisen, jota hyödyntämällä päätöksentekijät voivat saada lisäohjausta hankkeiden priorisointiin. Tämä tutkielma toteutettiin kahdessa osassa. Teoreettinen perusta matriisille rakennettiin sekä tekoälyhankkeiden käyttöönottoon vaikuttavien tekijöiden että tekoälyn luoman yritysarvon tutkivaa kirjallisuuskatsauksen varaan. Tämän jälkeen toteutettiin empiirinen tutkimus, jonka kautta kirjallisuuskatsauksen löydökset sekä arvo-toteutettavuus-matriisi validoitiin. Kvalitatiivisessa tutkimuksessa toteutettiin 11 puolistrukturoitua asiantuntijahaastattelua. Haastateltavat edustivat niin teollisuusyrityksiä kuin teknologiapalveluntarjoajia. Kvalitatiivisen tutkimuksen tulokset korreloivat vahvasti olemassa olevan kirjallisuuden sekä ehdotetun arvo-toteutettavuus-matriisin kanssa. Tämä tutkielma kykeni osaltaan vastaamaan systemaattisen tekoälyhankkeiden priorisiointiin liittyvään tutkimusaukkoon, sekä tuottamaan uutta tietoa olemassa olevaan kirjallisuuteen niin tekoälyhankkeiden käyttöönottoon vaikuttavien tekijöiden, kuin myös tekoälysovellusten luoman arvon saralla tuottamalla lisää empiiristä dataa. Tutkielmassa kehitetty arvo-toteutettavuus-matriisi voi toimia ohjaavana työkaluna tekoälyhankkeiden systemaattista priorisointia suunnitteleville organisaatiojohtajille.

Asiasanat: tekoäly, käyttöönotto, yritysarvo, priorisointi, teollisuus

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1 INTRODUCTION

Artificial intelligence (AI) is an extremely trending topic currently, both in the organizational and individual contexts. While the concept of artificial intelligence is decades old at this point, this area of technology has seen a recent surge in popularity after breakthroughs in technology in the past few years, especially on the front of generative artificial intelligence. For the purposes of this thesis, artificial intelligence can be defined as "an applied discipline that aims to enable systems to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals" (Enholm et al., 2022).

For individual consumers, highly advanced artificial intelligence-enhanced tools are easily accessible for the first time, while for organizations new opportunities to utilize AI are emerging in every sector. The availability of vast amounts of data, combined with the "emergence of sophisticated techniques and infrastructure" (Mikalef & Gupta, 2021), has made artificial intelligence a "top technological priority of organizations over the past few years" (Mikalef & Gupta, 2021). As artificial intelligence is well suited for working with large quantities of data and acting based on it, it is no surprise that the automation and optimization of various business processes (Burström et al., 2021; Enholm et al., 2022; Shollo et al., 2022) are some of the major areas where artificial intelligence has been implemented in organizations. Predictive maintenance (Burström et al., 2021; Kinkel et al., 2022) and engineering (Kusiak, 2018) are examples of the manufacturing industry utilizing the predictive capabilities that artificial intelligence can provide, when supplied with appropriate data. Discovering patterns and insights from data is another major area of utilization of artificial intelligence in organizations. Forecasting reports (Burström et al., 2021), customer segmentation (Mikalef & Gupta, 2021) and recommendation tools are examples of artificial intelligence applications that utilize vast amounts of data in order to discover previously unknown information or gain better insights into trends. Overall, supporting organizational decision making with such insights seems to be among the most important use cases for artificial intelligence in many organizations (Cao et al., 2021).

As organizations rush to implement artificial intelligence-powered tools and features into their services and products, they can be faced with the question of what to do first. While many studies research the impacts and value created by the use of artificial intelligence in organizations (Enholm et al., 2022; Latinovic & Chatterjee, 2022; Shollo et al., 2022), or the enablers and factors affecting the success of artificial intelligence adoption (Chatterjee et al., 2021; Enholm et al., 2022; Kinkel et al., 2022; Mikalef & Gupta, 2021), there isn't much research on how organizations should focus and prioritize their artificial intelligence initiatives. This thesis aims to see how organizations should systematically prioritize and evaluate different artificial intelligence applications. In order to develop a systematic model for the prioritization of artificial intelligence initiatives, this thesis explores what sorts of conditions and prerequisites facilitate the success of artificial intelligence adoption projects, what types of firm-level value are achievable through the utilization of artificial intelligence, as well as the process-level impacts and value creation mechanisms that lead to firm-level value gain. To address the identified research gap regarding the systematic prioritization of artificial intelligence initiatives, this thesis aims to answer the following research questions:

- RQ1. What are the essential conditions and enablers for successful AI adoption in organizations?
- RQ2. What types of value are achievable with organizational use of AI?
- RQ3. Can a combined assessment of achievable value and implementation factors provide a systematic method for prioritizing AI initiatives?

In order to answer the research questions, a two-part study was conducted. The theoretical foundations for the development of the prioritization model were established with a literature review. After identifying the research gap, two separate Scopus-queries, with one focusing on the factors and enablers affecting the implementation of artificial intelligence, and the other focusing on the business value created by artificial intelligence, were configured and searched. The resulting articles were then filtered for quality: the baseline was that the journal in which the article had been published should have a rating of two on both the Julkaisufoorumi (JUFO) and the Academic Journal Guide (AJG) rating scales. Sixty-five articles passed these checks, after which the ones deemed relevant for this thesis were used. Snowball sampling from this pool of articles was also conducted, and any articles found and used with this method were also reviewed with the quality criteria. Where necessary, established practitioner literature was used to describe latest business research about artificial intelligence, and its use in organizations.

The empirical data for this thesis was collected by conducting 11 semi-structured interviews with business and technology-oriented experts. The interviewees were selected to represent both industrial companies as well as technology providers, in order to gain insights from both the "client" and "provider" perspectives. The interviewees worked in organizations from both Northern Europe and North America. After the interviews were conducted, the transcripts were analysed with a directed content analysis, followed with a conventional content analysis (Hsieh & Shannon, 2005).

This thesis was commissioned by a Finnish company, specializing in providing technology and services to the pulp, paper, and energy industries. While the thesis is not a case study of the commissioning company, the selection of interviewees, as well as the overall area of organizational interest, was partly focused on the industrial sector due to the commissioning company's involvement in the same sector.

The rest of the thesis is structured as follows: chapter 2 explores existing technology adoption frameworks and previously identified factors affecting the implementation of artificial intelligence initiatives. Chapter 3 explores the types of value that artificial intelligence can help create in organizations, as well as the value creation mechanisms through which said value is created. Chapter 4 provides a summary of the literature review, as well as presents the proposed value-feasibility matrix for the systematic prioritization of artificial intelligence initiatives. Chapter 5 presents the methodology and research design for the empirical section of the thesis. Chapter 6 presents the findings from the interviews. Chapter 7 discusses and analyses the findings in more detail, while chapter 8 concludes and summarizes the thesis.

2 TECHNOLOGY ADOPTION

This chapter explores existing literature concerning technology adoption. As this thesis specifically focuses on organizational technology adoption, for the purposes of this thesis technology adoption can be defined as the process through which organizations integrate new technologies into their processes and workflows.

This chapter is divided into two subchapters. The first subchapter shortly reviews literature on the TOE framework, from which the three-contextual division for further discussion on implementation and adoption factors originates from. The second subchapter focuses on literature about artificial intelligence adoption in organizational settings, by reviewing multiple literature reviews on the topic and comparing their findings.

2.1 The TOE framework

Multiple technology adoption frameworks for both organizations and individuals have been conceptualized, tested, and validated in IS literature throughout the years. The most relevant and academically interesting general technology adoption framework for the purposes of this thesis is the technology-organization-environment framework (commonly known as the TOE framework).

The TOE framework utilizes three different contexts to help understand the process by which organizations adopt new technologies. By doing so, it is able to "exhaustively explain the factors impacting adoption decisions" (Chatterjee et al., 2021). It was conceived in 1990 by Tornatzky and Fleischer and has since been further adapted into other frameworks (Oliveira & Martins, 2011). It should be noted that the TOE framework explores technology adoption on an organizational level specifically, excluding the individual or consumer levels (Oliveira & Martins, 2011).

As the name suggests, the TOE framework examines the technology adoption process from three different contexts: the technological context, the organizational context, and the environmental context. The factors within the contexts may vary between studies (Oliveira & Martins, 2011), but the ones presented next are some of the commonly featured ones.

The technological context of the TOE framework considers the internal and external technologies relevant to the organization. Current practices and equipment can be thought of as the "internal" technologies, while available external technologies fall into the "external" category (Oliveira & Martins, 2011). In the original TOE model, developed in 1990 by Tornatzky and Fleischer, the technological context comprised of two factors, *availability* and *characteristics* (Oliveira & Martins, 2011).

The organizational context of the TOE framework has four factors: *formal and informal linking structures*, *communication processes*, *size*, and *slack*. These factors are descriptive of the organization itself, which in itself is a major factor in the success of technology adoption initiatives. Additional factors such as top management support (Enholm et al., 2022) or digital skills (Kinkel et al., 2022) have been added to the same context in later studies.

The (external task) environment context of the TOE framework inspects the factors affecting technology adoption projects from outside the organization. The factors described in the original TOE model are *industry characteristics and market structure*, *technology support infrastructure*, and *government regulation*. (Oliveira & Martins, 2011)

2.2 Artificial intelligence adoption

Considering that artificial intelligence is a technology among others, most existing technology adoption frameworks and models should intuitively apply to artificial intelligence projects and initiatives as well. But as discussed in literature (Enholm et al., 2022), the adoption of artificial intelligence can present new challenges and barriers. It has also been argued that because of the complexity of artificial intelligence as a technology, few existing adoption models would function in this context (Chatterjee et al., 2021). Therefore, research has been conducted on how artificial intelligence adoption projects have been conducted in organizations, and what special prerequisites and factors have arisen from practice.

This chapter is divided into three subchapters, with each focusing on one of the major literature reviews reviewed for this thesis on the factors and enablers that affect the success of artificial intelligence implementations. The third subchapter also reflects upon various factors found in other studies.

2.2.1 Study by Chatterjee et al (2021)

One of the more interesting studies regarding artificial intelligence adoption in B2B organizations (Chatterjee et al., 2021) combined multiple factors from the TOE and TAM models, which were then used to discover the importance of the criteria required for successful AI adoption projects. The TAM or Technology Acceptance Model is another model used for explaining technology adoption, but it is more aimed at the individual context, instead of the organizational context which the TOE framework focuses on. The conceptual model was subsequently tested with a quantitative study, utilizing 340 survey answers from employees in all sizes of organizations.

The further-developed conceptual model in the study contained key elements from both the TAM and TOE models, intraorganizational variables and external environment variables. All of the variables in the conceptual model by Chatterjee et al (2021) are presented in table 1. It is noteworthy that the four intraorganizational variables are present in some form or other in multiple studies concerning organization-level artificial intelligence adoption (Jöhnk et al., 2021; Kinkel et al., 2022; Mikalef & Gupta, 2021).

TABLE 1 Conceptual model variables (Chatterjee et al., 2021)

Variable	Slot in model	As defined in Chatterjee et al (2021)
Organizational competency	Internal environment	Employees skill, knowledge, capabilities, and other relevant traits essential for effective performance in an employment position
Organizational complexity	Internal environment	Level of inconvenience and constraints towards understanding and using a system. Also relates to the sense of ease of use.
Organizational readiness	Internal environment	Accessibility of the required organizational resources for adoption
Organizational compatibility	Internal environment	Level to which an innovation is considered to be consistent with the potential users existing values, previous experiences, and requirements
Competitive advantage	External environment	Level at which a technological factor seems to provide a better benefit for organizations
Partner support	External environment	Collaborative support from external partners, helps to develop internal knowledge
Perceived usefulness	Technological factor	The potential users' subjective possibility that using a system or the application of a system will enhance the job performance of the users within the context of the firm
Perceived ease of use	Technological factor	The extent to which a person has a belief that using a new system or a new technology would be free of effort
Leadership support	Moderates the linkage of PU and PEOU to intention to adopt AI	Sincere engagement of a higher ranking leader in the implementation of the new system

The study by Chatterjee et al (2021) found that organization-level adoption of artificial intelligence applications was impacted most by the perceived usefulness and the perceived ease of use of said applications (Chatterjee et al., 2021). These variables, introduced by the TAM, were in turn impacted by the internal and external environment variables found in table 1. The details of the impact of each internal/external environment variable on the technological factor variables, as explained in Chatterjee et al (2021), are as follows:

- **Organizational competency**, as demonstrated by competent and skilled employees being more willing to utilize AI, positively influenced the perceived usefulness variable.
- **Organizational complexity** was hypothesized to negatively influence both perceived usefulness, as well as perceived ease of use. The study confirmed these hypotheses, which aligns with the intuitive thought that more complexity and constraints negatively affect the adoption of new technology.
- **Organizational readiness** heavily supported both the perceived usefulness and perceived ease of use variables, due to organizational readiness being presented by factors such as clear strategies, sufficient resource mobilization, leadership support from both mid- and top levels, as well as clear communication.
- **Organizational compatibility** was found to strongly support the perceived usefulness variable, as the applications were seen to befit and enhance the existing architectures and standards. Curiously, organizational compatibility was not found to support the perceived ease of use variable, as the implementable artificial intelligence applications might cause changes in routines and existing practices.
- The **competitive advantage** variable was found to have a "strong impact" on both the perceived usefulness and perceived ease of use, thanks to the users of the applications understanding the strategic importance of such tools and technologies.
- **Partner support** was found to have a "significant and positive impact" on perceived usefulness, thanks to knowledge sharing from external partners, but not so much on the perceived ease of use.

2.2.2 Study by Kinkel et al (2022)

In another study surveying 655 representatives from the manufacturing industry, Kinkel et al (2022) analysed " the impact of various technological, organizational and environmental (TOE) prerequisites for a successful adoption of AI technologies in manufacturing" (Kinkel et al., 2022). It is noteworthy that the study based their research model on the TOE framework (presented in chapter 2.1), highlighting its relevance as a general organization-level technology adoption framework to this day. The research model can be seen below in figure 1.

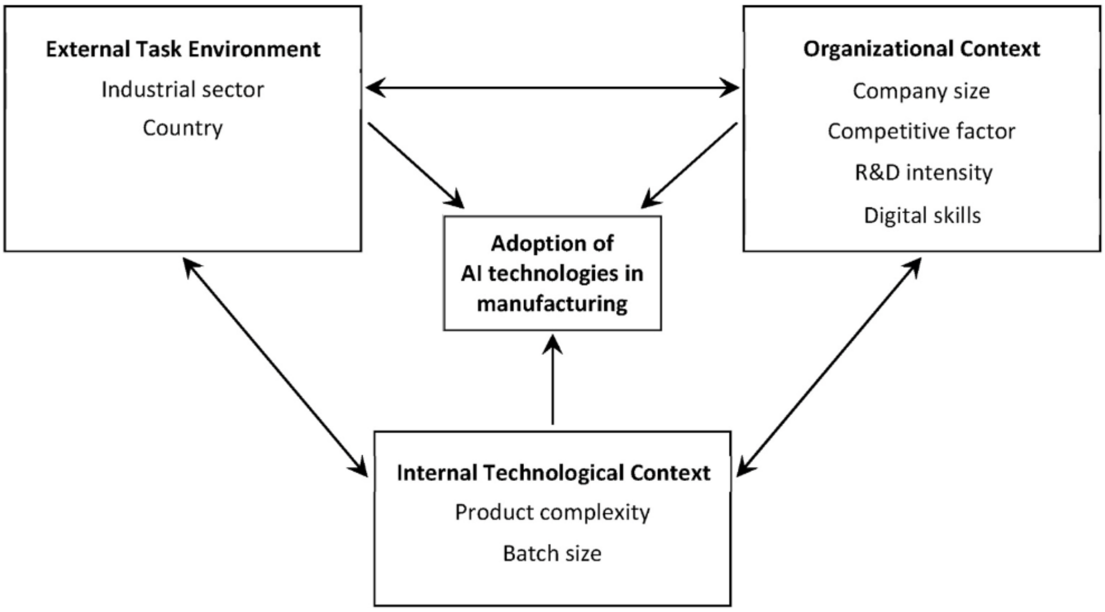

FIGURE 1 Research model of Kinkel et al (2022)

The variables of the research model used in the study by Kinkel et al (2022) differ slightly from the ones used in the conceptual model of Chatterjee et al (2021). Key additions to the organizational characteristics under investigation are the company size, and the intensity of research and development (R&D) activities.

The results of the study by Kinkel et al (2022) resonate strongly with the findings of the study by Chatterjee et al (2021). Although the technological and external environment factors played a role in the success of artificial intelligence adoption projects, the largest impact was generated by the internal organizational factors, such as the company size or the R&D intensity (Kinkel et al., 2022). Data-related digital skills were specifically mentioned in the study as having a "key role", as these specific technical skills were seen as a crucial for not only the successful adoption process, but also for the continued usage of artificial intelligence in organizations (Kinkel et al., 2022).

By basing the research model on the TOE framework and asking the research questions of how "[technological, organizational and environmental] prerequisites influence the adoption of AI in manufacturing" (Kinkel et al., 2022), the study was able to validate the applicability of the TOE framework as an appropriate lens to view artificial intelligence adoption in manufacturing organizations through (Kinkel et al., 2022).

2.2.3 Enholm et al (2022) and other studies

Perhaps the most relevant literature review for the scope of this thesis was conducted by Enholm et al (2022). The study reviewed both the main enablers and inhibitors for AI use, as well as the types of business value that can be achieved with the use of artificial intelligence (reviewed extensively in chapter 3). Enholm et al (2022), just like the previously reviewed studies (Chatterjee et al., 2021; Kinkel et al., 2022), also divide the factors affecting the success of artificial intelligence implementation projects into the three familiar contexts: technological, organizational and environmental.

The technological context is comprised of two factors: data and technology infrastructure (Enholm et al., 2022). Data was seen as a crucial prerequisite in implementing an artificial intelligence use case successfully, as the data that is used to train the artificial intelligence models needs to be sufficient in quantity and quality in order to produce any valuable outputs (Baier et al., 2019; Enholm et al., 2022). This is called the "garbage-in, garbage-out"-principle (Lee et al., 2019). Technology infrastructure was also seen as an important prerequisite for the adoption of artificial intelligence, as the training of machine learning models was said to require vast computing power. Cloud platforms were mentioned as a solution for smaller organizations to gain access to the required computing power. (Enholm et al., 2022)

Enholm et al (2022) defines the organizational context with six factors. Organizational readiness, compatibility, and top management support were also mentioned in the study by Chatterjee et al (2021), but new mentions in the study by Enholm et al (2022) are culture, AI strategy, and employee-AI trust. Having an innovative culture and an overall willingness to adapt to new ways of working were seen to have a positive effect on an organization's success with artificial intelligence. Approaching artificial intelligence by defining a strategy outlining the key goals and processes regarding the implementation was also seen as beneficial towards "reap[ing] the benefits of AI" (Enholm et al., 2022). The mentioned employee-AI trust factor could be linked to change management or the willingness-to-adapt-factor, as it concerned both the shifting of organizational roles, and the necessity for employees to effectively work alongside artificial intelligence. (Enholm et al., 2022)

The environmental context was defined with three factors: ethical and moral aspects, regulations, and environmental pressure (Enholm et al., 2022). Ethical and moral aspects should be guiding the implementations and use of artificial intelligence in organizations, as the technology should not promote any biases or lead to discrimination. Regulations were seen as steering the actual development of artificial intelligence applications, and the environmental pressure factor was defined as driving the adoption of artificial intelligence through pressure from the adopting organizations competitors. (Enholm et al., 2022)

Other crucial factors for successful artificial intelligence adoption projects in organizations, from various papers, are the availability and quality of data (Baier et al., 2019; Dubey et al., 2020), data processing capabilities or strong data science capabilities (Dubey et al., 2020; Shollo et al., 2022), deep domain knowledge (Shollo et al., 2022), and entrepreneurial orientation (Dubey et al., 2020), which loosely coincides with the organizational readiness capability as defined in Chatterjee et al (2021). Embracing a "high risk, high gains" mindset has also been seen as beneficial in artificial intelligence projects (Mikalef & Gupta, 2021). This could be combined with the organizational capability and competitive advantage factors, as discussed in Chatterjee et al (2021), to represent the broader context of organizational culture, resistance to change and willingness to adopt new ways of working alongside artificial intelligence. This sort of cultural transformation into coordinating and cooperating more interdepartmentally within organizations was also characterized in Mikalef and Gupta (2021) as an "AI orientation within the firm" (Mikalef & Gupta, 2021).

3 CREATING VALUE WITH ARTIFICIAL INTELLIGENCE

This chapter focuses on exploring the types of value artificial intelligence can help provide in organizational use, as well as diving deeper into the value creation mechanisms that artificial intelligence applications can provide value by. Existing ways of prioritizing between artificial intelligence initiatives are also shortly explored.

This chapter is divided into three subchapters. The first subchapter explores what types of business value can be gained through the use of artificial intelligence. The second subchapter explores the value creation mechanisms through which higher levels of value can be achieved. The third subchapter focuses on different ways of prioritizing between artificial intelligence applications.

3.1 Value provided by artificial intelligence

Artificial intelligence can provide multiple sorts of value to organizations. Mikalef and Gupta (2021) were able to verify in their study that developing AI capabilities in organizations positively influences and helps "realize gains in both [organizational] creativity and performance" (Mikalef & Gupta, 2021). According to Burström et al (2021), artificial intelligence "can provide a beneficial service for customers in various parts of the value chain", and that successful implementations in the manufacturing sector have been able to "lower maintenance and inspection costs and reduce the number of expensive production stoppages" (Burström et al., 2021).

The study by Enholm et al (2022) also reported on the multiple changes and types of value that the use of artificial intelligence brings to organizations. Instead of "value", the literature review (Enholm et al., 2022) describes these effects resulting from organizational use of artificial intelligence with the term "impacts". The impacts were divided into two subcategories, first- and second order effects. The division is logical, as the first-order effects describe changes and improvements on the process level, while the second-order effects reflect the performance outcomes of the first-order effects on the firm level. In other words, the first-order effects can be thought of as similar to the value creation mechanisms as discussed in chapter 3.2, which then help achieve various second-order effects and thus create value. The impacts of artificial intelligence use, as compiled by Enholm et al (2022), can be seen in figure 2.

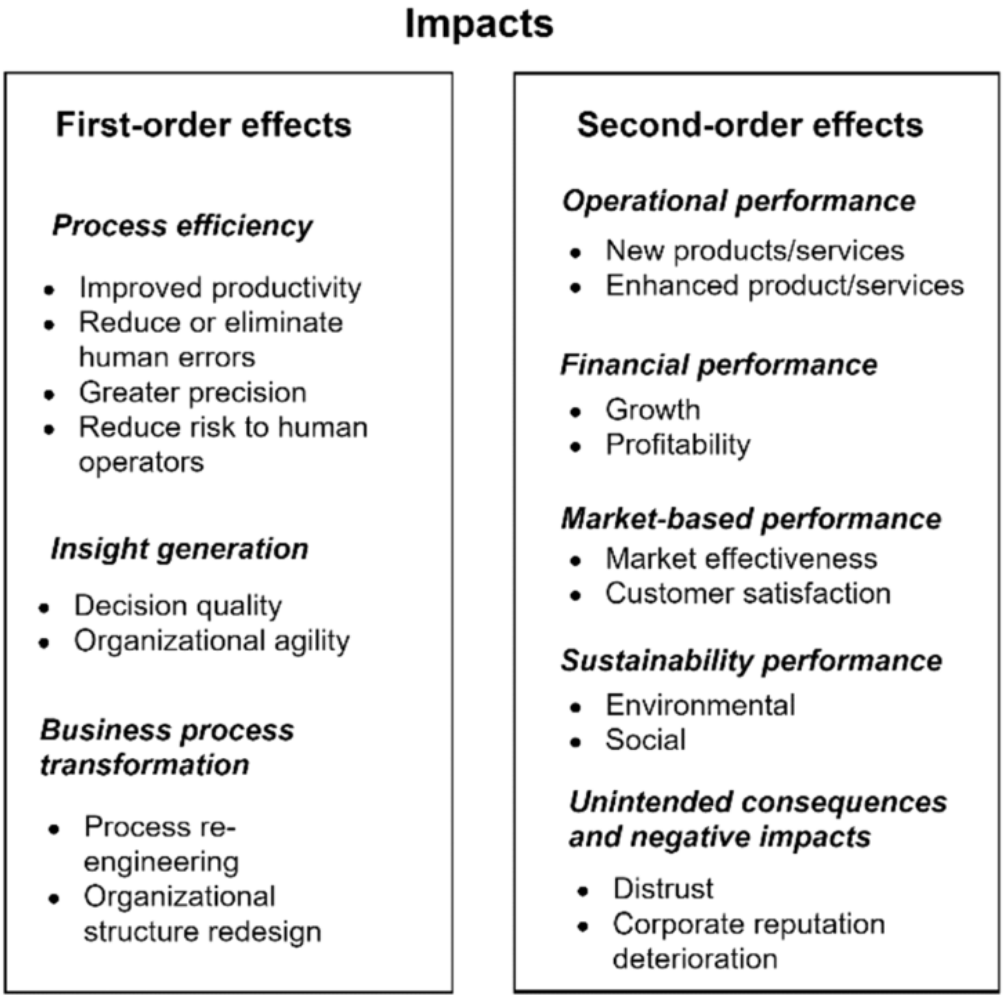

FIGURE 2 Impacts, as compiled by Enholm et al (2022)

Process efficiency is a first-order impact that concerns the automation of tasks, either leaving the human completely out of the loop or alternatively augmenting their tasks (Enholm et al., 2022). Benefits and value derived from process efficiency revolve around enhanced productivity and precision in tasks, reduced risk for human operators as well as reduced or even eliminated human errors in operations (Enholm et al., 2022). Automating tasks and processes also allows for shifting employees away from repetitive routine tasks into more knowledge-intense roles, creating additional value within the organization (Enholm et al., 2022).

Insight generation is also seen as a vital first-order impact that artificial intelligence provides in organizations, as it allows for both more insightful and informed decision-making, as well as for extended organizational agility thanks to the readiness of utilizing new data with AI even in real time. Better decision-making impacts nearly every facet imaginable in organizations, eventually leading to second-order impacts such as financial or operational performance.

Business process transformation was the third mentioned first-order impact in the literature review by Enholm et al (2022), and it encapsulates the innovative potential that artificial intelligence enables in organizations. Since artificial intelligence is so disruptive and enabling, existing processes can be rethought and -engineered with artificial intelligence in the center of the new processes. For example, thanks to the potential of automation, the role of human workers in certain processes can be shifted from a practicing role more into an overseeing role, or even out of the process entirely. This process-level impact describes the overall potential of artificial intelligence to transform businesses and "redraw the organizations' organizational chart" (Enholm et al., 2022; Eriksson et al., 2020).

Operational performance was the first second-order, or firm-level, impact mentioned in the literature review by Enholm et al (2022). Artificial intelligence affects the operational performance of companies in a positive manner, through the enhancements in products and services, or even by providing entirely new products and services. Market gaps for new products and services could be discovered with insight generation methods. Entirely new products and services are now possible with the introduction of artificial intelligence, allowing companies to tap into previously unattainable customer segments, for example. Existing products and services can be improved with extended automation or by "making them smarter" via similar methods as described when discussing the insight generation impact, or by the methods described in chapter 3.2 when discussing the knowledge creation and task augmentation value creation mechanisms. Personalization is also another way of enhancing existing products and services with artificial intelligence (Enholm et al., 2022; Kshetri et al., 2023).

Financial performance is a clear goal for many managers and leaders when discussing the possibilities of artificial intelligence, which makes it a self-evident second-order impact. Other impacts such as reducing costs or enhancing productivity can lead to better financial performance, and having clear structures built around artificial intelligence adoption and use seem to lead to even more financial performance (Enholm et al., 2022; Mikalef & Gupta, 2021).

Market-based performance, according to Enholm et al (2022), encapsulates the value extracted from the customers of an organization by utilizing artificial intelligence. Marketing tasks such as customer segmentation (Bag, Gupta, et al., 2021; Enholm et al., 2022) and content creation (Kshetri et al., 2023) can be enhanced with artificial intelligence. Customer segmentation can be followed by artificial intelligence powered personalization for targeted groups (Kshetri et al., 2023). It was mentioned that customer satisfaction can also be influenced with artificial intelligence, either positively by offering personalized recommendations and solutions (Enholm et al., 2022), or negatively by having the customers interact with unsatisfactory chatbots (Castillo et al., 2021; Enholm et al., 2022), for example. In any case, artificial intelligence can provide additional insight into the customers and help tailor their experience with the implementing organization.

Sustainability performance encapsulates the sustainability values provided by artificial intelligence use in organizations, both in the contexts of the environment, as well as social sustainability. Enhancing the productivity and lowering costs in both financial and resource contexts can help with organizations' environmental sustainability goals. In the context of social sustainability, artificial intelligence can help "reduce human bias in processes, such as recruitment and customer segmentation" (Enholm et al., 2022). One innovative idea was that thanks to automation and removing humans from certain processes, health and safety goals are easier to achieve as there is less risk of humans getting injured in previously hazardous processes (Enholm et al., 2022).

Another viable way of evaluating the value created by artificial intelligence applications could be by utilizing the components of the ADROIT framework. The six components in the framework, according to Mithas et al (2022), are:

- Adding revenues
- Differentiating or increasing willingness-to-pay
- Reducing costs
- Optimizing risks
- Innovating by generating and deploying knowledge and other resources and capabilities
- Transforming business models and processes

While the ADROIT framework seems to be quite general and not very cited in literature, it has been used in a study (Mithas et al., 2022) to explain the competitive advantage and value gained by utilizing certain Industry 4.0 technologies. At the very least, the six components in the framework could be helpful for assessing the type of value created by an artificial intelligence application.

3.2 Value creation mechanisms

Organizational value can be created by artificial intelligence in multiple different ways. Although the lack of research focus on the overall value and value creation mechanisms presented by artificial intelligence and its subcategories has been noted (Enholm et al., 2022; Mikalef & Gupta, 2021; Shollo et al., 2022), there are some exhaustive and applicable studies in peer-reviewed journals as well.

One of the most interesting studies concerning the value creation mechanisms of machine learning applications was authored by Shollo et al (2022). The study discovered and presented three broad types of value creation mechanisms (Shollo et al., 2022). These three types of value creation mechanisms are *knowledge creation*, *task augmentation* and *autonomous agent* (Shollo et al., 2022). The three value creation mechanisms can also be seen as rising in level of complexity and integration, with knowledge creation being the least complex/integrated, and autonomous agent being the most complex/integrated of the three. As shortly mentioned in chapter 3.1, these value creation mechanisms play a similar role in translating the usage of artificial intelligence into measurable organizational value as the first-order effects compiled in the literature review by Enholm et al (2022).

Knowledge creation was defined in the study as a value creation mechanism that "pursued the value target of organizational knowledge creation" (Shollo et al., 2022). Pattern sensing, trend identification, and the overall discovery of new knowledge from historical datasets are some of the ways that these types of applications create organizational value. In the paper, it was mentioned that many of the projects falling into this category "rarely ended directly in the implementation of productive IT systems", and that instead they "focused on prototypes" and low-technical maturity reports (Shollo et al., 2022). It was also mentioned that many of the projects in this category could be described as one-off analyses of historical data, done in order to discover general trends or drivers of specific phenomena. In short, these applications could be described as "tools", which only discover knowledge from historical data but leave all the decision-making and -taking to the humans in the organization.

Task augmentation as a value creation mechanism is more refined and continuous than the previous category of value creation mechanisms, knowledge creation. Applications utilizing task augmentation as a value creation mechanism are more ingrained in information systems, and they support their users in everyday tasks, as opposed to the one-off nature of knowledge creation-type systems. The authors split the task augmentation category in two subtypes, *high-discretion*, and *low-discretion*. The important distinction between these categories is that low-discretion systems are much more autonomous compared to high-discretion systems. In high-discretion systems the human still has the decision-making authority, whereas in low-discretion systems the role of the human was described as "rather [being] an actuator". (Shollo et al., 2022)

The **autonomous agent** value creation mechanism is the most sophisticated of all three mentioned in Shollo et al (2022). As the name suggests, humans being out-of-the-loop is essential to the value generated from applications of this type. This is also the main differentiator of this value creation mechanism, as compared to the task augmentation value creation mechanism. The autonomous agent mechanism is split into two subtypes, *process automation* and *intelligent products and services.* Process automation is focused on "reducing time and resources needed for process education" (Shollo et al., 2022), for example by automating a task completely. The example used in the article concerned the automated placement of ads on websites, with humans only deciding on the budget and everything else being controlled by a machine learning algorithm. The other subtype, intelligent products and services, also covers applications which are end-to-end automated, but the outputs of which are also changed by the algorithm. In short, the main difference between these subtypes is that process automation changes internal processes, while intelligent products and services also offer a new type of output. (Shollo et al., 2022)

In addition to the three discovered value creation mechanisms, Shollo et al (2022) also discussed the required conditions for utilizing each of the value creation mechanisms above. All eight conditions, and the types of value creation mechanisms they help realize, can be seen below in table 2.

TABLE 2 Conditions for value creation (Shollo et al., 2022)

Condition	**Value creation mechanisms where required**		
	Knowledge creation	Task augmentation	Autonomous agent
Strong data science capabilities	x	x	x
Deep domain knowledge	x	x	x
Mature data infrastructure		x	x
Strong DevOps capabilities		x	x
Strong UX capabilities		x	x
Integration with transactional systems and processes			x
Stable environment			x
Few legal and ethical constraints			x

The two necessary conditions for any level of value creation, according to Shollo et al (2022), are strong data science capabilities and deep domain knowledge. These were seen as crucial prerequisites for any machine learning project to succeed, as altering the model or presenting the results require data science skills, while understanding the importance, origin and possible biases in the data utilized by the machine learning applications can only be achieved with domain knowledge. (Shollo et al., 2022)

For creating value with the task augmentation mechanism, three additional conditions must be met. As the applications creating value via the task augmentation mechanism are more integrated and present in everyday work, the flow of data has to be well established. Mature data infrastructure is thus key to moving on from the one-off nature of the knowledge creation mechanism. In addition, due to the task augmentation mechanism applications still always having a human in the loop, the user experience needs to be refined. While it was not explicitly mentioned in the study by Shollo et al (2022), this condition could have a linkage to the perceived ease of use and perceived usefulness-variables as found in the TAM and the model by Chatterjee et al (2021). Strong DevOps capabilities were also seen as a key condition for the task augmentation mechanism, attributing to the continuous nature of applications utilizing this mechanism. (Shollo et al., 2022)

Finally, to evolve an application from the task augmentation mechanism to the autonomous agent mechanism, three additional conditions need to be met, increasing the total to eight. In order to achieve automation without a human in the loop, even more integration to existing systems is required. Shollo et al (2022) mentioned that many projects had struggled with complete automation, due to the difficulty of writing new data into existing systems (Shollo et al., 2022). Also due to humans missing in the loop, stability is required in the data generation processes. Finally, the autonomous agent applications have to operate within legal and ethical barriers by design, as no humans are in the loop to oversee every choice and operation done by the applications. (Shollo et al., 2022)

The three identified value creation mechanisms in Shollo et al (2022) seem to overlap with the first-order impacts of artificial intelligence use, as presented by Enholm et al (2022). The similarity is especially noticeable between the "knowledge creation" value creation mechanism (Shollo et al., 2022), and the "insight generation" first-order impact (Enholm et al., 2022). Based on this, it is reasonable to assume that since both the process-level impacts (Enholm et al., 2022) and the value creation mechanisms (Shollo et al., 2022) describe how artificial intelligence implementations provide value at the **process level**, the value creation mechanisms defined by Shollo et al (2022) could also lead to similar types of **firm-level** impacts (Enholm et al., 2022).

3.3 Prioritizing AI applications

When an organization needs to prioritize the implementation of different artificial intelligence use cases, what factors and criteria should be used to categorize and classify the use cases effectively? As this question is currently on the minds of many organizational leaders and managers, solutions are also being researched by consulting companies and technology service providers, in addition to academic literature.

One way of prioritizing artificial intelligence applications could be by assessing the current stage of digital maturity in the implementing organization and prioritizing the applications suitable for this level of maturity. Different organizations have different levels of digital maturity. The ease of implementation between different applications of artificial intelligence differs, and some organizations can be more prepared and more likely to implement an application successfully. Levels of maturity could be modelled for example with multiple steps, with each step representing a more advanced or digitally mature organization in terms of technical and cultural capabilities.

The study by Burström et al (2021) examined how artificial intelligence helps large manufacturers transform their business models (Burström et al., 2021). In the study, four levels of artificial intelligence applications, increasing in complexity, were found to indirectly represent the level of AI maturity in the examined manufacturing organizations.

According to the study by Burström et al (2021), the first level of artificial intelligence applications an organization was digitally mature enough to adopt comprised of forecasting applications. It makes sense that forecasting applications are seen as the "first step" for many organizations willing to adopt more artificial intelligence into their processes, as on a technical level forecasting applications mainly require existing data in order to be able to make predictions and forecasts. To have existing data from already-installed sensors and, for example sales records, is something that even most of the digitally "immature" organizations might have. (Burström et al., 2021)

The second clear level of complexity was argued to be seen in monitoring and control applications. In addition to having the required maturity to implement a forecasting application, organizations have to be able to implement functionalities of the "continuous" sort, demonstrating a clear upgrade in maturity. (Burström et al., 2021)

The third artificial intelligence maturity shift in organizations was seen to be represented by the implementation of optimization-oriented artificial intelligence. These sorts of applications of artificial intelligence applications utilize both "historical data and real-time-data" (Burström et al., 2021) in order to optimize the utilization of different equipment, such as machines or vehicles. Prescriptive maintenance is also possible to be conducted at this stage of maturity. (Burström et al., 2021)

The fourth and final stage of maturity was found to be represented by autonomous applications of artificial intelligence. These sorts of implementations leverage not only intraorganizational data, but also "data generated by the equipment of ecosystem partners" (Burström et al., 2021). Utilizing the data generated by the entire ecosystem around the business processes enables applications at this level to "facilitate decision making and corrections", and by utilizing deep learning, even "allow for automated improvements in operations". (Burström et al., 2021)

In the context of artificial intelligence adoption, digital maturity could be seen as having similar traits as the organizational readiness factor, presented in chapter 2.2.1. Jöhnk et al (2021) also conceptualized organizational artificial intelligence readiness factors, many of which correlate to the four levels of maturity as presented in Burström et al (2021). Data flow, for example, could be essential with the continuous nature first seen on the second complexity level in Burström et al (2021), monitoring and control applications. Then again, many of the factors like top management support, innovativeness, change management and AI-business potentials (Jöhnk et al., 2021) are essential to all levels described in Burström et al (2021).

A recent report by Microsoft (2023), aimed at business leaders drafting their strategies and roadmaps concerning the implementation of artificial intelligence capabilities, suggested that an effective way of starting the prioritization process of different artificial intelligence use cases would be to first define the relevant business objectives. First agreeing upon the relevant goals, such as "customer experience, productivity, revenue growth, [and] employee experience"(Microsoft,

2023) and their respective value measurement methods, is key to linking the prioritization decisions with sound business logic. (Microsoft, 2023)

Another way of prioritizing the implementation and adoption of artificial intelligence applications in organizations could be to evaluate both the value gained from a successful implementation of an artificial intelligence application, as well as estimating its ease of implementation. Once the use cases have been evaluated with these two categories in mind, it is then possible to map them onto a matrix comparing the ease of implementation to the value gained. These types of matrices that compare the impact of the use case to the feasibility of the use case have been used and presented in various practitioner literature sources (Baig et al., 2024; Krishnan, 2020; Velush, 2023), although with varying names for the axis. This sort of matrix can be helpful in giving a visual representation of what types of use cases should be approached first, as for example the use cases estimated to provide high value with a relatively easy implementation process should stand out from the rest.

4 LITERATURE REVIEW SUMMARY

This chapter concludes the literature review by summarizing the main findings and discoveries in the literature researched for this thesis. The key findings are reiterated in order to provide a cohesive foundation for discussing the key capabilities and maturity aspects an organization needs to have in order to successfully **implement** and **utilize** AI applications.

This chapter is divided into three subchapters. First, the enablers of successful artificial intelligence adoption will be reiterated. Second, the main types of firm-level value achievable through the use of artificial intelligence, and the value creation mechanisms and process-level impacts that lead to them, will be reiterated. Finally in the third subchapter, the enablers and the types of value will be utilized as the foundation of a model that's aiming to help organizations systematically prioritize their artificial intelligence initiatives.

4.1 Enablers of successful AI adoption

As previously discussed in chapter 2.2, successful organizational adoption and subsequent use of artificial intelligence applications relies on multiple factors and enablers. These can be roughly divided into three contexts, the technological, organizational, and environmental contexts, as first presented in the TOE framework by Tornatzky and Fleischer in 1990 (Oliveira & Martins, 2011). The factors presented next shall serve as the basis for the X-axis of the prioritization model, introduced in chapter 4.3.

Considering the technological context of organizational artificial intelligence adoption, good-quality, relevant **data** in vast quantities (Baier et al., 2019; Dubey et al., 2020; Enholm et al., 2022), modern, capable and scalable **technology infrastructure** (Baier et al., 2019; Enholm et al., 2022), and **product complexity** (Kinkel et al., 2022) stand out as leading technological factors regarding the success and ease of the artificial intelligence implementation. In addition to being mentioned in existing literature, it also makes intuitive sense that the overall technical complexity of the implementation, the infrastructure it is built upon, as well as the data it ingests to produce high-quality and relevant output, matter a lot in the overall feasibility or ease of implementation.

In the organizational context, six factors stand out from the literature review. The factors estimated to weigh in the most in the success of an artificial intelligence implementation relate to having an innovative and encouraging **culture** (Enholm et al., 2022; Lee et al., 2019), adequate **top management or leadership support** (Chatterjee et al., 2021; Enholm et al., 2022), **organizational readiness** (Chatterjee et al., 2021; Enholm et al., 2022), **internal skills**, including domain knowledge (Chatterjee et al., 2021; Enholm et al., 2022; Kinkel et al., 2022; Shollo et al., 2022), available **partner support** (Chatterjee et al., 2021), and overall **compatibility with the existing organization**, both in terms of strategy and values (Chatterjee et al., 2021; Enholm et al., 2022).

Finally, in the environmental context, **regulations** (Baier et al., 2019; Enholm et al., 2022) are thought to provide directions towards what kind of data can be used or what use cases are morally and ethically acceptable, while **environmental or competitive pressure** (Enholm et al., 2022) was seen as a driver for organizations yearning to stay ahead of their competitors.

4.2 Types of value gained from use of AI

Four main firm-level categories of value were identified in Enholm et al (2022). These were the financial performance, operational performance, market-based performance, and sustainability performance (Enholm et al., 2022). These categories shall serve as the basis for the Y-axis of the prioritization model, introduced in chapter 4.3.

According to Enholm et al (2022), artificial intelligence helps achieve these firm-level impacts through the process-level, or first order impacts also described in the article. These were process efficiency, insight generation, and business process transformation (Enholm et al., 2022). In addition to these types of process-level value, it is reasonable to anticipate that also the value creation mechanisms, defined by Shollo et al (2022), could also lead to the same firm-level value categories as defined by Enholm et al (2022). As mentioned in chapter 3.2, there is some overlap between the two studies, especially around the “knowledge creation” value creation mechanism (Shollo et al., 2022), and the “insight generation” first impact (Enholm et al., 2022). This further strengthens the hypothesis that it is possible to combine and analyse the value creation mechanisms (Shollo et al., 2022) and first order, or process-level impacts (Enholm et al., 2022) together.

4.3 Matrix for prioritizing AI use cases

Based on what was learned about the types of value that are achievable via organizational use of artificial intelligence, as well as the prerequisites, enablers and competencies that facilitate the success of artificial intelligence implementation projects, it is now possible to develop a model to help with prioritizing between different artificial intelligence use cases. Developing this type of model helps to start answering the third research question of this study, "Can a combined assessment of achievable value and implementation factors provide a systematic method for prioritizing AI initiatives?". The proposed model can be seen below in figure 3.

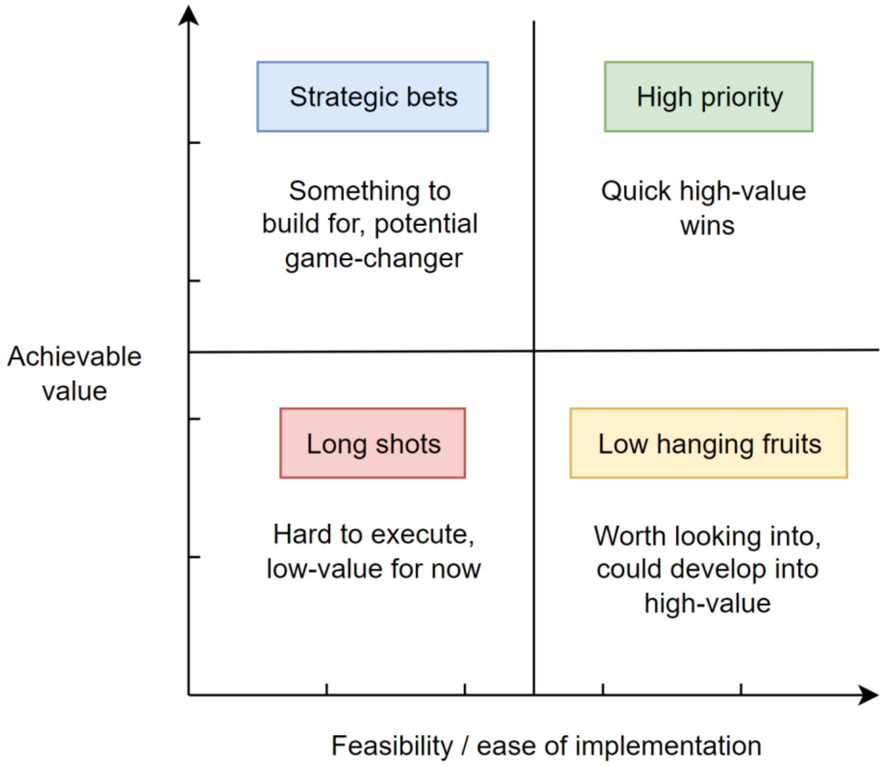

FIGURE 3 Proposed value-feasibility matrix

As we have explored the factors leading to the success of AI implementation projects, it can reasonably be thought that inversely, the ease of implementation (or feasibility) of a project can be roughly estimated from the number of these success factors present. Therefore, by identifying how many factors are present or easily achievable in a single artificial intelligence use case or initiative, we can score it on a scale of 1-5, for example. Use cases with few enablers and preconditions of successful adoption present would therefore have a low score and be placed more on the left side on the X-axis. Use cases or initiatives that have many of these enablers and other ease of implementation-affecting factors present would then score higher and be placed more on the right on the X-axis.

As the X-axis consists of the enablers and preconditions of successful adoption, or ease of implementation factors, the Y-axis then consists of the overall estimated achievable value of the use case or initiative. Having identified in previous chapters the types of firm-level value achievable with artificial intelligence implementations, as well as the value creation mechanisms and process-level impacts that lead to the firm-level values, it is now possible to start identifying these mechanisms and impacts present in single use cases or initiatives. This could also be estimated on the same scale of 1-5, as was the case with the X-axis. If a single use case or initiative is estimated to provide clear and impactful firm-level value through identifiable value creation mechanisms or process-level impacts, the achievable value is then scored higher, and the use case placed higher on the Y-axis. On the other hand, if no clear value can be estimated from the implementation of such an use case or the process-level impacts and value creation mechanism remain unclear, it should be scored lower and placed lower on the Y-axis. The matrix can be roughly divided into four quarters, which are elaborated on below:

- **Top-right quadrant:** *High priority*. Use cases or initiatives which are estimated to provide high organizational value and estimated to be relatively easy to implement. Should most likely be approached first.
- **Bottom-right quadrant**: *Low-hanging fruits*. Use cases or initiatives which are estimated to be relatively easy to implement, but not to provide transformational value. Could be used to further develop enablers and preconditions to successful AI implementations, such as technology infrastructure, AI-oriented culture, and enhanced access to high-quality data.
- **Top-left quadrant**: *Strategic bets*. Use cases or initiatives which are estimated to provide high value, but which are hard to implement. Preparations and planning for implementation should be initiated due to high value estimates.
- **Bottom-left quadrant**: *Long shots*. Use cases or initiatives that have been estimated to be hard to implement, and to not provide any significant value. Should be implemented last.

This matrix will be re-evaluated later in chapter 7, to see if the empirical data gathered from the interviews gives any suggestions to alter the matrix, the underlying assumptions, or the prioritization decisions in any way.

5 METHODOLOGY

This chapter presents the methodology for the empirical section of the thesis. Much of the research design was based on the interview instructions by Myers and Newman (2007), as well as the analysis instructions by Hsieh and Shannon (2005).

This chapter is divided into three subchapters. In the first subchapter, the research design, and choices regarding the collection of empirical data are explained. Afterwards, the second subchapter describes the data acquisition process in detail. Finally in the third subchapter, the chosen analysis methods are described.

5.1 Research design

The qualitative study method was chosen for the empirical section of this thesis. The choice was made as the goal of the research was to ultimately examine the factors leading into prioritization of artificial intelligence use cases in organizations, and qualitative methods were seen as the most appropriate way of gaining these insights. Semi-structured expert interviews were chosen as the method for gathering the empirical data, as this approach allowed for more flexibility in exploring the interviewees insights, while also ensuring that the key topics were covered. To gain an even deeper understanding on how both the enablers and preconditions of artificial intelligence implementation projects as well as the sought-after types of value are seen in the field, the choice was made to interview both representatives of "client" organizations, as well as "provider" organizations. As the thesis was commissioned by an industrial organization, the "client" interviewee organizations were also sought from the industrial field to ensure highly relevant insights. Focusing on interviewing representatives of industrial organizations was also seen as appropriate, as they have up-to-date information about the research questions from relevant sectors of the field. More details on the interviewees will be provided in the next chapter.

The interviews were planned with the advice by Myers and Newman (2007) in mind. The common problems and pitfalls, such as the elite bias, Hawthorne effects, and the ambiguity of language (Myers & Newman, 2007) were reviewed prior to designing the interviews, in order to avoid them as much as possible. After the interviews were conducted, they were consequently transcribed as soon as possible.

The interview questionnaire (seen in appendix 1) was large, and some questions are not seemingly connected to this thesis. This is due to the fact that the collected dataset is planned to be used not only for this thesis, but also in other scientific publications. The interviews were conducted by the author of this thesis, and an additional doctoral researcher. Of the 11 interviews used in this thesis, the author of this thesis conducted six interviews, while the doctoral researcher conducted five. In none of the interviews did the interviewer and the interviewee have any previous connections or familiarity with each other (other than setting up the interviews), ensuring that the interviews were as neutral as possible. Even though the dataset was collected in partnership with a doctoral researcher in standalone interviews, the analysis of the transcripts used for this thesis was conducted by the thesis author alone.

5.2 Data acquisition

Empirical data for this study was gathered with 11 semi-structured interviews. The interviewees were mainly sought from LinkedIn, using relevant job titles and organization names as keywords. Most of the interviewees were exactly the people first approached in the organizations via LinkedIn or email, while the rest were referred by the first contacts in organizations, in a snowball sampling-type approach. Refusals to be interviewed were few, and mainly due to the first contacts not having time to participate in the study, or because the first contacts thought that their colleague was a better fit to be a participant in the study. To avoid the elite bias problem, described by Myers and Newman (2007) as being a common pitfall with qualitative interviews, the chosen interviewees also represented different seniority levels within their organizations. Pseudonymized details on the interviewees can be seen in table 3 below.

TABLE 3 Description of the interviewees

Interview pseudonym	Represented industry	Interviewee job title	Interview duration
I1	Industrial, energy	Digital Lead, Data Science & AI	1h 14min
I2	Technology, software development	SVP (Industry Solutions)	1h 31min
I3	Industrial, heavy equipment manufacturing	Manager, Data & Analytics	1h 35min

I4	Industrial, heavy equipment manufacturing	Sales manager, Digital Services	57 min
I5	Industrial machinery for process industries	Lead Enterprise Architect	1h 52min
I6	Technology, software consulting	Director	1h 12min
I7	Software platforms for AI, BDA	BD Director	1h 15min
I8	Technology consulting	Data & AI Lead	53 min
I9	Technology	Chief Operating Officer	1h 8min
I10	Technology, consulting	Business Lead, Data Science & AI	1h 18min
I11	Industrial, marine and energy	Manager, ML and Advanced Analytics	1h 26min

The interviewees represented large industrial corporations, global technology providers, as well as smaller technology providers. The interviewees can roughly be divided into “client” and “provider”-groups, with five industrial interviewees representing the “client”-group and six interviewees representing the “provider”-group. As mentioned previously, this choice to interview both groups was made to gain insights from both perspectives of the implementation process, as many industrial organizations utilized the help of partners in implementing artificial intelligence. The size of the organizations the interviewees represented also varied; the smallest interviewed organization employed approximately 50 people, while the largest interviewed organizations employed hundreds of thousands of people. This further increases the diversity of the dataset, allowing for perspectives from both small and medium-sized enterprises, as well as large global enterprises.

The interviews were conducted in the spring of 2024. The interviews were held in Microsoft Teams virtual meetings, which allowed for the interviewee pool to be more unrestricted from a geographical point of view. Most of the organizations represented by the interviewees were headquartered in Finland, but some operated primarily in the United States. All represented organizations offered their products and services internationally.

The interviewees served in technology and business roles in their organizations, and they all had several years of experience in similar roles. All interviewees reported to have worked with topics surrounding artificial intelligence for some years already.

The interviewees have been pseudonymized and the interview quotes have been altered where necessary to remove any possible identifiers. These actions have been taken in order to avoid the any bias regarding the interviewed organizations, and also to keep the interviewees identities hidden as per agreement.

5.3 Data analysis

In order to gain insight from the transcribed interviews, the transcripts were first analysed with the directed content analysis method, as described by Hsieh and Shannon (2005). The directed content analysis method was chosen as the primary analysis method, as the existing literature provided well-established definitions and theoretical foundations for the initial coding. After re-reading the interview transcripts multiple times and seeking out mentions of pre-existing codes, as Hsieh and Shannon (2005) recommend doing when conducting directed content analysis, the transcripts were examined with the conventional content analysis methodology, also described by Hsieh and Shannon (2005), in mind.

Approaching the analysis of the transcripts from two different perspectives allowed for a richer understanding of the collected data. First examining the transcripts with the directed content analysis method ensured that the analysis was grounded in existing theory. After the theory-driven codes were identified, common themes were sought from the transcripts in an inductive manner in order to gain new insights. This combined approach of both deductive and inductive analysis, by using directed content analysis as well as conventional content analysis, ultimately ensured that the transcript data was understood as completely as possible, enhancing the overall validity of the findings.

In addition, by utilizing the directed content analysis as the primary analysis method, this study was able to validate and extend existing literature and theories (Hsieh & Shannon, 2005) on both the enablers and preconditions of artificial intelligence adoption, as well as the value aspects of organizational artificial intelligence use. This is one of the major theoretical contributions of the thesis.

6 RESULTS

This chapter presents the results of the analysis conducted on the transcripts of the collected interviews. The analysis methods for the transcripts are discussed in detail in chapter 5.3.

This chapter is structured as follows. First, the enablers and prerequisites of artificial intelligence adoption are examined. Next, the value that interviewees seek from the use of artificial intelligence is discussed. Third, the identified value creation mechanisms that lead into the sought-after firm-level value are discussed. Finally, the prioritization of artificial intelligence use cases in the organizations are discussed. The subchapters have been arranged in a way that corresponds with the different axis of the proposed value-feasibility matrix.

6.1 Enablers of adoption

Overall, the enablers and prerequisites of artificial intelligence adoption, as defined in the theory sections of this thesis, corroborated with the findings from the interviews. Dividing the enablers of adoption into the three distinct contexts first introduced by the TOE framework was found to be relevant and helpful in analysing the individual enablers of artificial intelligence adoption. Thus, this subchapter is divided into three more subchapters to analyse the identified enablers and prerequisites in their corresponding contexts.

6.1.1 Technological factors

When considering the technological enablers of successful artificial intelligence adoption, nearly all interviewees heavily emphasized the importance of data and the existing technology infrastructure in place. The mentions for each technological enabler for artificial intelligence adoption success can be seen below in table 4.

TABLE 4 Interview mentions of technological factors affecting the ease of implementation of artificial intelligence use cases.

Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	**Total**
Data	X	X	X	X	X	X	X		X	X	X	10
Technology infrastructure	X		X	X	X	X	X	X		X	X	9
Product complexity												0

Data was hypothesized to be perhaps the most crucial technological prerequisite of artificial intelligence projects, and based on the interviews it seems to be the leading enabler of success from a technological perspective. The importance of data was associated with artificial intelligence use cases utilizing practically any value creation mechanisms and first-order effects, as the common view among interviewees was that the more data you have, the better artificial intelligence is able to help achieve any intended goals.

> Of course, it’s very important to have the data on point. Without it you can’t really solve the problem as well as you could with quality data. (I1)
>
> To me, there's only one factor that makes all this work or break, and that's the data, so everything else is just a wrapper around it. (I5)
>
> I would say that even with all AI disciplines, I mean it's all about the data. (I5)
>
> Yeah, data seems to be the modern gold, and the more data you have, the more you annotate, understand, and convert it to a machine-friendly language, the better off you are with getting started. (I6)
>
> In the end, the business value or your competitive edge comes from your data, and how that enables you to differentiate yourself from the others. (I9)

The possession of data was not the only important enabler regarding data, but also factors such as data cleanliness and proper contextualization were seen as key factors in the implementation success. Also, the general understanding among the interviewees seemed to be that use cases utilizing generative artificial intelligence technology can operate with noisier and more unstructured data too, but that the contextualization of the data is still necessary. This finding suggests that the “garbage-in, garbage-out”-principle (Lee et al., 2019) is still highly relevant.

> [Large language models] have to be applied at the proper context of your company data and aspects, because like you can't just like turn ChatGPT 4 loose on all of [Company X] and then expect to get phenomenal results without it being properly contextualized information. Once that happens

> though, I think that the upside is tremendous and then also the cost of starting up and operating that environment is drastically cheaper than a traditional, commercial AI, ML organization. (I7)

Technology infrastructure was also seen as a key technological prerequisite for success in implementing artificial intelligence use cases. This finding also makes intuitive sense, as companies with suitable pre-existing technology infrastructure can be thought of as being more technologically capable and as having a technology-oriented culture overall, and thus more inclined to also succeed in implementing artificial intelligence. Pre-existing technology infrastructure can serve as base layer for running the artificial intelligence applications on. Many interviewees, both from technology provider companies as well as industrial organizations, reported that companies with pre-existing cloud infrastructure have a natural competitive edge in implementing artificial intelligence use cases.

> Companies which are cloud driven will probably have a competitive edge, because if you're a cloud driven company, your cloud providers will do all the heavy lifting for you. So Amazon, Google, Microsoft, for example if you have one of these big clouds, they will be the ones taking care that their solutions are compliant with the regulations. They will be the ones who will give you optimization possibilities and the infrastructure. So there I would say that from a company perspective, companies which are cloud first will be better prepared to utilize this and scale this up because it becomes very expensive very quickly and cloud is where you get the flexibility and you don't have to worry a lot about the infrastructure. (I5)

Although the vast majority of interviewees saw existing technology infrastructure as a major benefit for the success of implementing artificial intelligence, it wasn’t seen as a crucial prerequisite for successful implementation by all. For example, a representative of a global AI platform provider said the following:

> Part of the difficulty is breaking up the preconceived notion that everyone has to be at like a minimum starting point. I guess the minimum starting point would be that you have to have a company. And I think that we have done some incredible work with companies running completely off of Excel. They have no data lakes, they have no, there’s nothing's in the cloud. (I7)

Product complexity wasn’t mentioned in the interviews at all. This does not mean that the complexity of the products and services that the interviewed organization manufactures or provides wouldn’t affect the adoption of artificial intelligence, as suggested by Kinkel et al (2022), as the absence of mentions could also point to the interview questionnaire being lacking in terms of this factor.

6.1.2 Organizational factors

In general, the interviewees saw factors in the organizational context as the leading enablers of artificial intelligence implementation success. This is a major finding in the study. All mentions of organizational factors in the interviews can be seen below in table 5.

TABLE 5 Interview mentions of organizational factors affecting the ease of implementation of artificial intelligence use cases.

Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	**Total**
Culture	X	X	X	X	X	X	X	X	X	X	X	11
Top management support	X	X	X		X	X	X	X	X	X		9
Internal skills	X		X	X	X	X	X			X	X	8
Willingness to change ways of working (CCA)	X	X	X			X	X	X			X	7
Suitability with organizational AI strategy		X	X	X	X			X		X		6
Partner/vendor support			X	X	X					X	X	5
Organizational readiness					X	X			X	X		4

Culture was the most mentioned organizational factor concerning the success of artificial intelligence implementation projects in the interviews. Culture was a topic in every interview conducted for this study, and it was seen as perhaps the biggest individual factor that determines whether organizations can consistently succeed in artificial intelligence implementation projects. Some of the identified qualities of an organizational culture that's beneficial for the implementation success related to innovativeness, having a "fail fast" mentality, overall excitement about new technology and the capabilities it possesses, as well as a collective data-driven mindset. A major identified benefit of possessing a culture with values like these was the fact that use case ideas were easier to come by:

> [Implementation and utilization of AI] is really a company-wide, function-wide matter. Every function is now thinking what they can do better, starting with, let's say R&D, that GitHub Copilot can help you code faster, which is a really function-specific benefit. Then for example the marketing content creators get a lot of benefits from AI-powered translations, text / audio/ video generation, for example. (I2)

> Internally, we need to learn how to use this as soon as possible, and in the most effective way across different functions. So, we need to democratize the use of generative AI within the company, and that's what we're doing. (I5)

> How is an organization able to create such a culture that people would individually start to think what technologies such as artificial intelligence, the metaverse or other innovations could mean to their personal work? How do you implement this type of mindset on an individual, departmental, or even on an organizational level? (I9)

Interviewees also reported feelings of excitement among the employees when realizing the possibilities of artificial intelligence, or when seeing it in use:

> Mundane things such as summarizing meeting details, which may have been tasked to a secretary before, and now you give them Copilot for it… I don't know, all of these new things lead to a positive buzz you could say within the company, sudden moments of work motivation or something? It's a cool feeling, like having something brand new. (I3)

Having an organizational "fail fast", or otherwise risk-accepting mentality was seen as having a positive effect for the success of implementations in the long run:

> I would say that this is really a culture question. Obviously, you don't get to start a million-euro project "just for fun", at least without really explaining what we are doing this for, but if it's decided to be implemented and it fails, it's not the project managers fault but the company's fault. Then it just failed, we learn what we can and move on. But this [culture] isn't present in all companies. I've come across many companies in Finland where this ″try-out″-culture isn't present and when something is done, it always has to succeed. This just leads to these companies not doing anything because the fear of failure is so high. (I4)

> No matter which technology breakthrough we're talking about, the companies that have the willingness and ability to see opportunities, experiment with those opportunities, and then also fail quickly in those experiments will eventually win. In other words, such a culture of experimentation and openness to potential new operating models for the utilization of new technologies and the potential value production of new technologies, those things will also lead to success with artificial intelligence. (I6)

> With AI, an organization really needs a try-out culture, because a lot of implementations will fail regardless. This type of culture means that you start small and are able to validate really early if there is value in this implementation, and thus you are able to improve your chances at extracting real value with AI. It's also important to not get depressed because some use case failed, and if you go big early on some project which fails, there is a risk of AI becoming almost like a swear word in the organization. (I10)

Top management support was another organizational factor that was mentioned in the majority of the interviews as an almost crucial prerequisite for successful artificial intelligence adoption. Most of the interviewees saw that without consistent support from organizational leadership in terms of investment and other resources, the chances of success for the implementation project lower drastically. This finding aligns closely with existing literature on the factors explaining organizational adoption of artificial intelligence, where it has been shown that leadership support accelerates the adoption process (Chatterjee et al., 2021).

> The same goes for any IT project, that the top leadership has to be involved and they need a real “buy-in”. The project can’t also just be suggested and pushed by some IT department, you need to involve the end users and their perspective as well. (I2)

> Our guidance comes from our CEO directly on this, that we have to experiment and learn about this [generative AI]. (I5)

> And I think that the starting point is really the buy-in of leadership and the business, the P&L owners that want to adapt it to say “I want to adapt it.” Everything from there is more just logistics blocking and tackling, and small micro-pivots to make sure that the end result matches what they want it to be, and what's capable with current technology. But the biggest hurdle is someone saying ”I believe this is possible and yes, I want to do it.” (I7)

Often, the **organizational AI strategy** was mentioned around the same time as top leadership support was discussed in the interviews. The strategy was often seen important especially in spreading the utilization of artificial intelligence around various parts of an organization. This could be explained by the fact that one common goal of an organizational AI strategy seems to be to make sure that the organization is approaching artificial intelligence in a structured and holistic manner, combatting the possibility of “technical siloes” forming, where a certain department has access to a lot of tools that could benefit others as well.

> Kind of the mindset in the beginning for many companies is that they trial artificial intelligence in some specific function, some specific unit. They have a few data engineers who might try it for one use case and then that application just kind of stays there. But we see that one key success factor is to think what the impact of that use case could be throughout the organization. What could you do with that tool in the financial, HR, legal departments? (I8)

Some interviewees, especially from consulting and technology vendor organizations, even mentioned that a suitable organizational AI strategy is more important than intraorganizational technical skills:

> I would say that hard technical knowledge isn’t necessary. I would say that this [organizational implementation of AI] really starts from the strategy, and that there are people with technical knowledge and understanding in leadership positions. In a lot of companies, the technology road map and technological decisions are getting ever closer to the core business, which means that a lot of technology decisions are big business decisions at the same time and thus require that the leadership has good visibility into them. (I8)

On the other hand, having a clear AI strategy has not been a prerequisite of success for some companies which have, in their own words, gained real value from artificial intelligence:

> It's become clear to me that we should have a much clearer and concise strategy around artificial intelligence than what we currently have! (I4)

Skills, both as organizational capabilities and as individual technical skills of the employees, were mentioned in the majority of interviews as having a positive impact on the success of artificial intelligence implementation projects. This comes as no surprise, as organizational competency (Chatterjee et al., 2021) and digital skills (Kinkel et al., 2022) were seen to positively influence the perceived usefulness of artificial intelligence, as well as the continued success of artificial intelligence use in organizations. In the interviews, it was pointed out that the companies which tend to be technologically proficient are also the ones that will most likely be successful with implementing artificial intelligence as well:

> Those who are readier and have the "machine" already running, in terms of the operating model and the skills, and the organizational routine of this sort of development, will probably be able to extract the most value in the long term. (I10)

Some interviewees pointed out that with strong **partner support**, the technological hurdles of implementing artificial intelligence can be overcome with the assistance of external experts:

> Well, we've noticed that the deeper we go into AI, our own capabilities run dry and that's why we've had a discussion about what capabilities we need to develop in-house. (I4)

> So that's where we bring our partners in and try to think out the big picture, but then also they are the ones who are doing the machine learning pipelines and everything because we don't have that competency in-house. But now we're also starting to look at the question of should we build some competency in-house. (I5)

> The organizations with a competitive edge tend to have developed in-house skills and a strong partner network, with whom they've already for example created machine learning applications, already running in production. They've already shown their ability of leading such implementation projects and are mature enough to take on generative AI, for example. (I10)

In the end though, organizations also need to understand which skills and competencies must exist in-house, and which ones can be acquired from external partners without becoming too dependent on them:

> Some of these [data-intense use cases] exist in the very core of our business and that's why we shouldn't get all the capability from external partners. On the other hand, we still need to heavily partner up. We shouldn't aim to build everything involving AI by ourselves. We for sure face a lot of similar

issues that the others do as well, and for which a solution is being made somewhere around the world. (I4)

Willingness to change ways of working could be seen as a subset of the organizational culture, but the topic came up in the interviews so frequently that it deserves a code of its own. Loosely linkable to the perceived usefulness attribute that organizational compatibility was found to support by Chatterjee et al (2021), it comes as no surprise that when people are excited about the new possibilities and ways of working enabled by artificial intelligence, it supports the organizational adoption of artificial intelligence:

> I don’t think that in this sense, artificial intelligence is any different from other IT projects. In order to implement a use case successfully, you must be ready to adapt established ways of working, and you have to take into account the people whose ways of working are about to change. (I2)

> You can show someone what a better future looks like, but if the people are not willing to adapt to that and say this is what I want to do, then it doesn't matter what how good this platform or system is. (I7)

Organizational readiness could only be identified as a factor in four interviews, but. Defined as the “availability of the complementary organizational resources needed for AI adoption” (Enholm et al., 2022), examples of it were most often linked to competency centers or similar “sandboxes”, where clear resources had been directed towards the development of artificial intelligence applications.

> The idea behind the competency center is to sort of create a sandbox, where these innovations can be tested. At the same time, the competency center acts as a coordinating unit for the technical implementation of the innovations, they can do some of it by themselves, but they also know when to get assistance from partners with something. This lowers the barrier for taking an AI idea forward, as the one who came up with the idea no longer has to see it all the way through, but the implementation responsibility moves to this competency center. (I9)

> We now have this [competency center with an identifiable name] which we’ve chosen to invest into, as we’ve noticed that there is a need for this type of center of excellence to coordinate initiatives and develop our organizational capabilities. They think about how to coach our employees regarding AI, and they develop our AI roadmap. (I10)

6.1.3 Environmental factors

Environmental factors were mentioned less frequently than technological and organizational factors in the interviews. Based on this, it seems that companies consider the technological and organizational factors of artificial intelligence implementation to be more important than environmental factors, such as regulations or environmental pressure. All mentions of identified environmental factors in the interviews can be seen below in table 6.

TABLE 6 Interview mentions of environmental factors affecting the ease of implementation of artificial intelligence use cases

Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	**Total**
Regulations			X	X	X					X	X	5
Environmental pressure	X			X	X		X					4

Regulations were mentioned mainly in interviews with industrial organizations. The overall view on legislation and standards was quite neutral. Some were satisfied with the additional sensitivity around customer data, but regulations have also led to some anxiety and slowed down the implementation of various projects due to extra scrutiny. It is noteworthy to mention that practically each regulation that came up in the interviews, originates from the European Union, such as the GDPR and the proposed EU AI Act.

> Most of [parent company name] isn’t located in the EU, but we are, and yeah, all this privacy regulation such as the GDPR is quite relevant to us. I think it’s a good thing in the end, that we are being so sensitive around data and privacy. Some of our non-EU competitors aren’t as careful and polite with customer data as we are forced to be, but in a R&D context we also use everything we are allowed to use. (I3)

> In Finland for example, [core identifiable business process] is very regulated, which means that we have to be very precise with [process]. Whenever we implement artificial intelligence to [core products], we need to really make sure the output is always correct and reliable. There isn’t a chance to say that “Okay, today it didn’t really work”. (I4)

> It was called a “temporary AI task force” at first, but we now want to make it a bit more permanent, and we will be looking at basically incorporating our cybersecurity, our legal, our IP, and our privacy officers into the task force to screen the use cases because there is also regulation that is now coming up. So for example, the EU AI act wants us to inventory all these solutions that we have, right. So, our development process of new solutions and applications follows a process and we'll be incorporating these checks and balances in that process. (I5)

> Now, because of these increasing regulations, such as the EU AI Act for example, people are becoming anxious, as there is more scrutiny from the legal department. (I11)

Environmental pressure was mentioned as an implementation-altering factor in less than half of the interviews. The interview mentions coded under environmental pressure all roughly related to the desire to keep up with the competitors, exemplifying the concept of mimetic pressure (Bag, Pretorius, et al., 2021). The interviewees had noticed that the recent hype, especially around generative artificial intelligence technologies, had led to increased discussions about what the technology could mean to their respective businesses:

> Information about generative AI, in the form of hype and tons of news stories, has been so plentiful that people are coming to talk to me about AI use cases much more often nowadays. They've also seen how some AI solution has been applied to solve some problem elsewhere and that has made them think of ideas for our organization too. (I1)

Others, especially in competitive industrial sectors, mentioned that the way they feel environmental pressure relates to their desire to keep up with competition:

> Our business environment matters of course. We do look at our competitors. We need to keep up with them, that's absolutely essential. We have a clear goal of being the technological leaders in [industrial sector], and we must act accordingly. We know our competitors are developing these solutions too. (I4)

> So, it's human nature basically that, hey, my neighbour has this, why don't I have it or you know, I mean, we have whole business intelligence and competition teams who are checking the competition all the time. (I5)

6.2 Value sought from use of AI

The other major area of interest in the analysis were the types of value that the interviewees have sought and/or achieved by implementing artificial intelligence in an organizational context. By understanding what types of value the interviewees are trying to achieve by utilizing artificial intelligence, the prioritization of artificial intelligence use cases, partly based on the value they provide, becomes possible.

This chapter is divided into four subchapters, based on the categorization of firm-level impacts, or second-order effects, by Enholm et al (2022). Interview mentions of the second-order effects can be seen below in table 7.

TABLE 7 Interview mentions of second-order effects sought with the implementation of artificial intelligence use cases

Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	**Total**
Financial performance	X	X	X	X	X	X	X	X	X	X	X	11
Operational performance	X	X	X	X	X	X	X	X	X	X	X	11
Market-based performance	X	X	X	X	X	X						6
Sustainability performance				X	X					X		3

6.2.1 Financial performance

Financial performance was mentioned in every single interview as being a crucial type of value sought with organizational artificial intelligence. As every interviewee represented a for-profit organization, it makes sense that financial gain is the ultimate goal of each business process, investment decision, and technology implementation. Use cases and processes described by the interviewees didn't always directly correlate to more revenue, but financial performance was to be indirectly gained through each enhanced process, new insight, and saved resource.

> So I mean for a corporate organization, you know… there are basically… the main thing is to generate value for the shareholders. Everything else just enables it. (I5)

> Technology is to serve the means of the business. Otherwise, like what is it there for? If it's not there to increase the line items on the income statement or the balance sheet or drive revenue and you know drive gross profit, it's not doing those things. (I7)

> I think that all companies that utilize artificial intelligence, or are systematically trying to advance it, are performing measurably better. I think that the consensus in the studies at the moment is that artificial intelligence is able to bring growth and efficiency to the actual business. (I8)

> There's a real desire in companies in the process industry to find new revenue streams alongside their existing product business, especially with data and artificial intelligence powered services. That's a huge trend right now. (I10)

When asked about what kinds of value the interviewees expected to gain when implementing artificial intelligence solutions, many interviewees directly referenced the fact that they work in for-profit organizations, where achieving financial performance is also an obligation the companies have for their shareholders.

> If you think about it in an honest way, [parent company] is a global listed company, and the financial side is always the last driver there. (I3)

> But of course, the next step is to start generating revenue with these artificial intelligence solutions. We are a joint-stock company, not a registered association, and developing this stuff costs money so we need to get income from this too. (I4)

> In an industrial environment, what things matter or what is sought after? We are trying to reach profitability, growth, something under the bottom line. We are seeking profits for the shareholders. (I6)

Some interviewees also reported that they had been able to measure concrete value from the implementation and subsequent use of artificial intelligence solutions:

> We've been able to measure concrete EBIT-value from our use of artificial intelligence, which has also been a standard and desire in our other development projects too. I mean the measurement of concrete EBIT-value. (I1)

> The amount of change in the last 18 months that we've been able to bring to bear for companies and allow them to open up new markets, do 2/3/4 times the business with the same head count and so their profit margin grows very quickly. (I7)

6.2.2 Operational performance

Operational performance was another second-order effect that was reported as a highly sought-after value type by the interviewees. As defined by Enholm et al (2021), operational performance consists of new and enhanced products and services. Many interviewees reported that perhaps the clearest gains they had achieved with artificial intelligence so far related to internal efficiency gains, through applications like intelligent searching or digital twins:

> Talking about spare parts or the parts which our [machines] are built with, searching for knowledge about them is, I don't know how it is with others, but for us it is really advanced nowadays. It saves a lot of working hours every time we can find information quickly. (I3)

> And of course, we also use artificial intelligence to enhance our factory manufacturing processes. We have a full digital twin of our production line and of course we're constantly simulating changes to it with artificial intelligence to see how we can optimize our manufacturing processes. (I4)

> Of course, [one category of value interviewee organization has gained from AI] are the internal operational benefits, the things that we think that each company should do, which we are also doing ourselves, stuff like where we can conduct our operations better, more efficiently, with more quality, and offer our new services to clients. (I8)

> And then a third place to create value [with AI] is of course to augment our own products competitiveness with artificial intelligence, which is something that we really are an example of. (I9)

Although not many interviewees mentioned that they had been able to establish entirely new business models with artificial intelligence, it was in the plans for some:

> We are looking at enabling new business models with AI, we are not there yet, but if we proceed with our journey, I think it would be a matter of time, right? (I5)

> We've seen a trend with our industrial clients where they want to find new revenue streams along their existing product business, with creating new artificial intelligence and data-based services. (I10)

6.2.3 Market-based performance

Market-based performance was defined by Enholm et al (2021) as the gains that organizations gain from using artificial intelligence for marketing purposes and for measuring and increasing customer satisfaction. Quite a few interviewees mentioned that their organization is utilizing artificial intelligence for various marketing tasks:

> While for example our marketing department content creation processes benefit from these translations, text generation, video, and audio generation tools. (I2)

> One of the first use cases we have in our organization for artificial intelligence is identifying more opportunities for after-market services. (I4)

> Our marketing people are using various artificial intelligence tools. (I4)

> We are kind of using the real creativity of generative AI more in the marketing side where we perhaps have to write an e-mail or a marketing slogan, or we have to write an expose or Twitter post. (I5)

Bringing value to customers was emphasized as an almost existential value in itself to multiple industrial organizations, and a "customer-first"-mentality partly steered the development and implementation of artificial intelligence applications.

> While this all influences our finances, this customer-facing, customer satisfaction, what we call [identifiable slogan, same meaning as "customer first"] is the ultimate measure for us at all times. (I3)

> Well for us the number one value to be gained from the use of artificial intelligence is of course the value we can provide to our customers. That's the reason why we exist. (I4)

> We are trying to make things better for our customers and our employees. If AI is one of the things that helps us do it, we will do it. (I5)

6.2.4 Sustainability performance

Sustainability performance was the least mentioned second-order effect in the interviews. While no interviewee claimed that sustainability performance is not an important or otherwise sought after type of value, it didn't seem to have much impact on what types of applications would be implemented. For manufacturing organizations, sustainability seemed to steer development through regulations, highlighting the "governance" in "ESG":

> We might have a situation where a customer comes in and says that by 2035 their operations need to be fully carbon-neutral, and for that they need these types of products and services from us. (I4)

> A lot of companies focus on sustainability in this sector because these days you need a license to operate in some countries and unless you have [sustainability-based objectives], you cannot do that. So, in the end it all comes back to creating value for the shareholders. (I5)

One interviewed consultancy organization seemed to implement CO2 emission calculations into the feasibility assessment of artificial intelligence applications, suggesting that sustainability is not only a factor in the manufacturing industry.

> More and more, there's also this sustainability perspective, like is this, from a sustainability and compliance standpoint, something that we can do, plus does this align with our values and is it sustainable to do this? It might be that the use case is feasible to implement, but the gained value would be modest at best, and the CO2 emissions from us doing this would be so enormous that there's no sense in trying to solve this specific problem. (I10)

In the end though, while sustainability might not have been directly stated as a desirable value to be gained from the use of artificial intelligence in many interviews, it could be that organizations are also indirectly aiming towards more sustainable processes via efficiency boosts, for example.

6.3 Value creation mechanisms and first-order effects

This chapter examines the identified process-level impacts and value creation mechanisms, as mentioned in the interviews. For the purposes of this analysis, the choice to combine both the first-order effects as defined in Enholm et al (2022) and the value creation mechanisms, as defined in Shollo et al (2022), was taken as both concepts relate to similar ways of extracting organizational value throughout the use of artificial intelligence. Interview mentions of the first-order effects can be seen below in table 8, while mentions of value creation mechanisms can be seen below in table 9.

TABLE 8 Interview mentions of first-order effects, identified by Enholm et al (2021), in use by interviewed organizations

Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	**Total**
Process efficiency	x	x	x	x	x	x		x	x	x	x	10
Insight generation		x	x	x	x	x	x		x	x	x	9
Business process transformation	x						x	x	x	x	x	6

TABLE 9 Interview mentions of value creation mechanisms, identified by Shollo et al (2022), in use by interviewed organizations

Interview	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	**Total**
Task augmentation	X	X	X	X	X	X	X	X	X	X	X	11
Knowledge creation		X	X	X	X	X	X		X	X	X	9
Autonomous agent			X	X		X			X	X	X	6

6.3.1 Task augmentation

Task augmentation was perhaps the most utilized mechanism of value creation in the interviewed organizations. Originally defined by Shollo et al (2022) as "ML applications" pursuing the "value target of more effective decision-making by enabling humans to either make better or faster decisions" (Shollo et al., 2022), for the purposes of this analysis the code was chosen to also include Copilot-like augmentative generative artificial intelligence tools in everyday work, which have become widespread after 2022.

Perhaps the most often-mentioned artificial intelligence implementations falling in the task augmentation category were Copilot-like tools. Since the introduction of ChatGPT in late 2022 (OpenAI, 2022), generative artificial intelligence tools have become widely utilized for a multitude of roles. Many interviewees reported that their software developers utilize GitHub Copilot for enhancing their development productivity, while a lot of marketing specialists used Copilot-like tools for content creation and translations, for example. Enhancing the personal productivity of individual employees seemed to be the overall goal of these types of artificial intelligence tools. This individual-centric benefit can also be seen in the adoption process of such tools: many knowledge workers might be used to using ChatGPT in their daily lives and might continue utilizing such tools for work tasks too, without any defined organizational adoption process, for example.

> The amount of time available to do meaningful, creative work is constantly growing thanks to artificial intelligence tools sort of cleaning all of the mundane stuff away. That's in my view the number one mechanism that's creating value with these tools. (I2)

> Well of course, I mean generative AI is in daily use for us. Our developers bootstrap their projects with some kind of structure or boilerplate created by generative artificial intelligence. We use generative AI a lot for internal translations, as we have 24 languages in our organization. (I4)

> We use ChatGPT, and this GitHub Copilot. Those are pretty much our two most used [artificial intelligence] tools, and when I speak about us, I mean this digitalization business where we have software developers, designers, QA and DevOps engineers, and most of the gain for this lot we get from

> GitHub Copilot. Then there are obviously these image and video generators, such as DALL-E and Midjourney, and also for making PowerPoints we are using Microsoft Copilot. (I6)

> Instead of me spending time to write a full, polite email reply to a customer, I can ask Copilot to write the “basis” of the email and then I can fill in somewhere if needed. This way I can again remove the mundane, boring part of the job and thus refocus my time elsewhere. (I9)

In addition to Copilot-like assistants, some interviewees had already envisioned more advanced applications, tailored for their products and specific industry needs:

> The system is augmented with artificial intelligence. It gives the driver recommendations, such as to which tree to cut down. That tree there, that there, it gives optimized advice to the driver as to where to drive in order to reach as many trees as you can without moving the machine. Takes care of your distance to the previous tracks and so on. (I4)

6.3.2 Process efficiency

Process efficiency was defined as the automation of tasks or augmentation of human intelligence in an organizational setting in order to “improve business process performance by increasing efficiency indicators” (Enholm et al., 2022). This of course overlaps slightly with the other first-order impacts and value creation mechanisms being analysed, but many interviewees had also recognized the overall impact that artificial intelligence had already had in boosting the efficiency of their business processes.

> I think in the beginning especially, the number one value gained from generative AI is the overall efficiency gain for a large portion of the workforce in an organization. (I1)

> [When asked about what types of value had been gained from AI so far] The improvement of our overall process efficiency is one, output quality getting better is another, shorter time to market in our features and products, that’s one too. (I6)

> I think this report came out a few years ago already, but we managed to optimize the energy efficiency of [clients steel production plant] by an additional 10 percent just by optimizing the processes with artificial intelligence. (I9)

> I think for sure the main value our customers are trying to extract from the use of artificial intelligence in this market situation is efficiency in everything. During better times there was a lot of “how can I use this to create new business”-thinking, but right now the focus is on “how can we improve our efficiency?” We’re providing customer service efficiency benefits with these sorts of AI assistants, and we can also try to help enhance their R&D

> processes with AI solutions too. Overall, the focus right now is in efficiency, efficiency and efficiency. Automatization of different processes, or not even automatization but even getting rid of many processes via AI. Just trying to free up their expert's time for the harder things. Those sorts of things. (I10)

> Internally we've seen that making processes more efficient often leads to improvement in sales or a better-quality output, process efficiency is kind of a tool for reaching those benefits. (I10)

6.3.3 Knowledge creation / insight generation

One of the most common utilizations of artificial intelligence that surfaced during the interviews related to discovering new knowledge and insights from massive amounts of data, allowing for optimization and much more. As this phenomenon was described in Shollo et al (2022) as "tools for inductively identifying trends and patterns in historical data", and in Enholm et al (2022) as "unlocking insight and patterns hidden in large volumes of data", these theory-driven codes have also been merged for this analysis.

As about half of the interviewees represented industrial organizations, with the other half providing a multitude of services for the industrial sector, the amount of raw data produced by large industrial machinery was often a topic. With the advent of the Internet of Things and sensor technology becoming ever cheaper, nearly everything in these large and expensive machines is measured in real-time. Many interviewees reported their desire in analysing the vast amount of data with artificial intelligence methods, in pursuit of financial and operational performance among others. Reported use cases across the interviewed organizations varied from natural language document searching to predictive maintenance, both being mentioned in at least six different interviews.

As mentioned, natural language searching is a use case a lot of interviewees reported their interest or development in. Enabled by generative artificial intelligence technologies, implementations reportedly enable data searching from multiple sources with a problem formulated in spoken languages, instead of SQL or other query languages.

> We're looking at enabling information searching from a variety of complex information, such as OEM fault codes, maintenance logs, other data masses related to machine usage, their maintenance, customer data, sales, and individual parts and components. (I3)

> Let's say you had hundreds of thousands of PDFs or manuals of machinery. Now all of that can be loaded in the semantic search and applied against LLMs and so let's say you had, you know, fifty different versions of a machine and different life cycle stages and you were trying to troubleshoot traditionally. You would have to have someone with a lot of domain expertise and find the right manual and then try to find what the problem is, whereas now you could kind of query "Hey, this is the model number. Here's the symptoms of the problem. What should I troubleshoot and check

> first?" You can get an answer in a couple of minutes all off of what was ingested from PDF documents. (I7)

> Another use case for AI in our organization is analytics. This is something that I as a leader really like, because earlier the capability of our analytics related directly to how good I am at using Excel or Power BI, but now the capability is only limited by my imagination. I can directly talk to a Copilot-like interface, and point out that "There's a data source, I would like to understand these types of things from it" and the AI will do the visualization for me. I can then continue the dialogue with it to do some modifications until I like the final product. The skills required are no longer related to pivot tables in Excel but to how good I am at formulating my problems and figuring out what I really want to find out from this data source. All I have to do is point out data sources and ask away. It's really empowering, I finally get the answers that I've wanted. (I9)

Predictive maintenance was another often-mentioned use case that many of the industrial interviewees had already started implementing. As many of the interviewed organizations produce and sell machines that cost millions, it's not surprising that shutdowns and equipment failures are not something that neither the service provider nor the customer want to happen.

> We've anchored a hydraulic pump and built an algorithm around it, which can then, based on the pump's sensor data, figure out when the pump is going to break. We did it to two pumps and got down to an accuracy of a few hours on when it will malfunction. This concept is great as we can scale it up to other parts of our [product] and be able to warn the operators in time. (I4)

> Smart maintenance, how can we identify that a machine is about to fail? How can we avoid shutdowns, unnecessary equipment swaps and such, these are the things that we can do better with data now. The data tells us about parts getting dirty, about their performance. Data gives us this type of situational awareness to different layers now as well, from a specific part to the system, environment, and factory level too. (I6)

6.3.4 Autonomous agent

Autonomous agents, especially the "process automation"-subtype, were defined by Shollo et al (2022) as "using automation to increase productivity by substituting human labor through ML-based agents" (Shollo et al., 2022). Applications utilizing full automation without humans in the loop came up a lot less frequently in the interviews as compared to applications which supported human decision making and work processes.

> Our services marketing team who are creating real-time pricing for our machine configurations and talking to all the suppliers about what certain parts cost today and so on. It's a real chore, and we could use our internal

> teams to help with automating this process and save a lot of working hours. (I3)
>
> Our cloud-connected [products] upload a ton of signal data, I think it's every 8 seconds or so. The data has everything from engine RPMs to diagnostic codes, and were looking into sort of utilizing AI to automatically shift through and help with the diagnostic codes quality control and supervision. (I3)
>
> In one of our reference cases, we built our customers R&D department an analytics platform to help with creating better engine control algorithms. The platform also helps them to develop their soft sensoring, where instead of using physical sensors, they can now get similar information from the overall data and use it for emission measuring or similar. (I6)

6.3.5 Business process transformation

Business process transformation was a first-order impact defined in Enholm et al (2022), and it described the impact of artificial intelligence in business processes on quite a general level. Overall, this type of transformative impact was brought up in the interviews on a similarly general level, and with perhaps the vision being more in the future.

> It helps a lot with decision-making and it often alters some of our critical processes, whether they are internal or something on the side of the end-customer. (I1)
>
> I would say here in the last 18 months, generative AI has one, just kind of reignited the public conversation, but then two, the speed in which people are seeing vast amounts of change in their organization has gone from months and years to days and weeks, and even though they're kind of light applications of like, hey, we're connecting a couple of data sources and we're just solving for this one thing, the change is very stark. It's "Wow. This is wildly different than what my process was before in a better way. "And so, people are getting the value much sooner. (I7)
>
> I think for many, the first thing they start to think about is how will this change my job and my ways of working. Say you work in customer service at a bank, you might think that "OK, we could record these customer phone calls and maybe create a support package or loan template automatically from it" (I8)
>
> Now that these [artificial intelligence] tools have spread to other industries too, I can see that the same thing will happen there, that someone figures out that "Hey, I can do this in a totally different and new way now", and that they then get to break the existing structures of the market (I9)

6.4 Views on prioritization

In general, it seems that the hype around generative artificial intelligence does not seem to affect the technological architecture design choices behind use case ideas. The recent trend of popularity around artificial intelligence technologies, especially with generative artificial intelligence, could have driven organizations to adopt a technology-first approach towards solving their business problems, but many interviewees reported that they don't let the "hype" cloud their decision-making, and that they still base their prioritization decisions on the actual monetary value they estimate gaining from the implementations.

> Our final prioritization choices really relate to how much real EBIT-value we estimate getting from implementing something. (I1)

One interviewee even reported that they approach the problem of prioritization between different use cases through a standardized approach, where they evaluate the implementation through similar lenses as the value-feasibility matrix, presented earlier in chapter 4.

> We have this kind of four-dimensional framework that we use pretty much without exception in our projects nowadays. We assess the business viability of the use case, as in how much business value there is to be gained from this implementation. Then there's the feasibility aspect, where we assess if we have the data or the documentation and the technology to actually make this happen. (I10)

7 DISCUSSION

The aim of this thesis was to see how organizations should systematically prioritize and evaluate different artificial intelligence applications. To do so, a literature review was conducted, focusing on both the essential conditions and enablers affecting the success of artificial intelligence adoption in organizations, as well as the types of achievable value and the mechanisms through which this value can be created using artificial intelligence. After exploring the research on these two aspects of artificial intelligence initiatives, a value-feasibility matrix was developed and presented in chapter 4. With the theory-based matrix developed, an empirical study was conducted. After analysing the data gained from the interviews, this study has answered the following research questions:

- RQ1. What are the essential conditions and enablers for successful AI adoption in organizations?
- RQ2. What types of value are achievable with organizational use of AI?
- RQ3. Can a combined assessment of achievable value and implementation factors provide a systematic method for prioritizing AI initiatives?

In general, based on the conducted empirical study and its findings, it seems that the existing research regarding the enablers and prerequisites of organizational artificial intelligence adoption, the categories of value that can be achieved with the use of artificial intelligence, as well as the mechanisms through which artificial intelligence applications create value, align closely with the experiences from the field.

This chapter is divided into four subchapters. First, the value-feasibility matrix and the factors it's built with are reviewed, in light of the interview findings. Second, the theoretical contributions of this thesis are highlighted. Third, the managerial implications of this thesis are presented. Finally, the limitations of this study and its dataset are discussed, along with recommendations and ideas for future research.

7.1 Validating the value-feasibility matrix

Based on the empirical data gathered from the interviews, we can inspect the validity of the value-feasibility matrix, which was developed by utilizing existing theory, and presented in detail in chapter 4.

The proposed model included both the factors affecting the ease of implementation of artificial intelligence use cases, as well as the types of value achievable with artificial intelligence use cases. As the findings show, the factors affecting the ease of implementation align remarkably well with existing research, with only a few exceptions.

In the technological context, almost all interviewees identified having access to rich and relevant data (Baier et al., 2019; Dubey et al., 2020; Enholm et al., 2022) and modern, capable and scalable technology infrastructure (Baier et al., 2019; Enholm et al., 2022) as key factors for successful artificial intelligence implementations. Although mentioned in existing research, product complexity (Kinkel et al., 2022) was only mentioned as a factor in only one interview. The reason for this could not be determined from the gathered dataset.

In the organizational context, the theory-based factors also hold up well. Having a culture that fosters innovation (Enholm et al., 2022; Lee et al., 2019) was seen by every interviewee as a major benefit in the success of artificial intelligence implementations. Almost as popularly mentioned were top management support (Chatterjee et al., 2021; Enholm et al., 2022), internal skills (Chatterjee et al., 2021; Enholm et al., 2022; Kinkel et al., 2022; Shollo et al., 2022), and the overall compatibility with the implementing organization (Chatterjee et al., 2021; Enholm et al., 2022). The willingness to change ways of working was also mentioned in the majority of the interviews as having a positive effect on the success of artificial intelligence implementations. This factor was identified directly from the dataset, adding to the factors extracted from existing theory. Organizational readiness (Chatterjee et al., 2021; Enholm et al., 2022) was identified in four interviews as a factor, while partner support (Chatterjee et al., 2021) was identified in five interviews, mainly with representatives of industrial organizations.

In general, the environmental context was seen as the least important of the three contexts in the interviews. As hypothesized, regulations (Baier et al., 2019; Enholm et al., 2022) were seen in the field to have mainly a steering effect on what data could be used for the applications, while environmental or competitive pressure (Enholm et al., 2022) served as a driver or motivator for artificial intelligence development overall.

Of the four firm-level values defined by Enholm et al (2022), financial and operational performance stand out as the most sought-after firm-level values according to the interviewees. Most of the realized value with artificial intelligence so far had been achieved in these two categories. In addition, the task augmentation value creation mechanism (Shollo et al., 2022), along with knowledge creation / insight generation (Enholm et al., 2022; Shollo et al., 2022), were identified as the most utilized value creation mechanisms in the field currently. This finding suggests that when utilizing the value-feasibility matrix to prioritize artificial intelligence use cases, more emphasis should perhaps be placed on those with high estimated financial and / or operational performance, as well as on those that utilize the aforementioned value creation mechanisms. Some interviewees also reported that they base their prioritization decisions on the estimated monetary gains of the implementation, further encouraging the prioritization of financial performance.

The value-feasibility matrix, with its theory-driven and empirically validated factors, can be seen below in figure 4. The firm-level values and value creation mechanisms presented on the Y-axis are the ones where and how the interviewees had reported achieving value, while the factors in the three contexts on the X-axis are those that the interviewees identified as positively affecting the success of artificial intelligence initiatives.

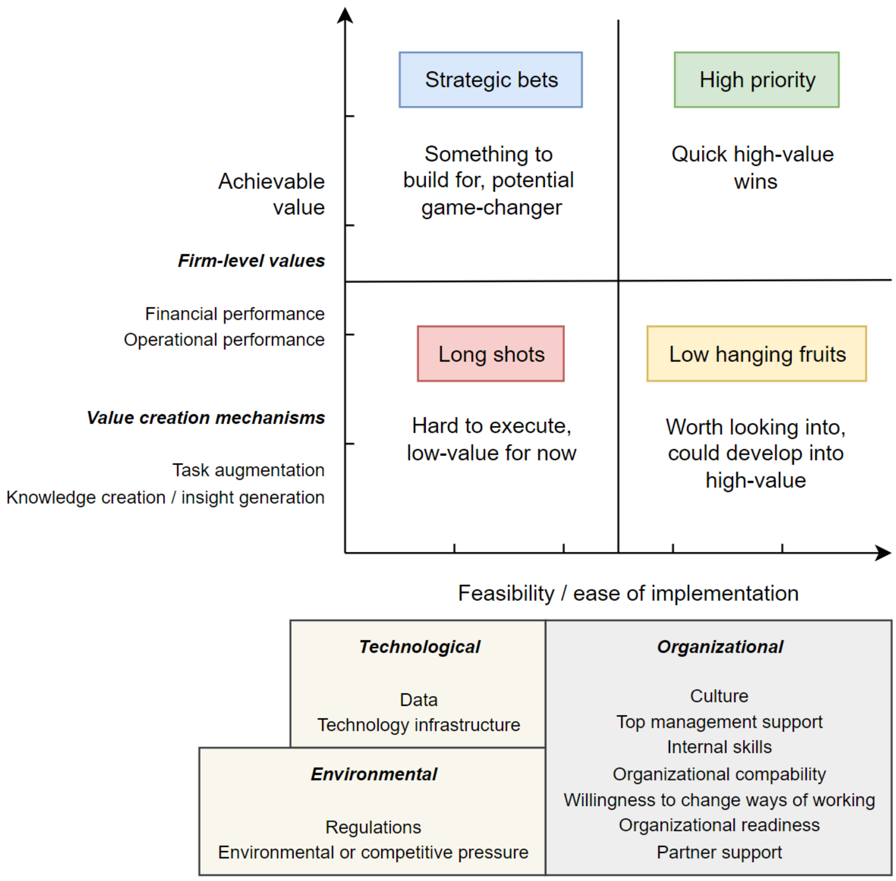

FIGURE 4 Value-feasibility matrix, with relevant firm-level values, value creation mechanisms, and factors affecting the ease of implementation

The objective of the model is to essentially map different artificial intelligence use cases on a matrix, based on their estimated ease or feasibility of implementation, and the estimated value gained from conducting such an implementation. The model assists organizations in planning their approach towards implementing artificial intelligence use cases in two clear ways.

First, the process of mapping the collected use cases on the model forces the implementors to estimate and summarize the key factors for each use case. This alone allows for the implementing organization to gain a holistic overview over the bottlenecks in their organization when it comes to the implementation of artificial intelligence: existing data, its accessibility, quantity and quality have to be reviewed, organizational strategies and skills have to be reviewed, and so on.

Second, after the mapping process is complete, the model provides clear guidance into the decision-making process regarding the prioritization of the collected artificial intelligence use cases. After mapping the use cases on the matrix, they are clearly categorized into different priority groups, which allows for a systematic approach into the actual implementation process.

7.2 Theoretical contributions

The ultimate research goal of this thesis was to develop a model for systematic prioritization of artificial intelligence use cases. The working principle of the model is that use cases are compared to each other through their estimated achievable value, as well as by their estimated ease of implementation. To be able to estimate both the achievable value and the ease of implementation, or feasibility, of a single use case, both aspects had to be properly defined. This was the essence of the conducted literature review.

The theoretical contributions of this thesis are numerous. First, the factors affecting the ease of implementation of artificial intelligence use cases in organizations were extensively reviewed. These factors were sought from highly relevant literature reviews (Chatterjee et al., 2021; Enholm et al., 2022; Kinkel et al., 2022), as well as various other sources (Baier et al., 2019; Dubey et al., 2020; Mikalef & Gupta, 2021; Shollo et al., 2022). The recurring enablers and preconditions of successful artificial intelligence implementations among these studies were then combined into a collection of crucial factors to be taken into account when evaluating the ease of implementation of an artificial intelligence initiative. This collection of various factors from multiple different sources contributes to existing research about the adoption of artificial intelligence in organizations, as their relevance and importance was also empirically validated in this study.

Secondly, this thesis also contributes to existing research about the business value that artificial intelligence helps organizations achieve. By combining the findings relating to the value creation mechanisms from Shollo et al (2022), and the process-level impacts from Enholm et al (2022), even clearer insight into how artificial intelligence can contribute towards firm-level impact has been gained. During the analysis phase of this thesis, it was discovered that perhaps the most common mechanisms organizations are using to gain firm-level value are the task augmentation value creation mechanism (Shollo et al., 2022), and by a combination of the insight generation process-level impact (Enholm et al., 2022) and the knowledge creation mechanism (Shollo et al., 2022). Autonomous agents with no humans in the loop were still quite rarely used. In other words, most of the measurable value that artificial intelligence applications had been able to provide in organizations according to the interviewees came from either boosting the efficiency of human workers, or by aiding the decision-making processes through enhanced data-driven insights. This finding also contributes to existing research by providing up-to-date insights from the spring of 2024.

The third theoretical contribution of this thesis relates to the group of interviewees. The dataset used in this thesis consists of representatives of both industrial “client” companies and technology “provider” companies. By interviewing and gathering insights from both sides of the artificial intelligence implementation process, from those implementing artificial intelligence and those supplying artificial intelligence solutions, the validity and relevance of the findings is even further strengthened.

Finally, the fourth theoretical contribution to artificial intelligence adoption research is the developed value-feasibility matrix. As mentioned in the introduction, a research gap was identified in the systematic prioritization of artificial intelligence initiatives. A model for exactly this has been developed in this thesis, and it’s built upon existing literature and new empirical data from the field. Future research could validate the model even further by applying it in practice and assessing its effectiveness in various organizations.

7.3 Managerial implications

The main takeaways from this study for organizations and organizational leaders can be divided into three parts. First, the study revealed that organizational factors are perhaps the most important of the three contexts concerning the successful implementation of artificial intelligence in organizational settings. The organizational factors can be thought to affect the organizations overall continuous success with artificial intelligence, while the technological factors are more use case specific. The essence of what a “successful” organization in terms of artificial intelligence implementations and use, as discussed in the interviews, boils down to the following organizational factors: having a culture that fosters innovation, where piloting new solutions and projects is encouraged, where failure is accepted and where there is an overall willingness to adapt the ways of working. **Cultivating this type of culture within the organization should thus be a priority for leaders wanting to continuously succeed with artificial intelligence**. Top management support was also found to be crucial in order to secure enough investment into implementations. Utilizing partners in getting started was also seen as having a positive effect on the artificial intelligence adoption journey, but many reported that recognizing internal core competencies and developing them simultaneously was key in not becoming dependent on the partners.

Second, in order to successfully implement artificial intelligence solutions, the data and the technology infrastructure need to be in place. **Having solid foundations upon which to build various applications is a clear key success**

factor. Problematic systems within the existing infrastructure should be reviewed and, if needed, modernized to enable faster and more reliable artificial intelligence implementations. Organizational data and access to it should also be mapped and reviewed, in order to find poor-quality sections and other areas of development. As artificial intelligence applications operate on a "garbage-in, garbage-out"-principle regarding data (Lee et al., 2019), it is highly important that any data planned on being utilized by artificial intelligence applications is relevant, plentiful and accessible.

Third, this thesis provides a way for organizational leaders to prioritize their artificial intelligence initiatives. By utilizing the newly developed value-feasibility matrix, decision-makers can easily see which initiatives should be approached urgently, and which ones can be prioritized lower. By mapping artificial intelligence use cases on the matrix, organizational leaders also get a holistic understanding of what types of use cases are being ideated in the organization, what kinds of bottlenecks have been identified in the organization in both the technological and organizational contexts, and a sense of what kinds of value creation mechanisms apply best to their situation. **Thus, the value-feasibility matrix can serve as a valuable tool for assessing the overall organizational readiness for artificial intelligence implementations, as utilizing the matrix forces leaders to identify the current bottlenecks and limitations regarding the implementation process.**

7.4 Limitations and future research

While the study had a dataset comprising of 11 interviews with representatives of both manufacturing organizations as well as technology service providers and consultancies, the interviewees were mainly located in Northern Europe and North America. While no link could be established between the interviewee's experiences with organizational implementation of artificial intelligence, the value gained from it and the interviewees geographical location, future studies could gather a more global dataset to see if experiences differ in the Asia-Pacific or South American regions, for example.

Another limitation regarding the dataset concerns the target industry. Since the "client" focus group for the interviews mainly consisted of representatives from manufacturing organizations, the recorded experiences and analysis of ease-of-implementation factors and the value achieved through the use of organizational artificial intelligence may be skewed perceptions specific to the manufacturing industry. Other industries, such as the medical field, may have different experiences in terms of achieved value, the implementation process, and the factors affecting it. Therefore, it is recommended that future researchers should also interview representatives from other industry sectors to gather more diverse insights.

A third future research suggestion relates to the sustainability performance firm-level impact, as first observed by Enholm et al (2022). The findings of this study show that sustainability performance was the least sought-after firm-level impact in the interviewed organizations. Any explanation for this phenomenon couldn't be extracted from the collected dataset. Exploring the reasons behind why sustainability performance lagged behind other firm-level impacts, as well as an overall analysis on how artificial intelligence could help achieve organizational sustainability goals, could be of interest for future research.

8 CONCLUSION

The objective of this thesis was to develop a model for the systematic prioritization of artificial intelligence use cases. To achieve this, the thesis explored the existing literature on the factors affecting the success and ease of artificial intelligence implementations in organizations, the value that artificial intelligence can help achieve in organizations, and the mechanisms through which artificial intelligence creates that value.

The research questions this thesis aimed to answer revolved around what factors and enablers affect the success of organizational artificial intelligence implementation projects, what types of business value artificial intelligence can create, and if the systematic prioritization of artificial intelligence use cases is possible through comparing between their estimated ease of implementation and the estimated achievable value. In order to answer these questions, a study was conducted in two parts: first, a literature review in order to establish a theoretical foundation, and an empirical qualitative study to validate existing theory and the prioritization model.

The conducted literature review suggests that the factors affecting the success and ease of artificial intelligence applications can be logically divided into three contexts: the technological, organizational, and environmental contexts. This division was present in multiple reviewed studies, and it was also used in the development of the model produced in this thesis. The value that artificial intelligence can help achieve in organizations was also divided into separate categories. It was theorized that the firm-level impacts (Enholm et al., 2022) are created not only by the process-level impacts (Enholm et al., 2022), but also by several value creation mechanisms (Shollo et al., 2022). Based on the literature review, a model for the systematic prioritization of various artificial intelligence use cases was developed and presented in chapter 4, along with a summary of the literature review.

To validate both the reviewed literature and the model for prioritizing artificial intelligence use cases, empirical data was collected and analysed by conducting a qualitative study. The study comprised of 11 semi-structured expert interviews: five with representatives from industrial organizations, and six with representatives from artificial intelligence service providers, technology companies or consulting companies. The choice to interview both the “clients” and the “providers” allowed for insights from both perspectives, those implementing artificial intelligence and those supplying the artificial intelligence solutions.

The findings from the interviews correlated strongly with existing literature. The three strongest factors leading to the success of an artificial intelligence implementation related to having a culture that fosters innovation, having access to rich and relevant data, and possessing a modern, capable, and scalable technology infrastructure. Concerning the achievable business value with artificial intelligence, most interviewees reported seeking firm-level gains in financial and operational performance with artificial intelligence, while market-based and sustainability performance were less sought after. The most common ways of extracting value with artificial intelligence were through the task augmentation and the insight generation / knowledge creation value creation mechanisms.

This study was able to address the identified research gap on the prioritization of artificial intelligence initiatives in an organizational setting, by developing a model that helps decision-makers in comparing between the estimated ease of implementation and the estimated achievable value of each initiative. In addition, this thesis contributed to research on the adoption and use of artificial intelligence in organizational settings by combining existing literature reviews and new empirical findings on both the key factors regarding implementation success, as well as the types of business value that artificial intelligence can help achieve in organizations.

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APPENDIX 1 INTERVIEW QUESTIONNAIRE

Warm-up questions

1. Tell me about your current role?

2. How do you consider your industry in terms of turbulence (technological, customer, competitor), complexity and technology/data intensity?

3. What is your understanding of AI and machine learning? (What do you consider as AI)

4. What is your area of expertise?

Have the requirements/prerequisites and drivers for AI use changed after the emergence of commercial generative AI (GAI)? How can organizations evaluate their maturity for AI use?

5. Could you describe the journey/stages of AI adoption in your company? How has GAI effected this journey? (possible follow-up questions related to in-housing, outsourcing and using licensed commercial options like ChatGPT, Bing, MS Copilot, Salesforce etc., use cases vs. technology, top-down or bottom-up)

6. What kind of factors have you perceived/experienced important in AI use? How has GAI changed these factors in your opinion/experience? (possible follow-up questions related to skills, organizational factors, technology, data)

7. What have been the drivers behind AI use? How have they been different between GAI and other AI? (possible follow-up questions related to institutional pressures, urgency, perceived benefits etc.)

8. How do you see the need for maturity in terms of technologies, skills, data, culture, and other organizational and technical factors in adapting AI? How has GAI changed this?

9. How do you see the role of technical expertise of managers and employees in utilizing GAI?

What are the mechanisms through which AI is generating firm value? Are these different between "traditional AI" and GAI? Has GAI changed how companies generate firm performance using AI?

10. What kind of value are you seeking to gain by using AI? How has GAI changed the perceived value? (main focus on firm-level impacts, such as operational and financial performance)

11. How is AI generating this value? How is GAI different in this matter? (main focus on mechanisms/second order value targets, such as productivity & automation, knowledge/insight creation and task augmentation)

12. What value have you gained by using AI? How is GAI different in this matter? (If firm performance effect is not measured, focus on second or value targets or perceived value)

13. How important do you consider technological and organizational factors, such as possession of data, technologies, technical talent and data-driven culture in reaching these benefits? What is the role of environmental factors, such as industry characteristics? Is this different between traditional AI and GAI?

14. How are you using AI to generate new business models? How are you using GAI differently in this respect?

<u>How can organizations evaluate the potential of AI applications?</u>

15. What kind of AI applications/use cases are you conducting or planning? How has GAI changed this? (possible follow-up questions regarding the data utilized by the AI models)

16. How are you evaluating the potential of AI applications? Is it different with GAI?

17. How are you measuring the performance of AI applications? Is it different with GAI?

<u>How are organizations organizing around and managing their AI initiatives?</u>

18. How have you incorporated AI in your strategy? Has GAI changed this? (possible follow-up questions whether AI is in corporate or business line/unit strategy, is AI as itself or as a data [or similar] strategy?)

19. How have you organized your AI efforts? Has GAI changed this?

20. How are you managing your AI initiatives? Has GAI changed this?

21. How have you ensured that resources for AI applications are used effectively? Has GAI changed this? (possible follow-up questions regarding how it is ensured that correct method is used to solve the problem and whether GAI has affected this)

Extra question

22. How are you prioritizing between GAI applications and other AI applications?